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TO WHAT EXTENT DOES IN-PERSON SCHOOLING CONTRIBUTE TO THE SPREAD OF COVID-19? EVIDENCE FROM MICHIGAN AND WASHINGTON

Dan Goldhaber
Scott A. Imberman
Katharine O. Strunk
Bryant Hopkins
Nate Brown
Erica Harbatkin
Tara Kilbride

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To What Extent Does In-Person Schooling Contribute to the Spread of COVID-19? Evidence from Michigan and Washington
Dan Goldhaber, Scott A. Imberman, Katharine O. Strunk, Bryant Hopkins, Nate Brown, Erica Harbatkin, and Tara Kilbride
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ABSTRACT

The decision about how and when to open schools to in-person instruction has been a key question for policymakers throughout the COVID-19 pandemic. The instructional modality of schools has implications not only for the health and safety of students and staff, but also student learning and the degree to which parents can engage in job activities. We consider the role of instructional modality (in-person, hybrid, or remote instruction) in disease spread among the wider community. Using a variety of regression modeling strategies , we find that simple correlations show in-person modalities are correlated with increased COVID cases, but accounting for both pre-existing cases and a richer set of covariates brings estimates close to zero on average. In Ordinary Least Squares (OLS) specifications, in-person modality options are not associated with increased spread of COVID at low levels of pre-existing COVID cases but cases do increase at moderate to high pre-existing COVID rates. A bounding exercise suggests that the OLS findings for in-person modality are likely to represent an upper bound on the true relationship. These findings are robust to the inclusion of county and district fixed effects in terms of the insignificance of the findings, but the models with fixed effects are also somewhat imprecisely estimated.

Dan Goldhaber
Center for Education Data & Research
University of Washington
3876 Bridge Way N Ste 201
Seattle, WA 98103
dgoldhab@uw.edu

Scott A. Imberman
Michigan State University
486 W. Circle Drive
110 Marshall-Adams Hall
East Lansing, MI 48824-1038
and NBER
imberman@msu.edu

Katharine O. Strunk
College of Education
Michigan State University
238 Erickson Hall
620 Farm Lane
East Lansing, MI 48824
kstrunk@msu.edu

Bryant Hopkins
Education Policy Innovation Collaborative
Michigan State University
236 Erickson Hall
620 Farm Lane
East Lansing, MI 48824
hopki213@msu.edu

Nate Brown
Center for Education Data & Research
University of Washington
3876 Bridge Way N Ste 201
Seattle, WA 98103
nathanael.brown12@gmail.com

Erica Harbatkin
Education Policy Innovation Collaborative
236 Erickson Hall
620 Farm Lane
East Lansing, MI 48824
harbatki@msu.edu

Tara Kilbride
Education Policy Innovation Collaborative
Michigan State University
236 Erickson Hall
620 Farm Lane
East Lansing, MI 48824
kilbrid9@msu.edu

1. Introduction

There is substantial concern about the extent to which in-person K-12 schooling may increase the spread of COVID-19, both within schools and their wider communities. As of late autumn, 2020, school systems around the nation have been in flux. Many districts – and in particular large, urban districts – have been for the most part operating remotely since March of 2020 (Meckler & Strauss, 2020). In other districts, many students have been learning in-person at least a portion of the time since the beginning of the 2020-2021 school year (Sawchuk, 2020). As COVID infection rates reach unprecedented levels across the United States (Hanna & Wolfe, 2020), many state and local education policymakers are shuttering school buildings in favor of remote learning while others are making plans to remain in-person or to open buildings for in-person learning (Education Policy Innovation Collaborative, 2020; Sawchuk & Gewertz, 2020).[1]

As policymakers consider whether and how to open school buildings for in-person instruction or shift to remote learning, they are forced to balance fears about COVID risk with the potential for severe learning loss for school-age children (Dorn et al., 2020). There is a growing concern that remote schooling is not working well for students in general, and in particular for students who have been traditionally underserved by the public school system: Black, Latino, and low-income students, as well as students with disabilities (Agostinelli et al., 2020; Dorn et al., 2020). These concerns are beginning to be borne out in the literature: Evidence of learning loss is apparent across the country and in other countries where schools closed (Donaldson, 2020; Kuhfeld, Soland, Tarasawa, Johnson, Ruzek, & Liu, 2020a).[2] There are also concerns about the impact of school closures on the economy as parents—and women in particular—are forced to reduce work hours to provide childcare and support remote learning (Green et al., 2020; Miller, 2020).

The debate about whether or not to open schools for in-person learning has become heavily intertwined with political beliefs about the risk-reward tradeoffs inherent in the pandemic (Valant, 2020). In the summer of 2020, for instance, President Trump noted the importance of schools being open in the fall, "So what we want to do is we want to get our schools open. We want to get them open quickly, beautifully, in the fall" (Trump, 2020).[3] Trump's Council of Economic Advisors has also stressed the view that having students back in schools in person is key to economic recovery from the pandemic as it allows parents of young children to return to work (Council of Economic Advisors, 2020).

President Trump and his administration are hardly alone in their view that schools should be open for in-person learning. In the midst of rapidly growing COVID spread across the country, a bipartisan (though mainly Democratic) group of seven northeastern governors released a statement in November 2020 in favor of in-person schooling (with appropriate protections), despite the growing spread of COVID (Blad, 2020a), and President Joseph R. Biden Jr. has

[1] Schools in Detroit, New York City, Indiana, and Kentucky, for instance, had been open for in-person schooling for some students, but went fully remote in the face of rising COVID rates (Balingit, 2020; Richards, 2020; Wisely, 2020). Michigan closed all high schools for in-person learning for three weeks starting on November 18, 2020 (Oosting et al., 2020). This "pause" was extended through the winter holiday break. As a result, there was a 200% increase in the proportion of districts operating fully remotely in December relative to the beginning of November (Education Policy Innovation Collaborative, 2020).

[2] Notably, Kuhfeld et al (2020) cautions that there is likely bias in NWEA estimates of learning loss, as a full quarter of students – largely low-income and minority students – are "missing" from the sample.

[3] President Trump also, at the time, encouraged adherence to Centers for Disease Control and Prevention (CDC) guidelines for school openings. Interestingly, those guidelines were removed from the CDC website on October 29th, 2020 (Frick, 2020).

called on Congress to provide necessary funding to safely reopen schools during his first 100 days in office (Blad, 2020b). The view that schools can be open in person with a reasonable degree of safety also reflects positions held by various groups such as the American Academy of Pediatrics, the National Association of School Nurses, and the National Academy of Sciences, Engineering, and Medicine, all of which emphasized the importance, during the summer of 2020, of having students physically present in schools (American Academy of Pediatrics, 2020). Most recently, the Centers for Disease Control and Prevention issued guidance that schools could safely operate in-person (Centers for Disease Control and Prevention, 2021a).

Yet these professional and academic groups have not unequivocally backed in-person schooling. Rather, they have recommended in-person schooling only with appropriate safety measures (and funding for these measures) to mitigate the risk of COVID transmission. This is broadly consistent with the position taken by the nation's two largest teachers' unions, although the unions have demanded far more stringent mitigation strategies than have many other stakeholders, going so far as to support local decisions to sue or strike should teachers feel unsafe when required to return to in-person instruction (Perez Jr, 2020; Reiss & Bellware, 2021; Will, 2020).

One of the reasons for uncertainty about whether schools should be open for in-person education has been the shifting evidence about whether children transmit the coronavirus, at all and/or at rates that might be dangerous for in-school or community spread. President Trump, for instance, suggested at several points in the summer of 2020 that children do not transmit COVID (Dale et al., 2020). Since then, the CDC has made it clear that children, while typically having milder reactions to infection, can transmit the virus both to other children and to adults (Lopez et al., 2020).[4]

While it is now clear that children do transmit the virus, a growing number of health experts suggest that they are less likely to be vectors of the disease than are adults (see, for example, Weisberg et al., 2020). As evidence of this, researchers point to school systems both in the U.S. and around the world, noting that there are few places where schools appear to be vectors for large COVID outbreaks (Barnum, 2020; Lewis, 2020).[5] Indeed, the best evidence to date –using data from the United States and from Germany and Sweden – suggests that schools are not major spreaders of the coronavirus (Isphording et al., 2020; Oster, 2020; Stage et al., 2020; von Bismarck-Osten et al., 2020). That said, there are documented cases of outbreaks tied to spread inside school buildings (Furfaro & Bazzaz, 2020), so the question of community spread is whether having in-person schooling changes the rate of spread in the communities in which students are enrolled in schools. This will depend both on the use of measures to prevent COVID spread in schools as well as the counterfactual of how students and their families might behave if they were not in school.

In this paper we use data from two states – Michigan and Washington – on COVID case rates at the county level linked to information on school district instructional modality to assess the relationship between in-person schooling and the spread of COVID in communities. We estimate a series of models that predict county-level COVID rates, growth, and spread (the amount of time it takes to for COVID cases to double) and account for previous trends in

[4] There is mixed evidence about the likelihood that children are more likely than adults to transmit the virus (Garabedian and Haffajee, 2020), but the most current evidence is that older children are more likely than younger children to pass the virus on to others (Lewis, 2020).
[5] Other developed countries generally appear to prioritize keeping schools open, while closing bars, restaurants, etc. (Cook, 2020; Porter, 2020).

COVID spread. We also estimate models that separately predict COVID incidence and spread by age group. This allows us to examine whether or not there are differential impacts of in-person schooling on COVID rates for those who are school-age relative to adults within various age ranges.

The estimated relationship between instructional modality and COVID outcomes is likely to be correlated with various district and county level factors. The ordinary least squares (OLS) models we estimate include a rich set of covariates designed to control for these, such as mask wearing, geographic and population features, and political partisanship. In addition, we estimate specifications with school district or county fixed effects, exploiting within district or county (over time) variation so as to better control for unobserved factors that may influence COVID spread, particularly in ways that may cause spurious correlations between instructional modality and disease outcomes.

On the whole, our findings suggest that school districts' choices to offer hybrid or fully in-person instruction are not significantly contributing to COVID spread in communities when there are low or modest pre-existing case rates in the population. But there are some important reasons to be cautious about this conclusion. In particular, we do find, consistent with epidemiological predictions, that in-person schooling is predicted to lead to community COVID spread when pre-existing case rates in the counties in which school districts are located are high. Our estimates suggest that this relationship becomes statistically significant around the 95th percentile of pre-existing COVID case rates during our observation period in Michigan and the 75th percentile in Washington. And, as we describe below, community case rates in Michigan and Washington were quite different during the period we model, so the case rate in which in-person schooling is estimated to lead to increased community spread in Washington is considerably lower than the case rate in Michigan.

We reach our conclusions based on a number of econometric models and specification checks. It is clear the correlation in simple regressions between in-person and hybrid school district modalities and COVID case rates is positive. Models that account for the potential that the effects of in-person schooling could differ by community case rates and include covariates that attempt to control for compliance with social distancing and virus mitigation strategies result in significant reductions of the coefficients on instructional modality. In these models, on average, the relationships between instructional modality and COVID case rates are close to zero and no longer statistically significant. We estimate alternate models that use districts' estimated proportion of students actually attending school in each modality and find that, in Michigan, districts in which low proportions of students return to school in person or in hybrid modalities are particularly unlikely to contribute to spread, though even at higher levels of in-person take-up there is no evidence that returning to classrooms drives COVID outcomes in the surrounding communities, except at very high levels of existing community spread. In Washington, it appears that how districts bring students back to school buildings matters; when case rates in surrounding communities are at the 50th percentile or above, districts in which the far majority (over three-quarters) of students attend school in-person appear to contribute to COVID spread. These findings also hold for different age categories in the population.

There are three important caveats about the above findings. First, our analyses focus on the relationship between school modality and COVID case rates in the fall of 2020, which predates the spread of new strains of the coronavirus that are believed to be more transmissible (Centers for Disease Control and Prevention, 2021b). Second, our characterization of what constitutes "low", "moderate", and "high" (describe in more detail below) community case rates are based on the data we utilize from the fall of 2020. But this corresponds to a period when COVID spread was far less extensive than they are in the winter of 2020-2021.

Finally, we are cautious about overinterpretation of the point estimates given the strong possibility that our results could be biased based on unobserved factors that affect school modality offerings or choices to attend in-person schooling and are also related to COVID spread in communities. Our findings from models that include district or county fixed effects help account for unobserved heterogeneity and are broadly consistent with the OLS in terms of the insignificance of the findings for in-person schooling. Because these models are also somewhat imprecisely estimated, we employ a bounding exercise suggested by Altonji et al. (2005) and Oster (2019) to assess the degree to which our main results may be biased by unobserved factors that are correlated both with instructional modality decisions and community spread. This exercise suggests the OLS findings on in-person modality likely represent an upper bound on the true relationship. In other words, if the estimates from our OLS models are biased, it is likely in the direction that would overstate rather than understate the relationship between in-person modality and COVID spread. All together these results across multiple model specifications that address different types of statistical bias suggest that we can reasonably rule out modest positive average causal effects of modality on COVID spread in communities with low to moderate levels of pre-existing COVID case rates.

2. Background

The tension between school safety and potential and realized learning losses associated with remote schooling underscores the debate about whether schools should offer in-person instruction. While there is some documentation of COVID spread that can be traced to individual schools (Furfaro & Bazzaz, 2020; Martin & Ebbert, 2020; Razzaq, 2020; Stein-Zamir et al., 2020; Wisely, 2020), the public narrative, buoyed by safe school openings in parts of Asia, Europe, and Australia (Macartney et al., 2020; Yoon et al., 2020), is that in-person schooling is not associated with significant increased viral transmission (Harris & Carpenter, 2020; Issa, 2020; Oster, 2020; Simchuk, 2020). However, it remains unclear if this holds during periods of increasing infection rates like the U.S. experienced in late autumn of 2020.

At the same time, emerging research suggests that many students are not well served by the shift to remote instruction.[6] There is mounting concern about students suffering from learning loss. This is especially true for lower performing students (Hart et al., 2019; Heppen et al., 2017; Loeb, 2020) . Estimates from a variety of different localities suggest significant learning losses among already disadvantaged students (Dorn et al., 2020; EmpowerK12, 2020; Hoffman & Miller, 2020; Korman et al., 2020; Kuhfeld, Soland, Tarasawa, Johnson, Ruzek, & Lewis, 2020; Kuhfeld, Soland, Tarasawa, Johnson, Ruzek, & Liu, 2020b; Malkus, 2020; von Hippel, 2020).[7] These learning losses are estimated to have lasting negative impacts both on the

[6] There are concerns that teachers and schools may lack the necessary resources to transition to remote learning (Cummings et al., 2020; Kamenetz, 2020; Organisation for Economic Co-operation and Development, 2020; Weir, 2020), and that student engagement may be lower with remote than in-person instruction (Dorn et al., 2020). One estimate suggests that as many as three million students across the United States have not received any formal education since schools closed their physical doors in March 2019 (Korman et al., 2020).

[7] A large literature on summer slide provides some context for understanding the implications for learning loss that researchers and policymakers can extrapolate to pandemic-driven school closures (von Hippel, 2020). More recently, however, losses are estimated based on interim tests. One such study found that third- through eighth-grade

future earnings of these students and the U.S. economy as a whole (Azevedo et al., 2020; Hanushek & Woessmann, 2020; Psacharopoulos et al., 2020).

Evidence for school closure as a mitigation strategy for the spread of COVID-19 comes largely from retrospective analyses of school closures during prior flu outbreaks and pandemics. These studies, many of which focused on the 2009 H1N1 pandemic, largely found that efficiently timed school closure during a flu outbreak was an effective measure for reducing spread (Bin Nafisah et al., 2018; Jackson et al., 2014, 2016). Descriptive studies of non-pharmaceutical interventions during the 1918 flu pandemic found that cities that closed schools had lower death rates than cities that did not close schools and that cities that implemented control measures that included school closure had lower spread (Bootsma & Ferguson, 2007; Winslow & Rogers, 1920). School closures during the 1918-1919 flu pandemic did not appear to have negative effects on student learning or future adult outcomes such as wages—though these closures lasted for shorter periods than COVID closures (Ager et al., 2020).

While knowledge from past pandemics provided a foundation for developing virus mitigation measures early in the current pandemic, there are health reasons to wonder about the degree to which school closures may not have the same mitigating effects on the spread of COVID as they appeared to have on earlier outbreaks, and on influenza outbreaks specifically (Viner et al., 2020). In particular, children are more likely to become infected with the flu and transmit the flu than are older adults (Wallinga et al., 2006), whereas there is some evidence that children may be less likely to become infected with COVID than older adults (Goldstein et al., 2020; Lee et al., 2020).[8] A literature review on children's role in the spread of COVID-19 finds that while children do transmit the virus, they are less likely to seed outbreaks (Ludvigsson, 2020). However, another study finds evidence that children do, in fact, both contract COVID at similar rates to their teachers and spread it even when they are asymptomatic (von Bredow, 2020). The closest analogy to schools and COVID-19 transmission may therefore come from research on school closures in response to other coronaviruses, such as the 2013 severe acute respiratory syndrome (SARS) outbreak, when closures did not appear to reduce spread (Cowling et al., 2008; Pang, 2003; Viner et al., 2020).

The handful of studies that have examined whether COVID infections in schools appear to spread within and outside of the school reach mixed conclusions. Two retrospective case studies—one in three schools in northern France and one in two Helsinki area schools—find that infected students did not appear to spread COVID beyond the school setting (Dub et al., 2020; Fontanet et al., 2020). A study of children who were infected with the virus in Mississippi finds

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students performed similarly in reading in fall 2020 as their counterparts in fall 2019, while math achievement was 5-10 percentile points lower for these students. Note, however, that the magnitudes of these effects are a bit uncertain for two reasons in particular. First, a large number of students were not tested. Second, the exams were taken at home and were not proctored (Kuhfeld, Soland, Tarasawa, Johnson, Ruzek, & Lewis, 2020). Region-specific data from the United States point to much more troubling trends (e.g., EmpowerK12, 2020; Donaldson, 2020). A study drawing from national exams taken in person in the Netherlands found that students lost approximately 20% of a school year following an eight-week lockdown (Engzell et al., 2020).

[8] Children are also less likely to exhibit COVID-19 related symptoms or to exhibit only mild symptoms (Nikolai et al., 2020), though it is not clear whether the presence of asymptomatic or mildly symptomatic cases would increase or decrease spread. On the one hand, being asymptomatic may be indicative of lower viral load (Zhou et al., 2020) and hence a reduced risk of transmission to others. But it is also possible that asymptomatic but infected students are more likely to infect others because they are not identified as being contagious. Even children without symptoms can carry viral loads high enough to infect others (Hu et al., 2020; T. C. Jones et al., 2020), and limited testing capacity, combined with lower demand for testing among those who are asymptomatic or at lower risk for severe symptoms, may lead to an undercount of cases among children (Couzin-Frankel et al., 2020).

that children who were infected were no more likely to have attended school or child care than control group children who were not infected (Hobbs et al., 2020). However, a study tracing a large outbreak in an Israeli high school shows that the outbreak was seeded by two cases and spread beyond the school (Stein-Zamir et al., 2020). Most recently, studies from North Carolina and Wisconsin have shown that within-school transmission of COVID is extremely limited especially when mitigations strategies are in place (Falk, Benda, Falk, Steffen, et al., 2021; Zimmerma, Ibukunoluwa, Brookhart, Boutzoukas, et al., 2021). One can also look to higher education for evidence; Mangrum and Niekamp (2020) show that students returning from spring break led to large increases in COVID cases in the wider communities around colleges, and there is also evidence of higher death rates in communities in close proximity (Ivory et al., 2020).

There are also concerns that school-based spread could impact the adults who work in the schools. Indeed, this has been one of the primary arguments from the national teachers' unions. One study found that 42 to 51% of school employees had increased risk or potentially increased risk of severe COVID (Selden et al., 2020). But there is also little evidence about how adults in K12 schools are impacted by in-person schooling, with two observational studies and one simulation providing evidence that in-person schooling may contribute to higher rates of infection among staff and their partners, while a third suggests that childcare providers did not have a higher risk of infection (Cohen et al., 2020; Gilliam et al., 2020; Ismail et al., 2020; Vlachos et al., 2020).[9]

A growing literature has examined the role of instructional modality in community spread of COVID. A small number of papers investigate whether school *openings* are associated with increased community spread, including three rigorous studies that employed quasi-experimental approaches to isolate the impact of school re-opening. This research has found that re-opening K12 schools was not associated with increased community spread (Isphording et al., 2020; Stage et al., 2020; von Bismarck-Osten et al., 2020).[10] A U.S.-based study found that school openings were not associated with increased hospitalizations when baseline hospitalization rates were low, but that openings may be associated with increased hospitalizations when baseline rates were high (Harris et al., 2021).

A larger set of papers examine whether school *closures* are an effective strategy for mitigating community spread. The majority of these studies are correlational and yield mixed results; several suggest that closing school buildings is associated with reductions in COVID spread (Auger et al., 2020; Haug et al., 2020; Liu et al., 2020; Yehya et al., 2020), whereas others find that building closures were ineffective in stemming the spread of the disease (Chang

[9]A study of school transmission in England found higher rates of incidence among staff than students and higher rates of staff-to-staff and student-to-staff transmission than the other way around (Ismail et al., 2020). A study comparing infection rates of parents, teachers, and teachers' partners under in-person versus remote learning in Sweden found that the group exposed to in-person instruction was more likely to test positive for COVID-19 (Vlachos et al., 2020). A simulation drawing from data in one Washington county suggested in-person schooling would increase the infection rate of students, teachers, and staff in the school building (Cohen et al., 2020). By contrast, a study using self-reported survey data from United States child care providers in spring 2020 found that exposure to child care was not associated with increased risk of infection (Gilliam et al., 2020).

[10] Two of these studies employed quasi-experimental methods by exploiting exogenously determined staggered school reopening dates after summer break in Germany and found that re-openings were not associated with increased case counts (Isphording et al., 2020; von Bismarck-Osten et al., 2020). A descriptive paper on school re-openings found that openings in Denmark and Norway were not associated with increased community transmission (Stage et al., 2020).

et al., 2020; Iwata et al., 2020).[11] One of the quasi-experimental studies on re-openings in Germany also examined school closures and found that they were not associated with significant decreases in transmission among children or adults (von Bismarck-Osten et al., 2020).

There is to date a dearth of evidence from the U.S., where extant studies are either survey-based (Gilliam et al., 2020) or draw on data aggregated to the state-level to estimate the effect of statewide mandates, or both (Auger et al., 2020; Yehya et al., 2020). Because local context and the timing of the modality decision play significant roles in the extent to which school closures mitigate spread or school openings exacerbate it, the effect of these local decisions on community spread is relevant yet relatively unexplored thus far in the literature.

The role of in-person schooling in community COVID spread is of central importance to children, teachers and other school staff, families, and the broader economy and has been at the heart of the public debate about local, state, and national responses to the pandemic. There are, however, two significant empirical challenges associated with determining whether instructional modality – in-person, remote, and hybrid variations in between – influences the community spread of COVID. The first is that there is no systemic data collection about transmission in schools. This is perhaps best exemplified by the fact that Robert Redfield, at the time the Director of the CDC, referenced a voluntary (schools self-report) COVID tracker for virus spread inside K-12 schools.[12] Particularly problematic for this work is the fact that limited COVID testing capacity, combined with lower demand for testing among those who are asymptomatic or at lower risk for severe symptoms, may lead to an undercount of cases among children (Couzin-Frankel et al., 2020). Even when children do get tested, rapid antigen tests appear less likely to detect the virus (Albert et al., 2020). When cases are identified, inadequate resources for contact tracing may undermine the ability to trace cases back to schools. Limited resources for testing and contact tracing are especially evident in the United States, where testing has not kept pace with the rising infection rates (Johns Hopkins University, 2020).

A second challenge is that there are good reasons to think that associations between instructional modality and COVID spread could be driven by spurious relationships. On the one hand, it is likely that any relationship between in-person schooling and COVID incidence or spread in the United States is inflated given that in-person schooling in the U.S. has been highly politicized. There is evidence, for instance, that political sentiment was a stronger predictor of school opening decisions than local case counts at the beginning of the 2020-21 school year (Center on Reinventing Public Education, 2020; Gross et al., 2020; Valant, 2020). More specifically, districts are opting to open in-person in communities that are more heavily Republican-leaning, and/or that have a greater tolerance for the risks of COVID spread in school.[13] In addition, there is mounting evidence that Republicans are less likely to practice

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[11] An interrupted time series analysis of statewide school closures in the U.S. found they were associated with reduced state-level incidence of COVID-19 in spring 2020 (Auger et al., 2020), and an observational study of virus mitigation strategies in the U.S. found that states that closed schools later in the outbreak experienced higher rates of mortality (Yehya et al., 2020). Two studies examining the effects of closures across multiple countries found that closure was among the *most* effective mitigation strategies for reducing COVID-19 spread (Haug et al., 2020; Liu et al., 2020). By contrast, another multiple-country study found that school closure was the *least* effective mitigation strategy (Banholzer et al., 2020), and observational studies in Australia and Japan also found that school closures did not appear to reduce incidence of covid-19 (Chang et al., 2020; Iwata et al., 2020).

[12] For more detail on this tracker, see https://covidschooldashboard.com.

[13] Additionally, teachers unions, which have more power in blue states where mask-wearing and social distancing are more prevalent (Allcott et al., 2020; Katz et al., 2020), have opposed what they see as “reckless re-openings” and threatened strikes in response to planned re-openings (Cassella et al., 2020).

physical distancing amidst the pandemic, and that political ideology matters more for the use of COVID mitigation strategies than other factors such as COVID rates and demographic characteristics (Adolph et al., 2020; Brenan, 2020; Clinton et al., 2020; Gollwitzer et al., 2020; Grossman et al., 2020; Schneider, 2020; Van Kessel & Quinn, 2020). Yet these same communities, on average, have higher rates of COVID-19 infection and death (Jones & Kiley, 2020). As such, it is difficult to disentangle whether in-person schooling is causing COVID rates to increase, or whether any relationship between in-person schooling and COVID rates is caused by the surrounding communities' COVID risk tolerance which drives both COVID spread and the decision to return to in-person schooling.

Assigning the likely direction of bias in models estimating the relationship between in-person schooling and COVID spread is not straightforward. There may be factors that lead to a spurious relationship in the opposite direction, suggesting a relationship between remote instruction and COVID spread where there may be none. In particular, there is evidence that U.S. schools in urban areas and with high rates of low-income families were more likely to begin the 2020-21 school year with remote learning (Center on Reinventing Public Education, 2020; Gross et al., 2020). Lower income workers are also less likely to have the opportunity to work from home. As a result, we might expect differential spread among adults at work based on income (Gould & Shierholz, 2020; Schaner & Theys, 2020). This makes it possible, and even likely, that there is increased COVID spread in the same communities in which districts are opting for remote instruction, but for reasons unrelated to modality decisions, thus creating a spurious correlation between remote schooling models and COVID incidence. In addition, the concern raised above about inadequate testing leading to artificially low COVID case rates could be particularly the case in communities that offer in-person schooling. If in-person schooling suggests a higher tolerance for risk and/or lesser concern about the potential dangers associated with the disease, then it may be that communities that embrace in-person instruction are precisely those that are less likely to get tests in the event they feel ill or are asymptomatic after encounters with a COVID-positive person. This would lead to an underestimate of COVID spread in communities with in-person schooling, which would then bias any estimates of the relationship between instructional modality and COVID rates or growth.

It is also worth noting that the estimated effect of in-person schooling on COVID spread greatly depends on what students and staff are doing under the counterfactual condition of no in-person schooling. While it may be natural to assume that removing students from contexts in which they are in close quarters in school buildings will allow for greater social distancing and COVID mitigation practices, the counterfactual for students and school personnel who are not in public school buildings is not necessarily a safer environment. For instance, some families whose schools closed for in-person education formed "learning pods," in which groups of students learn together with a tutor, parents, babysitter, or a certified teacher (Blum & Miller, 2020). In other communities, local community centers and nonprofits helped families to form pods and provided an adult caregiver who could help to oversee students' remote learning (Pillow, 2020). These pods may be in private homes or other contexts that do not require or allow for social distancing and mitigation strategies. Moreover, it is likely that individuals mix across and beyond their pods, as students in a pod then socialize with other children or family members outside of school hours (Natanson, 2020). Some families are moving their children to private schools, which are more likely to offer in-person schooling and may have varied safety practices (Dickler, 2020). Other families are sending their children to child care centers or hiring babysitters, both of which require the mixing of adults and children across family units and thus could on their own foster disease spread (Gilman, 2020). In short, we do not know what students do if school buildings are not open for instruction, but it is unlikely that the majority of students learn by themselves from home and do not interact with other children or adults outside of their family units. Thus, COVID spread can occur at the same or even greater rates in communities that are keeping school buildings closed.

It is also critical to consider the possibility of heterogenous modality effects. There is variation across school districts by a given modality in the local level of COVID cases. Having schools open in a local context where there are high levels of the virus would likely play a different role in community spread than doing so where the virus is less pervasive (Auger et al., 2020; Cohen et al., 2020; von Bismarck-Osten et al., 2020). Thus it is important that researchers consider the level of pre-existing community COVID rates when modeling instructional modality effects on COVID outcomes.

For all these reasons, it is important to be cautious when interpreting findings about the role of instructional modality in COVID spread. In the next section, we describe how we attempt to control for the various non-school factors that could influence community spread, and account for the potential of heterogeneous effects across counties. Our paper adds to the extant literature in several ways. First, we are able to include a near-census of districts in two states that have reacted very differently to the pandemic, Michigan and Washington. In these two states, we have data on the instructional modality as well as estimated enrollment by modality for nearly every school district in each state, which we pair with county-level measures of COVID case rates. Second, we examine the relationship between instructional modality and COVID outcomes for different age groups, enabling us to better understand whether public schools induce COVID spread across the age spectrum. Third, we are able to assess not only the initial school re-opening decisions in each district, but also changes they made in each month of the fall semester. This enables us to assess the relationship between changes in modality and changes in community-based COVID spread within individual counties, thus holding constant many of the unobservable characteristics that may contribute to the COVID incidence and to district decisions about instructional modality.

The remainder of the paper proceeds as follows: Section 3 reviews our data from both Michigan and Washington, highlighting similarities and differences across the two contexts. Section 4 outlines our methods of estimating the relationship between instructional modality and COVID spread in the surrounding communities. Section 5 describes our results. Section 6 concludes with a discussion of our results and implications for decisionmakers during this time of uncertainty.

3. Data and Measures

We focus our study on two states that have approached responses to COVID quite differently since the beginning of the pandemic – Michigan and Washington – and use data from several sources to understand how districts’ instructional modality decisions (fully in-person and fully remote schooling at the extremes) and students’ attendance by modality influence the spread of COVID-19. We primarily utilize data on reported COVID-19 cases collected by the CDC, as well as the respective state health agencies (i.e., Michigan Department of Health and Human Services [MDHHS] and the Washington Department of Health [WADoH]). District-level information on educational modality is collected by each of the states’ departments of education, in Michigan from the Michigan Department of Education and the Center for Educational Performance Information and in Washington from the Washington Office of the Superintendent of Public Instruction, via monthly surveys administered to school districts. The data used for the analysis are relatively consistent across both states, but, below, we provide details on slight differences between states in the data as well as context about COVID incidence and school modality in each.

COVID-19 Data in Michigan and Washington

Daily counts of newly confirmed COVID cases are available publicly for all counties in both Michigan (N=83) and Washington (N=39). As we show in Figure 1, both states experienced significant increases in new reported COVID cases relatively early in 2020. Like nearly every state, infections again rose during the summer months and reached unprecedented levels in November. However, the patterns of community spread across the two states are somewhat different. In particular, while both states show relatively low and slightly growing cases from the late summer through mid-October, cases in Michigan start to pick up and grow exponentially around mid-October. We do not see evidence of exponential growth in Washington, though there is some acceleration in November.

We calculate average daily COVID incidence counts across a rolling 7-day window, creating a more stable measure compared to single-day counts which tend to fluctuate due to reporting irregularities, particularly on weekends and holidays. We then use county population estimates from the 2019 U.S. Census county population totals to convert these average counts to relative rates per 100,000 county residents. The resulting 7-day average rates per 100,000 residents form the basis of the main outcome measure of COVID growth used in our analysis: the 7-day average rate on the first day of the month. We also examine our outcomes for COVID cases broken down by age groups by county using the following categories: 0-19, 20-39, 40-59, 60 years and older. In Michigan, these daily rate data are obtained through a data use agreement with the MDHHS. In Washington, these data are publicly available as weekly rates via the Washington Department of Health. We are particularly interested in the 0 to 19 year age group, as these numbers should reflect COVID spread amongst the school-age population, arguably where school related COVID outcomes would most likely appear.

In addition to the average daily COVID incidence counts, we examine three additional measures of COVID spread as specification checks for our main models. The first is the relationship between modality and community spread using unadjusted COVID-19 case counts and a negative binomial specification to account for the fact that underlying case counts are integers and do not drop below zero, which could generate specification bias in OLS models. The second is the rate of exponential growth in 7-day averages (calculated as described above) between the last and penultimate weeks of the month. A number of studies estimate this measure of growth to model the exponential nature of viral spread and to correct for outliers with very high case rates (Bursztyn et al., 2020; Courtemanche et al., 2020; Lyu & Wehby, 2020; Mangrum & Niekamp, 2020). Exponential growth is widely used to model spread in the early phases of epidemics when cases are relatively low (Bertozzi et al., 2020).[14] Since the 2020-21 school year began prior to the second wave, an exponential growth model could capture the beginning of the fall wave. The third outcome is COVID-19 doubling time (Muniz-Rodriguez et al., 2020), or the number of

[14] As is evident in Figure 1, there does not appear to be exponential growth occurring until relatively late in the fall of 2020 for Michigan (and not in Washington), so we consider these growth measures to be specification checks for our main measure.

days it would take to double the cumulative case count. A higher doubling time points to lower transmission while a smaller doubling time points to higher transmission. For context, the doubling time in the United States was estimated at 2.7 days in the early peak (Lurie et al., 2020).[15] Following Ebell & Bagwell-Adams (2020), we calculate doubling time using the 5-day rolling average. As with the 7-day averages described above, this approach helps to mitigate noise from local reporting idiosyncrasies in small counties.

District Instructional Modality Data

Both states' departments of education are surveying school districts monthly to collect information about the mode in which instruction is being delivered during the pandemic. In Michigan, districts are asked to indicate how they plan to deliver instruction in each upcoming month, while in Washington, districts report the mode in which instruction was delivered on the final day of the month. In order for the timing of the surveys to align as closely as possible across states, we assign Washington end-of-month surveys to the subsequent month. (e.g., Michigan districts' modalities at the beginning of October are compared to Washington districts' modalities on September 30th). Michigan modality data are available for the months of September, October, and November. Because the first Washington survey was conducted on the last day of September (which we infer as representing instructional modalities for the beginning of October), these data are only available for the months of October and November.

The definitions of instructional modalities vary slightly between the two states due to differences in the ways their surveys are structured. For Michigan, the definitions of instructional modality are based on what districts offer their general education students. We define "in-person" districts as those that provide general education students with the opportunity to receive full-time in-person instruction; in some cases students may opt for either hybrid or remote instruction. "Hybrid" districts are those that offer some or all of their general education students in-person schooling at least some portion – usually two to three days – of a week. "Remote" districts are as those that provide all instruction in a remote or virtual format for all of their general education students. These definitions are mutually exclusive and are based only on the mode of instruction provided to general education students and therefore may not reflect the modality provided to special populations of students. For instance, if a district provides fully remote instruction to all general education students and fully in-person instruction to all special education students, it would be classified as a remote district. (See Education Policy Innovation Collaborative (2020) for more detail on the Michigan modality definitions.)

Washington districts are classified as "in-person" if they indicated they provided "typical/traditional in-person" instruction to elementary, middle, and/or high school students, classified as "remote" if all of their students, or all except small subgroups of students, received fully-remote instruction, and classified as "hybrid" if all students received "partially in-person" instruction or the district used a "phase-in" approach where some students received partially or fully in-person instruction while others still received remote instruction.

One concern with discrete district instructional modality data is that not all students choose to enroll in the in-person or hybrid modality even if it is offered. Districts in each state were also asked to approximate the share of students who received different modes of instruction

[15] In Michigan, the doubling time was 2.7 prior to the March 24, 2020 stay-at-home order (Executive Order 2020-21) and 21.5 when the order was in place. In Washington, it was 4.3 prior to the March 23, 2020, stay-at-home order and 31.9 during the order (Lurie et al, 2020).

(in Michigan districts were asked to estimate in-person and hybrid separately and in Washington they were asked whether students were "receiving some level of in-person instruction"). In Michigan, districts were asked to select one of the following percentage ranges: 0%, 1-24%, 25-49%, 50-74%, 75-99%, or 100%. The Washington survey is structured similarly, but uses slightly different percentage ranges: 0%, 1-10%, 11-25%, 26-50%, 51-75%, or 76-100%. In various specifications we use these estimates of student enrollment by modality to assess the relationship between estimated actual in-person or hybrid enrollment and COVID case rates and spread.

Community Characteristics

We utilize a rich set of covariates that are hypothesized to influence both instructional modality and COVID-19 incidence. First, we consider factors associated with an increased risk of spreading COVID-19 and/or an increased risk of adverse outcomes for members of the community who contract the virus. We use population size and age group estimates from the American Community Survey (ACS) to capture information about private school enrollment to county population and the age distribution within each county.[16] We focus specifically on the proportions of county residents that are school-aged children (because their risk of exposure is most impacted by decisions to open or close school buildings) and adults aged 65 or above (because they are at a higher risk of severe illness if infected). To account for the high levels of risk among nursing home residents and staff, we estimate the proportion of residents living in these facilities using the total number of occupied beds reported in the COVID-19 Nursing Home Dataset (Centers for Medicare and Medicaid). We also include the numbers of religious institutions and religious adherents per capita from the U.S. Religion Census (Religious Congregations and Membership Study, 2010), as gathering in churches or similar community institutions other than schools may pose more opportunities for the virus to spread.

We also consider contextual factors believed to shape local responses to the pandemic. As a proxy for efforts taken by members of a community to mitigate the risk of COVID-19 spread, we include county-level estimates of mask usage from a July 2020 survey conducted by The New York Times and Dynata and estimates of the share of people in a county who stay at home in a given day from the Bureau of Transportation statistics at the US Department of Transportation.[17] To capture local economic conditions, we include 2019 unemployment rates from the Local Area Unemployment Statistics program (Bureau of Labor Statistics) and individual poverty rates from ACS. For information about the political climate of a county, we also include the share of votes from each county in the 2016 presidential election that were cast for Donald Trump (drawn from the County Presidential Election Returns 2000-2016 dataset from the MIT Election Data and Science Lab).

Table 1 provides summary statistics by state, month, and modality. School districts in Michigan were far more likely than those in Washington to offer in-person schooling. In September, 58% of Michigan districts offered fully in-person instruction, typically as one option

[16] We use 1-year estimates of county population and age distribution from the 2019 ACS, and 5-year estimates of private school enrollment and poverty from the 2014-2018 ACS (as 1-year estimates are only available for counties with populations of at least 65,000).

[17] NYTimes data are publicly available here: https://github.com/nytimes/covid-19-data/tree/master/mask-use. The US DOT statistics are available at https://data.bts.gov/Research-and-Statistics/Trips-by-Distance/w96p-f2qv.

available to parents along with hybrid or fully remote instruction. Twenty-four percent provided only remote instruction with no fully or partially in-person options, and most of these districts were located in or near large urban areas. The remaining 18% adopted a hybrid model where students attend in-person for part of the week and participate in remote instruction for the remainder of the week. By contrast, in Washington, the vast majority of districts were either in a fully remote (64%) or hybrid (27%) model; the remaining 9% of districts, located predominantly in rural areas, were in-person.

In both states, districts that began the year with fully remote or hybrid instruction tended to shift toward modalities with more in-person instruction in subsequent months. By the beginning of November, 64% of Michigan districts provided fully in-person instruction to at least some of their students, while 20% provided hybrid instruction, and the remaining 16% were fully remote. In Washington, there were about half as many fully remote districts in November (33%) as there were in October. Most of these districts shifted from fully remote to hybrid instruction, while a few transitioned to fully in-person instruction; 48% of the state's districts provided hybrid instruction in November, while 12% provided fully in-person instruction.

Since we weight our regressions by student enrollment to better model the relationship between modality and COVID spread, Table 1 provides weighted summary statistics. As can be seen at the top of each panel of the table, the weighted shares of students enrolled in in-person districts is much smaller than the share of districts offering that modality (reflecting the negative correlation between district size in the likelihood of being in-person). In Washington, although approximately 10% of districts offer in-person instruction across the two months, only approximately 2% of students are enrolled in these districts, reflecting the largely rural and smaller nature of in-person districts. Because of this small share we combine in-person and hybrid districts into a single category for Washington.

In both states, there are notable economic, political, and racial divides between districts offering in-person and remote instruction. Remote districts in Michigan tend to have larger shares of Black students than in-person and hybrid districts, and this gap widens after September. Similarly, remote districts tend to have larger shares of Hispanic students compared to in-person districts. Remote districts in both states also tend to be in counties with lower shares of votes cast for Donald Trump in the 2016 election, and more frequent mask usage when compared to in-person districts, while in Michigan remote districts tend to have more people staying at home regularly. Although we observe discrepancies in poverty rates across in-person and remote districts in both states, they occur in opposite directions. In Michigan, remote districts tend to be in higher-poverty counties, while they tend to be in slightly lower-poverty counties in Washington. In both states, these economic discrepancies increase in magnitude over time as more districts shift toward in-person modalities.

In each state there are a set of districts that did not report their instructional modality in each month, as shown in Appendix Table 1A. Less than 3% of districts in Michigan are missing modality data in any given month. In Washington, approximately 3% of districts are missing data in October and 10% in November. The districts with missing modality data are similar to the districts without missing data, although in Michigan districts with missing data have a larger share of economically disadvantaged students and special education students, and in Washington districts with missing data have a larger share of Black students and are more likely to be located in suburban/town locales.

4. Methods

To begin to examine the association between school district instructional modality choices and county-level COVID-19 incidence, we estimate equation (1) by ordinary least squares:

$$COVID_{c,t+1} = \alpha + f\left(IP_{jct}, H_{jct}\right) + \gamma_1 Mask_c + \gamma_2 ShareAtHome_{\mathrm{ct}} + \gamma_3 TrumpShare_c + \boldsymbol{\Omega}' \boldsymbol{X}_{ct} + \delta_t + \varepsilon_{jct} \quad (1)$$

where *COVID* is one of three measures of COVID-19 incidence for county *c* at the beginning of month *t*+1: a) 7-day average COVID cases per 100,000 individuals; and as specification checks b) exponential COVID growth rate;[18] and c) doubling time[19]. For outcome (a), we also include lagged, 7-day average COVID-19 case rates per 100,000 individuals ending on the final day of each of the last four weeks of month *t*-1, which we refer to as "pre-existing cases", along with the square of this value. We include lagged COVID rates in this way to allow for growth rates to be high when existing cases are low (exponential growth) but to slow at higher case rates as behavioral responses and increased immunity "bend the curve" and start reducing growth. The second and third specifications do not adjust for pre-existing COVID-19 cases in month, *t*-1 as these are mechanically included in the dependent variable. In alternative specifications we also estimate our models using unadjusted COVID-19 case counts and a negative binomial specification, as well as age-specific outcomes for the following age groups: 0-19, 20-39, 40-59, and 60 years and over. All regressions are weighted by district enrollment and standard errors are clustered at the county level.

Our primary interest is the extent to which community spread is influenced by instructional modality, which is captured by the in-person (*IP*) and hybrid (*H*) variables for school district *j* at time *t*. These variables are captured multiple ways and slightly differently by state as described in Section 3. Hence, we utilize a few different specifications in how we consider modality. First, in Michigan we estimate models using the modality chosen by the school district:

$$MI_1 \colon f\left(IP_{jct}, H_{jct}\right) = \beta_1 IP_{jct} + \beta_2 H_{jct} \quad (2).$$

As noted in the prior section, in Washington, although approximately 10% of districts offer in-person instruction, only about 2% of students are enrolled in these districts. Given this, we combine the variables into a single combined indicator:

$$WA_1 \colon f\left(IP_{jct}, H_{jct}\right) = \beta_1 IP\_H_{jct} \quad (3).$$

In both states, for outcome (a), we also estimate models that interact these indicators with pre-existing COVID rates to allow for the impact of instructional modality to vary with baseline COVID rates:

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[18] $COVIDGrowth_{ct} = \ln(COVIDCases_{ct} + 1) - \ln\left(COVIDCases_{c,t+1} + 1\right)$ where $COVIDCases_{c,t}$ are total cases at time *t*.

[19] $COVIDDoubling_{ct} = \frac{t\ln(2)}{\ln\left(1+\frac{r}{100}\right)}$ where *t* is time in days between observations and *r* is the percentage growth rate in the five-day rolling average of cases per 100k persons during period *t*.

$$MI_2: f(IP_{jct}, H_{jct}) = \beta_1 IP_{jct} + \beta_2 H_{jct} + \beta_3 IP_{jct} \times COVID_{c,t-1} + \beta_4 H_{jct} \times COVID_{c,t-1} + \beta_5 IP_{jct} \times COVID_{c,t-1}^2 + \beta_6 H_{jct} \times COVID_{c,t-1}^2 \quad (4)$$

$$WA_2: f(IP_{jct}, H_{jct}) = \beta_1 IP\_H_{jct} + \beta_2 IP\_H_{jct} \times COVID_{c,t-1} + \beta_3 IP\_H_{jct} \times COVID_{c,t-1}^2$$

Importantly, many epidemiologists argue that in-person schooling is less likely to risk health and safety if cases in the community are low, but considerably riskier when cases are high (Boyle, 2020). This specification provides us with the ability to estimate levels of existing COVID rates where a given modality starts to affect overall disease spread.

Our data also include measures of district reported shares of students who enroll in in-person or hybrid modality when given the option. One issue with using the district modality choice is that even if a district is in-person or hybrid they will often give parents the option of keeping their children in a remote instruction, and evidence suggests that take-up of this option may be substantial (e.g., Education Policy Innovation Collaborative, 2020). Hence, while the district modality is a policy decision, the impact of modality on COVID rates is a function of the interaction of modality preferences of parents and the district policy; for this reason, we interpret findings on district modality as intent to treat estimates.

In both states, districts report estimated shares of students in-person in ranges. Though as we note above, the ranges and specificity by modality differ across states. We use this information to estimate model (1) with the following modality variables:

$$MI_3: f(IP_{jct}, H_{jct}) = \sum_g \begin{pmatrix} \beta_1 IP_{jct}^g + \beta_2 H_{jct}^g + \beta_3 IP_{jct}^g \times COVID_{c,t-1} + \\ \beta_4 H_{jct}^g \times COVID_{c,t-1} + \beta_5 IP_{jct}^g \times COVID_{c,t-1}^2 + \beta_6 H_{jct}^g \times COVID_{c,t-1}^2 \end{pmatrix} \quad (5)$$

$$WA_3: f(IP_{jct}, H_{jct}) = \sum_g \left(\beta_1 IP\_H_{jct}^g + \beta_2 IP\_H_{jct}^g \times COVID_{c,t-1} + \beta_3 IP\_H_{jct}^g \times COVID_{c,t-1}^2\right)$$

where $IP_{jct}^g, H_{jct}^g, IP\_H_{jct}^g$ are indicators for whether the district reports student enrollment falls in modality group g. In Michigan $g \in (1\% - 24\%, 25\% - 49\%, 50\% - 74\%, 75\% - 100\%)$ Washington $g \in (1\% - 25\%, 26\% - 50\%, 51\% - 75\%, 76\% - 100\%)$. In both states, remote-only districts are the omitted category.

We also include variables designed to account for non-schooling risk factors for COVID spread as controls. $Mask_c$ is the share of individuals in county i, who report "always" wearing face masks when in public as of July 2020. $ShareAtHome_{\mathrm{ct}}$ is the seven-day average from the last week of month *t* of daily county-level estimates of the share of people who stay at home calculated by the US Department of Transportation. These variables serve as proxies for compliance with social distancing measures. $TrumpShare_i$ is the share of the 2016 presidential election vote for President Trump, which serves as a measure of political leanings in the county. **X** is a vector of time-invariant county-level characteristics including the 2019 county unemployment rate; the 2018 individual poverty rate; the shares of the population that attend county public schools, the share of the school population in private schools, is age 65 or older, and lives in a nursing home, share of population that is not White or Asian (underrepresented minority groups), urbanicity, the shares of religious congregations and religious adherents per capita in 2010 (the most recent year of data available), whether the county has a college or university, and whether the county has a prison;[20] δ is a month fixed effect; and ε is an error term. The vector also includes the share of public school students relative to the population of each county as we might expect the risk of community COVID spread due to in-person schooling to depend on how important the student population is in a county.[21]

The above models will produce unbiased estimates of the influence of in-person schooling on community spread if $Cov(\varepsilon_{cjt}, InPerson_{cjt}) = 0$ and $Cov(\varepsilon_{cjt}, Hybrid_{cjt}) = 0$. But, as we described in Section 2, there are reasons to believe that instructional modality decisions are correlated with unobserved COVID mitigation strategies by individuals or institutions. However, the signs of $Cov(\varepsilon_{cjt}, InPerson_{cjt}), Cov(\varepsilon_{cjt}, Hybrid_{cjt})$ are uncertain. On the one hand, it is reasonable to assume that counties that emphasize safety are likely to both limit in-person schooling and take other steps to mitigate COVID transmission that are not accounted for by the covariates in equation (1). This would lead the estimates on modality to be biased upward. Alternatively, the counterfactuals to students (and teachers) being in public schools could be less safe in terms of COVID spread (e.g., learning pods) and parents may seek social engagement for children in non-socially-distanced environments. Again, if the covariates fail to account for this, the estimates would be biased, but possibly downward.

To try to account for unobserved heterogeneity in mitigation strategies across counties, we exploit the longitudinal nature of the data (i.e., the repeated observations of COVID cases and instructional modality) by estimating specifications of all models that include district fixed effects. These models identify the impact of in-person modality based on within district variation and have the advantage of accounting for any *time-invariant* characteristics of districts that are associated with COVID spread.[22] Note that in these models we cannot include the pre-existing COVID rates as they generate a specification bias when including the fixed effect. These models are "two-way fixed-effects" models that, by exploiting changes in modality over time, provide difference-in-differences estimates of the impact of modality on COVID spread. Because the far majority of districts in both Michigan and Washington move from relatively remote to relatively in-person modalities (see Table A2 in the Appendix for a transition matrix detailing this modality changes), this fixed effects strategy for the most part isolates the effect of "school opening," or moving from remote to hybrid or in-person schooling.[23] We also estimate county fixed effects models to confirm results from our district fixed effects strategy.

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[20] Our measures of COVID case rates exclude cases in prisons, but we nonetheless control for whether the county has a prison as cases in prisons could themselves spread to local communities.
[21] Variables with missing values are set to the overall mean. We include indicators for whether a variable is missing in the regressions.
[22] In specifications with district fixed-effects, time-invariant county-level characteristics included in previous specifications are automatically dropped from the models.
[23] For instance, in Michigan, no districts that were in-person in September switched to remote in October, and 1% switched to a hybrid modality. By contrast, 11% of hybrid and 14% of remote districts in September switched to in-person in October and 14% of remote districts switched to in-person. Similarly, between October and November, 2% of in-person districts switched to remote and 0.4% switched to hybrid, whereas 5% and 9% of remote districts switched to in-person and hybrid modalities, respectively. In Washington, between October and November, 38% and 5% of remote districts switched to hybrid and in-person, respectively, and 11% and 0% switched from in-person to hybrid (n=3) and remote, respectively.

5. Results

We are interested in describing the relationship between instructional modality and the spread of COVID-19. The findings for COVID cases per 100,000 are reported in Table 2, but we also report findings for the other measures of spread in Appendix A: COVID growth rate (Table A3); doubling time (Table A4); and unadjusted cases counts (Table A5).[24] The findings for the effect of instructional modality on all four of our COVID measures are qualitatively similar, though we note a few ways in which they differ in the discussion below.

Recall that we include three school modalities in Michigan (in-person, hybrid, and remote) while we only include two for Washington (in-person/hybrid and remote) given the small percentage of students (about 2%) who are in districts with in-person public schooling. The models also differ across states because there is an additional wave of data for instructional modality in Michigan, so the Michigan models include controls for both September and October, while in the Washington models we only include a control for October. November is the reference category in both states.

Section 5.1 describes results from models that include district modality. In Section 5.2, we discuss findings for models that replace these with the percentage of students who participate in a particular modality type; in-person, hybrid, and remote for Michigan, and in-person/hybrid versus remote for Washington. Finally, in Section 5.3, we describe the relationship between instructional modality and the spread of COVID-19 among individuals in the following age categories: 0-19, 20-39, 40-59, and 60+ years of age, both by reported district modality and the district estimates of the percentages of students in each modality type.

5.1 COVID Spread and Instructional Modality

In Panel A of Table 2 we present results from models predicting COVID community spread (cases per 100,000) in Michigan and analogous models for Washington in Panel B.[25] We begin with sparse models (column 1 for Michigan and 5 for Washington) that include only instructional modality and controls for existing COVID cases per capita, the square of cases per capita, and the month of the instructional modality measure. In Michigan, the coefficient on in-person schooling is positive and significant and the coefficient for a school district having a hybrid modality is also positive, albeit smaller in magnitude and only marginally significant. Given that the standard deviation of the COVID case rate in Michigan is about 19, this naïve specification suggests that a school district being in-person has a sizable effect on COVID case rates per capita, nearly 30% of a standard deviation. In Washington, the combined in-person/hybrid variable is positive but less precise and only very marginally significant (at the p=0.13 level) but the suggested magnitude is similar, about 24% of a standard deviation.[26] In both states the controls for pre-existing COVID rates suggests a parabolic relationship with cases rising quickly at low levels of community infection, then leveling off and declining.

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[24] Again, given the growth rates shown in Figure 1, we consider the growth measures of COVID spread more informative in Michigan than Washington.

[25] Some covariates in each of these specifications are not reported in the accompanying tables. See the notes at the bottom of each table for additional included control variables. The estimates for these are available from the authors upon request. We also estimated models that include the share of students in a county enrolled in private schools and the results were unaffected.

[26] The standard deviation of case rates per capita in Washington and Michigan is 11.4 and 19.1, respectively.

In columns 2 and 6 we add several controls for community characteristics. These are designed to account for physical features of communities that may affect disease spread (e.g. urbanicity, religious congregations), demographic characteristics (i.e., county population over 65 years old per 100,000, percent of students in district who are underrepresented minorities), as well as factors that may be related to the ability or desire to social distance (i.e., poverty rate, percent reporting mask wearing, Trump 2016 vote share, share staying at home, religious congregations and adherents). These covariates are jointly statistically significant in both states,[27] and their inclusion in the model greatly diminishes the coefficients on instructional modality in Michigan but not in Washington. In Michigan, none of the instructional modality variables are close to being statistically significant and the standard errors suggest one can rule out (with 95 percent certainty) that districts having in-person or hybrid instruction increases spread of COVID by more than 2 cases per 100,000.[28] In Washington, however, in-person/hybrid modality is statistically significantly associated with 2.9 cases /100,000.

A key concern, however, is that instructional modality may matter more depending on the overall number of COVID cases in a community. More specifically, if there are no COVID cases in a community, then schools cannot be a risk factor contributing to spread. And, if everyone in a community is infected, schools also cannot *contribute* to spread. To account for this hypothesized nonlinear relationship between instructional modality and case counts, we estimate a variant of the model that interacts the pre-period case count variables with the instructional modality indicators (column 3 for Michigan and column 7 for Washington). In these models the main effects of instructional modality remain insignificant, though they are more imprecisely estimated. But here it is necessary to focus on both the main effects and the interactions to understand how instructional modality is related to COVID spread along the pre-existing COVID case rate distribution.

In Figure 2, for Michigan (Panel A is for in-person and Panel B is hybrid) and Figure 3, for Washington, we explore the extent to which there appear to be heterogeneous effects of community COVID spread associated with instructional modality and the level of COVID case rates in the communities in which districts operate. The estimates are generated based on model 3 (without district fixed effects) in Table 2, where we interact modality with a quadratic function of COVID rates in the prior month, and are calculated as:

$$MI_{IP}: \Delta COVID_c = \hat{\beta}_1 + \hat{\beta}_3 BaselineCOVID_c + \hat{\beta}_5 \times BaselineCOVID_c^2 \quad (7)$$
$$MI_H: \Delta COVID_c = \hat{\beta}_2 + \hat{\beta}_4 BaselineCOVID_c + \hat{\beta}_6 \times BaselineCOVID_c^2$$

$$WA_{IP\_H}: \Delta COVID_c = \hat{\beta}_1 + \hat{\beta}_2 BaselineCOVID_c + \hat{\beta}_3 \times BaselineCOVID_c^2$$

such that in these figures we show how COVID rates in a county are predicted to change if the modality of all districts in the county shift from remote only to in-person or hybrid in Michigan or remote to combined in-person/hybrid in Washington. The x-axes in these figures are set to the 99th percentile of COVID rate in Michigan. The 99th percentile in Washington is far lower, but we keep the Michigan scale to preserve comparability across states, and, in each state mark the 50th, 75th, and 90th percentiles so as to show how these correspond with pre-existing COVID case

[27] The F-tests are 13.98 and 9.22 for Michigan and Washington, respectively.

[28] While not our primary focus, a few other findings are also notable. For instance, in both states, Trump share of the vote in a county is positively correlated with COVID spread and mask wearing is negatively correlated in Michigan. In Washington, mask wearing is positively correlated with COVID case rates and significant at the 10% level).

rates in communities. We note that as a result, Figure 3 shows estimates that are very far out-of-sample in Washington as the 99th percentile of pre-existing COVID rates in Washington is 17 COVID cases per 100,000, but the scale (the X-axis) goes up to 30 cases per 100,000.

Both figures suggest that shifts from remote to hybrid or in-person schooling has a limited impact on community COVID spread at low case rates in the community. In Michigan the results for hybrid modality are statistically indistinguishable from zero throughout most of the range of pre-existing COVID rates, although very slightly positive and significant in the range of 19 to 26 cases per 100,000 (Panel B). The results for the in-person modality (Panel A) are statistically insignificant for case rates less than 21 but are marginally significant and positive in the range of 21 to 37 cases per 100,000, and insignificant but still increasing beyond that point. In Washington, the estimates of COVID spread associated with school districts being in-person/hybrid compared to fully remote are not statistically different from zero until community case rates rise to around 5 cases per 100,000.[29]

While the shape of the overall relationship across both states is similar, it is striking that that school modality appears to influence community spread at far lower case rates in Washington than in Michigan. We check whether these differences may be related to differences across states in specification or data availability by re-estimating our main specification for Michigan combining the in-person and hybrid classifications and excluding September modality data (as in our Washington analyses). Neither of these specifications for Michigan (shown in Appendix Figures A1 and A2) yield results similar to those in Washington in Figure 3. When we exclude September from our data, we find estimates that are statistically indistinguishable from zero throughout the entire range of pre-existing COVID rates. When we combine hybrid and in-person modalities, we find that the operating schools in-person or hybrid contributes to COVID spread when pre-existing case rates in the surrounding communities are greater than about 19 cases per 100,000.

Another plausible reason that we see somewhat different patterns across states is the nature of the comparisons in each state. In particular, it is the contrasts between the omitted and included categories that inform the estimates in each state. While the omitted category in both states is remote school districts, it is possible that community practices in the omitted category relative to the included categories differ. For instance, if communities in Washington with in-person schooling are relatively more likely to exercise COVID transmission mitigation strategies, as compared to communities with in-person schooling in Michigan, the relative risk of school-based transmissions could be more dangerous in Washington. Similarly, if communities in Michigan with in-person schooling are being relatively safe, the relative risk of in-person schooling might be lower. We cannot speak directly to these possibilities, but there is evidence in Table 1 that, for instance, there is a bigger contrast between mask wearing in in-person and remote districts in Michigan than there is in Washington. This might suggest that there are also unobserved differences across states in the contrast between districts by modality.

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[29] Models that estimate these interactions non-parametrically with dummy variables and interactions indicating case rates below the 25th and above the 75th percentiles, provided estimates consistent with the quadratic functional forms. Results available by request. We also estimated local linear models where we first estimate regressions of COVID rates on the demographic and social distancing variables, then take the residuals from this regression and estimate local linear regressions of COVID rates on lagged COVID rates and the interaction of lagged COVID with modality. These regressions are centered at each integer value of lagged COVID and have bandwidths of 10 cases per 100k on each side. These estimates are provided in Appendix Figures A3 and A4 and, while noisier, are consistent with the parametric quadratic models.

It is also important to stress that, in both states, the values where we find evidence of school district mode-related spread are relatively low compared to COVID case rates as of mid-December, which were 44 per 100,000 in Michigan and 36 per 100,000 in Washington. However, at the times when pre-existing COVID rates in the regression models were recorded (early August, September, and October in Michigan; early September and October in Washington) statistical significance begins at the 95th and 75th percentiles of the county level COVID rate distributions in Michigan and Washington, respectively. As a result, the point at which our results suggest that district decisions to offer in-person (or in-person and hybrid in Washington) instruction may have led to increases in COVID spread are only found in counties with relatively high incidence rates as of early late summer/early autumn 2020. Moreover, Figure 2 shows that in-person modalities even in Michigan communities with high case rates are associated with moderate increases in spread; at 21 pre-existing cases per 100,000 there are an additional 3.56 cases per 100,000 associated with in-person modality.[30] The risk of additional spread is higher in Washington relative to pre-existing rates, but since pre-existing case rates were far lower than in Michigan (particularly toward the end of 2020, see Figure 1) the differences between states in the point in the distribution of pre-existing cases in which in-person schooling becomes significant is smaller. We return to the issue of heterogeneity of the instructional modality findings with the pre-existing case rate distribution in Section 6 in the context of discussing state guidance on school openings.

As a check on these findings, in Appendix Tables A3 and A4, we report the results from regressions using the exponential growth and doubling rates, Again, we do not include controls for lagged COVID rates in the first two models since they are directly incorporated into the construction of the dependent variables. Further, doubling rates should be interpreted as negative values indicating more spread (the time to doubling decreases). For exponential growth (A3) the estimates are statistically insignificant in all models. For doubling rates (A4), there are statistically significant relationships with modality when we do not account for other factors, but the estimates drop to statistical insignificance and close to zero when we add controls. Nonetheless, we are most interested in these measures for Michigan, where growth rates appear to be exponential (see Figure 1) from mid-October into November which is latter part of the time period under study.[31]

The above analyses suggest that instructional modality is not strongly related to COVID spread at low levels of pre-existing COVID rates, but it is at high levels of pre-existing COVID rates. Nonetheless, as we emphasized earlier, there are good reasons to be concerned that the instructional modality coefficients could be biased by unobserved heterogeneity across communities that is related to both COVID spread and instructional modality decisions. We can address heterogeneity related to time-invariant district factors leveraging the longitudinal nature of the data and including school district fixed effects. In these specifications, which are reported in columns 4 and 8 of Table 2, the estimates on the instructional modality variables are identified based on within district variation in modality over time.[32] As noted previously, including prior COVID rates as a control and fixed-effects at the same time creates specification bias, hence we

[30] With a standard deviation of 19 cases per 100,000 in Michigan over the time period under study, 3.56 cases per 100,000 is approximately 19% of a standard deviation increase associated with in-person instruction when pre-existing COVID cases were at 21 cases per 100,000, or at the 95th percentile of the distribution of pre-existing COVID rates.

[31] We provide results from a negative binomial specification using case counts (rather than counts per 100k population) in Appendix Table A5. Adjusting for scale differences the results are similar to our baseline estimates.

[32] All of the time invariant district and county covariates are excluded from these models.

only include modality indicators and consider the average relationship. Given this, the appropriate comparisons for columns 4 and 8 are the results in columns 2 and 6. The estimates for Michigan are negative and insignificant while for Washington they are larger but also insignificant. It is important to note that, given the limited number of districts switching modality categories (see Appendix Table A2), the coefficients are far less precise (particularly in Washington) than those reported in the earlier specifications that rely on both variation over time and across districts. The 95% confidence intervals can rule out average effect sizes of in-person modality of 2.2 cases/100,000 in Michigan but in Washington the upper bound is 12.4 cases/100,000. Nonetheless, the coefficients are substantively similar to those we see in models without district fixed effects, hence we treat these models as a check on our OLS estimates. We note, however, that the relationship between hybrid modality and doubling rates (Appendix Table A4) in the Michigan estimates with district fixed effects are larger and marginally significant. We also estimate a variant of the district fixed effects model, this time using county-fixed effects. These results align with our district fixed effects estimates and are available from the authors upon request.[33]

5.2 Using District Estimates of Students Attending School Hybrid and/or in Person

The above estimates of the association between district instructional modality and COVID spread are useful to some extent in assessing the implications of district-wide modality decisions, but the relatively crude modality measures may also mask variation in the degree to which public school students are physically present in schools. It is unclear, for instance, from our definition of a "fully in-person option" district in Michigan (classified as "in-person") what percentage of students who are offered some form of in-person instruction take-up that mode and spend time in the school building. Similarly, in Washington the definition of "phase-in" suggests that some students are receiving instruction, at least partially, in-person, but which grades (and fully or partially) are brought back is unclear.

To understand if finer grain information about the proportion of students who are attending schools suggests a different picture than the above modality findings, we turn to surveys in each state of the proportion of students who are either in-person or in hybrid settings (in Michigan) and who are in-person (in Washington). Specifically, we replace the district modality measures used in Table 2 with a vector of categorical indicators for the proportion of students who are attending schools in a particular modality.[34]

In Figures 4 and 5, we report the coefficient estimates from these models for Michigan and Washington, respectively. Figures 4a, b, and c show estimates from the fully interacted models and their 95% confidence intervals for the effects of in-person and hybrid enrollment in Michigan districts on COVID cases in the surrounding counties when county-level pre-period

[33] We also considered estimating an instrumental variables model that uses the strength of local teachers' unions (proxied by the restrictiveness of their negotiated collective bargaining agreements) to instrument for whether a district offers in-person instruction. Such an approach would rely on the assumption that teachers' union power influences instructional modality decisions but has no direct impact on community spread. We do not include any details on this exercise as the first stage regression showed only a weak relationship between union strength and district in-person instruction once we conditioned on appropriate pre-trends and relevant covariates.

[34] As we describe in Section 3, the Michigan survey was more precise than the Washington survey about the percentages of students attending hybrid versus in-person schooling, but the Washington survey included more categories for the percentage of students attending in-person. Washington also does not distinguish between fully in-person and hybrid attendance for this measure.

COVID rates are at the 25th, 50th, and 75th percentiles of each state's COVID rate distributions, respectively. Figure 5 provides the same estimates and confidence intervals for Washington, but with in-person and hybrid enrollment combined. We have finer-grain categories for take-up of in-person/hybrid instruction in Washington than we do in Michigan, as reflected by the categories shown on the x-axes in Figures 4 and 5. In Michigan we see that none of the estimates are statistically significantly different from zero at the 5% level. Nonetheless, there is some indication that districts in which relatively few (less than 25%) students enroll in-person may lead to slight reductions in COVID cases. Indeed, at low pre-existing case rate levels (below the 25th percentile), districts with only a few students in person see a reduction in cases relative to those that are fully remote.

In Washington, Figure 5 shows that county level COVID cases do not significantly increase unless pre-existing cases are high (at the 75th percentile of pre-existing cases in the community), though the point estimates for the 76+ (top) share of students in-person are consistently higher than for the other categories. This suggests that additional COVID spread can be kept low even at moderate levels of pre-existing community spread when districts are in-person or hybrid provided that not all students return to school at the same time (e.g., because a substantial portion of students choose a remote instruction alternative or because schools bring back students in a cohort or phased approach). Nonetheless, we again caution that during our study period, COVID rates in Washington were far lower than in the late autumn of 2020, and so these results may not apply when rates are higher. Further, while they are not statistically significant, the estimates are generally positive throughout the figure, indicating that this pattern may be due to imprecision in the estimates.

5.3 Findings for Various Age Groups

In Table 3 we report the findings for COVID cases per 100,000 for the various age categories. Panel A has the findings for Michigan and Panel B for Washington. In each state and for each age category, we report the results for hybrid or in-person schooling relative to remote (or, as above, hybrid/in-person combined for Washington). We show the findings from the fully saturated OLS model (from columns 3 and 7 of Table 2). To aid with interpretation, we present estimates for the relationship between modality and COVID cases per 100,000 at the 25th, 50th, and 75th percentile of pre-existing COVID cases per 100,000 individuals. We provide full model results in Appendix Tables A6-1 through A6-4.

The fact that younger individuals tend to experience less severe COVID symptoms combined with the lack of universal testing raises some questions about which age categories might be expected to show COVID spread due to instructional modality. That said, we believe it is reasonable to assume that the 0 to19 year age category is likely to be most sensitive to spread related to students being in public school buildings. The estimates of instructional modality are insignificant in Michigan for the 0 to19 year age category and only significant at the 75th percentile of pre-existing COVID rates in Washington. Nonetheless, despite the hypothesis that we would see more spread emanating from instructional modality in school-age children, estimates for other age categories, differ little from the 0 to19 year category in both states. Further, only one of the other estimates in the table are statistically significant. In Washington the estimates are similar to those for COVID rates across all ages shown in Figure 3.

5.4 Robustness/Bounding exercise

The major concern that we have tried to address in the models described above is accounting for the potential that communities that choose a particular school modality may also employ other strategies or practices that mitigate or exacerbate COVID spread. There is evidence, for instance, from the table of means (Table 1) that, in both states, districts offering in-person modality also tend to be relatively less likely to report mask wearing, more likely to have voted for President Trump in 2016, and have higher unemployment rates. This is reflected in the diminishment in the coefficient for in-person instruction from Columns 1 to 2 in Table 2 in Michigan, and to a lesser extent from Columns 5 to 6 in Washington. These models of course only account for observable factors in the models. The district fixed effects specifications reported in columns 4 and 8 of the table account for all *time-invariant* models and are generally consistent with the more saturated models, but they are also quite imprecise and could still be subject to bias. In particular, COVID spread is often fast-moving in communities. It is not hard to imagine that forward-looking public health or schooling officials might have information based on conditions on the ground that inform school modality decisions, i.e., information that *varies* over the fall of 2020 so is not fully addressed by the inclusion of district fixed effects.

Thus, as a final robustness check, we employ methods outlined in Altonji et al. (2005) and Oster (2019) that quantify the likely direction of bias and help to bound the estimates we present. If we assume, as is common, that the selection on unobservables is comparable to selection on the observables in the models (i.e., a δ equal to 1 in the Oster (2019) framework),[35] we find for both states that the coefficient on in-person modality declines. In Michigan, it falls from 0.34 to -1.79 (statistically insignificant).[36] In Washington, this robustness exercise leads to an attenuation of the in-person/hybrid variable from 2.7 (significant at the 10% level) to 1.7 and insignificant. Put another way, this robustness exercise suggests that the OLS model estimates for COVID case rates are an upper bound on the relationship between districts offering an in-person/hybrid modality and increased COVID spread.

We repeat this exercise for exponential growth and doubling time. In Michigan there is virtually no change in the school modality coefficients for growth, but both in-person and hybrid coefficients become substantially larger and significant for doubling time (again with a δ equal to 1), but recall that this indicates that in-person or hybrid modality offerings decrease the rapidity of COVID spread. In Washington there is little change in the in-person/hybrid coefficient for doubling time, but the coefficient becomes substantially larger and significant for growth. This is unexpected given the bounding exercise suggests that all the other modality coefficients are conservatively estimated, but it likely reflects the fact that our models of exponential growth in Washington fit the data poorly given that COVID growth rates in Washington are not growing exponentially in the fall of 2020 (see Figure 1).

[35] We use the models specified in columns 2 and 6 of Table 2 for this exercise to avoid the complexity of programming associated with the interactions between the modality treatment and the pre-existing case rates (the methods developed in Oster (2017) and Angrist et al. (2005) do not describe how to handle this type of model. As an alternative, we estimate the same specifications for counties with COVID case rates above the 50th percentile and apply the bounding exercise as above. These findings, available upon request, are broadly consistent with those discussed below for all districts.

[36] The coefficient on hybrid schooling decreases from .34 to -1.03 and remains insignificant. In this robustness check, we are implicitly treating the school modalities that we do not focus on as covariates. However, we also estimate variants (in Michigan), where we compare in-person or hybrid to an excluded category that includes a combination of the other two categories. Findings from this test are nearly identical to those where we treat the other modality as a covariate.

Last, we test the extent to which selection on unobservables may bias the age-specific case rate results (reported in Appendix Tables A6-1 through A6-4). For every age category, the bounding exercise shows decreased coefficient estimates assuming a δ equal to 1 for both in-person and hybrid coefficients in Michigan, and the in-person/ hybrid coefficients in Washington. Thus, here too the bounding exercise suggests that the OLS coefficients we report are a conservative upper bound on COVID spread.

6. Discussion and Conclusion

Using district and county level data from Michigan and Washington, we investigate how the instructional modality in public K-12 schools – in-person, hybrid, or remote – in the wake of the COVID-19 pandemic influences spread of COVID in the wider community. We find that community COVID rates are strongly positively correlated with in-person and hybrid forms of schooling in simple, naïve regression models. But for an important exception described above in Section 5 and again summarized below, these findings do not persist when we allow the effects of school modality to differ according to the level of community spread in the population and add covariates that account for various district and community factors, such as mask wearing and political preferences. These general findings hold up under a variety of OLS and fixed effects model specifications.

The important exception is that we *do* find some evidence that in-person modality is associated with increased COVID spread in communities with relatively high pre-existing levels of COVID. In Michigan, for instance, districts offering an in-person instructional modality show increased COVID spread for daily average case counts over 21 cases per 100,000 (this is about the 95th percentile of the pre-existing case count distribution in our data). Similarly, districts offering a hybrid instructional modality show COVID spread for daily average case counts between 19 and 26 cases per 100,000. In Washington, which has significantly lower average case counts than Michigan during our study period, we find evidence that the offer of in-person/hybrid modality is associated with additional community spread when average pre-existing daily case counts are over 5 cases per 100,000 (about the 75th percentile), but not at lower levels of pre-existing community spread. These findings are consistent with much of the epidemiological literature that suggests that the risks of public schools leading to increased COVID spread rise with the level of pre-existing COVID infection in communities. However, we caution that we are basing these estimates on periods of time when COVID cases were low relative to late autumn of 2020. Hence, any application of our results to the context of periods with high case levels (such as in the winter of 2020-21) would be making out-of-sample predictions that are highly sensitive to modeling assumptions.

We also provide some evidence that uptake (as opposed to the district offer of a particular modality) of the in-person or hybrid modality may matter. In particular, in Washington the state survey of school systems asks districts to report the proportion of students attending schools in-person in relatively narrow categories. Using this measure, rather than district modality offerings, we see that the findings on modality, described above, appear to be driven mainly by school systems with relatively high proportions of students, over 75%, attending schools in person. Further, we see some evidence that districts in Michigan where less than 25% of students are in-person may reduce COVID rates relative to remote-only instruction, provided existing community spread is relatively low (at the 25th percentile of pre-existing COVID rates in the community). While it is unclear why this occurs, one possibility is that for these children, in-person instruction may substitute for social and educational engagements that are less structured and less able to maintain social distancing (e.g., group childcare or teaching pods).

All of the results above are important considering recent discussion about the need for state guidance to help local districts determine when to offer in-person instruction, and what kind of risk mitigation strategies might be important if students are in public schools, and when to move to remote instruction in order to mitigate disease spread. As noted above, the CDC has renewed calls for schools to open in-person. Many states, including Michigan and Washington, have provided schools with guidance that calls for localities to make modality decisions based on community transmission rates combined with the school system's capacity to carry out safety measures (e.g., cleaning, physical distancing, ventilation, face covering) and the school and health systems' capacities to monitor symptoms, provide sufficient testing, and conduct contact tracing. However, states differ according to where they "draw the line" for safe in-person learning amidst community spread, and strategies change quickly as more is learned about COVID spread and its relative risks and dangers as well as about the likely damage caused to children, families, and the economy as students are held out of school.

Michigan's original guidance, released on June 30, 2020, calls for fully remote instruction when local spread is very high and health care capacity is low. This roadmap lays out a six-phase state reopening "Safe Start Plan" based on community spread, such that communities in phases 1-3 (i.e., those with increasing cases, persistent spread, or even gradually declining cases) must offer only remote instruction, while communities in Phase 4 (i.e., declining cases, hospitalizations, and deaths) may provide in-person instruction with required face coverings in common areas for all students and staff, and in classrooms for staff and students in grades 6-12 (COVID-19 Task Force on Education Return to School Advisory Council, 2020). Spacing desks at least six feet apart is "strongly recommended" but not required. Requirements for safety measures scale back as communities move into phases 5 and 6, the waning phases of the pandemic. In general, these guidelines point to remote instruction when local cases and deaths are consistently in decline, the local health system has sufficient capacity and personal protective equipment availability to manage a surge, and testing and tracing efforts are sufficient. In early fall 2020, the MDHHS released an updated guidance matrix that suggested school buildings in counties with fewer than 15 cases per 100,000 should consider at least some degree of in-person instruction with reduced density and the use of mitigation strategies.[37] As COVID rates increased in the late fall, a statewide order was issued in mid- November to close all high schools for in-person instruction, but since then began to again high schools to re-open. Most recently, Michigan encouraged *all* districts to return students to in-person instruction, giving a target date of March 1st, 2021 (French, 2021).

The Washington guidance, updated Dec. 16, 2020, lays out an approach that would allow some in-person instruction even in a high community transmission context.[38] It provides guidelines for communities to classify community transmission as high, moderate, or low, drawing from local case rates per capita, test positivity rates, and trends in cases and hospitalizations. Specifically, the guidance suggests in-person learning for all students only after the community has a case rate of less than 50 per 100,000 population and a test positivity rate of

[37] MDHHS guidance is available from https://massp.com/sites/default/files/inline-files/SCHOOL%20MATRIX%20DRAFT%20091620.pdf and https://www.michigan.gov/coronavirus/0,9753,7-406-100467_100913---,00.html

[38] Washington State Department of Health guidance is available at https://www.doh.wa.gov/Portals/1/Documents/1600/coronavirus/DecisionTree-K12schools.pdf

less than five percent, with decreasing trends. At higher levels of community transmission, the state recommends a "phase in" approach beginning with grades pre-K through three and students with special needs and providing small group instruction with cohorts of 15 students or fewer. In general, the guidance does not call for a remote-only approach to all grades, but rather recommends a targeted approach to in-person learning that focuses on the highest needs and youngest students. The updated guidelines, for instance, point to mostly remote instruction (which the state calls "phase in" for the youngest students), when the local case rate is higher than 350 per 100,000 population over 14 days (or, in the terms we use in our models, 25 cases per 100,000 per day), and the test positivity rate is higher than 10 percent.

Our models are broadly consistent with the spirit of this guidance, at least in Washington, as we find no significant impact of modality on COVID rates at low levels of community spread, but significant impacts at higher pre-existing levels of spread. More generally, however, we would urge caution against using the specific estimates in this study to set thresholds for shifting to remote instruction as they are subject to many modeling assumptions and data limitations. The key assumption is that we have accounted for potential confounders in estimating the relationship between modality and COVID cases, more specifically that our observable measures sufficiently account for behavioral responses of individuals and districts with respect to COVID, such as social distancing, that also may be related to modality. While we attempt to address this by using district (and county) fixed effects, this method only accounts for *time-invariant* sources of bias. And while our fixed effects findings are consistent with the OLS results, they are relatively imprecise.

For the reasons noted above, we also attempt to bound our estimates using methods developed by (Altonji et al., 2005) and Oster (2019). Given that the models described above explain a large amount of the variation we observe in COVID cases, there is limited potential that our estimates are biased based on unobservables. Thus, it is not surprising that the bounding exercise suggests that the OLS estimates we describe are not likely to be significantly biased and, in fact, represent an upper bound on the impact of COVID spread from in-person or schooling relative to fully online/remote instruction.

We also hesitate to offer specific recommendations about specific case rate thresholds given that, as with any econometric model, there is uncertainty in our estimates. Moreover, given sample size and associated power considerations, we are unable to rule out small changes in COVID spread that may result from decisions to offer or enroll in in-person schooling. In addition, statistical tests of significance rely on the use of 95% confidence intervals, which means that we can assert with a certain degree of confidence that our results do not show significant average relationships between in-person schooling modalities and COVID spread. However, health experts, parents, and policymakers may wish to apply different standards when interpreting relationships with this level of consequence and using different standards of certainty could lead to different assessments of risk.

We are also limited by the available data. We rely on COVID case rates at the county level as it provides us a high frequency and high variability measure of COVID incidence. Case rates, however, are not just a function of incidence but also testing. Hence if the likelihood of getting tested at a given underlying incidence varies with modality, that could bias our estimates. This concern is mitigated by the fact that unlike early in the pandemic, testing was widely available during the period we study, but we do not know the degree or ways in which testing might vary across communities. Nonetheless, in future work we will include models that predict COVID test positivity rates to help assess the extent to which this should cause concern. It would also be useful to examine other measures of COVID impact, such as hospitalization and potentially death rates.

Another important concern is that the COVID pandemic has hit communities of color and low-income communities much harder than others (e.g., Sandoiu, 2020). Ideally, we would be able to conduct analyses that focus on the modality impacts in these communities as they may be at higher risk of COVID spread. Unfortunately, our outcome data – which is at the county level and not broken down by racial, ethnic, or income subgroups – make this infeasible. We attempted to address this question by examining counties with large minority population shares. However, our estimates primarily rely on cross-county variation and very few counties have high enough minority populations to provide accurate evidence on this – in Michigan the county at the 75^{th} percentile of underrepresented minority share (non-white and non-Asian) has only 10% underrepresented minorities, while in Washington there is only a 5% underrepresented minority population in counties at the 75^{th} percentile of the distribution. Further, when we estimated models restricted to these counties with (marginally) larger shares of underrepresented minorities, our estimates are too imprecise to draw clear conclusions. Hence, we caution that our overall results may not hold in these populations, but we are unable to determine the extent to which this may or may not be the case.

A further data limitation is that we do not have good information on what is happening inside schools or other community institutions.[39] In particular, there are no systematic data collected about strategies that schools or school districts employ to mitigate contagion such as mask requirements, temperature checks, social distancing among students and teachers, and other risk mitigation strategies. Such risk mitigation strategies are thought to be influential in determining COVID spread in schools (Guthrie et al., 2020). Clearly the collection of this type of information would enhance the ability to understand the role instructional modality might play in COVID spread and would be important for understanding how to mitigate risk in the case of future disease outbreaks that make in-person schooling a risky endeavor.

Even with these limitations, however, we believe this work can be useful to decision-makers concerned with how best to balance protecting students, school staff, and the greater community from COVID while working to ensure the academic and socioemotional well-being of children. There are also, of course, considerations that differ across local contexts; for instance, it has become well-established that low-income communities and communities with high proportions of underrepresented minorities have been harder hit by the pandemic and may have greater concerns about taking on additional risk via in-person schooling. Nonetheless, the takeaway here is that in-person schooling modalities do not appear to contribute to COVID spread above and beyond what is already occurring in the community at low-to-medium levels of spread. We hope that these results help provide a roadmap for local and state decisionmakers as they consider how and when to re-open school buildings and, equally important, how and when to re-shutter them.

[39] For instance, as noted above, we do not have good information across all counties about higher education institutions. We hope to add this in future updates to this work.

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Table 1: Summary Statistics by State, Instructional Modality, and Month

Panel A: September

	Michigan			
	All	In-person	Hybrid	Remote
N districts	810	472	144	194
% districts	100.00	58.27	17.78	23.95
% districts, weighted	100.00	47.69	17.21	35.10
County				
School/county population ratio	0.15	0.15	0.15	0.15
Nursing home residents per 100K	320.11	344.59	303.42	296.19
65+ population per 100k	17,565.96	18,300.53	16,974.40	16,800.81
Percent always wears a mask	63.37	60.02	64.71	67.23
Share to stay at home	22.82	21.79	23.31	24;97
Trump vote share 2016	47.08	51.98	45.35	41.34
Religious congregations per 100k	95.44	114.32	84.86	74.36
Religious adherents per 1k	424.07	418.84	414.11	436.68
Unemployment rate, 2019	4.15	4.22	4.01	4.10
Individual poverty rate	15.08	14.94	14.71	15.40
Correctional facility	39.75	30.72	47.22	56.19
College/University	79.01	70.13	83.33	97.42
Lagged cases per 100k	6.94	5.92	7.27	8.18
District				
Black students	0.18	0.13	0.13	0.26
Hispanic students	0.08	0.09	0.07	0.08
Econ disadvantaged students	0.50	0.50	0.46	0.52
Special education students	0.13	0.13	0.12	0.13
Urban	0.24	0.18	0.20	0.34
Suburban/Town	0.58	0.53	0.62	0.63
Rural	0.18	0.29	0.18	0.03
Outcomes				
Cases per 100K	8.64	9.75	7.84	7.52
	(6.43)	(8.63)	(3.33)	(2.84)
Exponential growth	0.05	0.02	-0.04	0.02
	(0.26)	(0.19)	(0.19)	(0.23)
Doubling time	108.07	138.15	153.93	129.40
	(72.15)	(73.62)	(67.00)	(73.61)

Panel B: October

	Michigan				Washington				
	All	In-person	Hybrid	Remote	All	In-person	Hybrid	In-Person or Hybrid	Remote
N districts	810	511	162	137	286	27	77	104	182
% districts	100.00	63.09	20.00	16.91	100.00	9.44	26.92	36.36	63.64
% districts, weighted	100.00	56.27	25.06	18.67	100.00	1.77	8.18	9.95	90.05
County									
School/county population ratio	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
Nursing home residents per 100K	320.11	340.16	299.28	289.80	174.38	182.72	186.66	185.96	172.79
65+ population per 100k	17,565.96	18,177.20	17,061.76	16,292.35	15,800.05	17,974.89	19,938.96	19,589.75	15,342.13
Percent always wears a mask	63.37	61.07	65.76	67.01	69.81	66.49	67.25	67.11	70.11
Share to stay at home	25.42	24.58	26.02	27.82	26.90	27.05	26.59	26.67	26.93
Trump vote share 2016	47.08	51.10	44.28	38.85	40.16	52.51	50.35	50.73	38.89
Religious congregations per 100k	95.44	108.26	78.39	78.51	91.94	127.48	121.14	122.27	88.42
Religious adherents per 1k	424.07	423.05	420.20	433.50	349.75	344.18	332.79	334.81	351.26
Unemployment rate, 2019	4.15	4.20	4.05	4.08	4.50	5.69	5.53	5.56	4.36
Individual poverty rate	15.08	14.83	14.46	16.55	11.74	15.99	13.58	13.99	11.46
Correctional facility	39.75	29.94	51.23	62.77	72.63	66.68	41.06	45.53	75.63
College/University	79.01	71.82	85.80	97.81	93.99	76.24	80.26	79.56	95.58
Lagged cases per 100k	6.26	6.04	5.56	7.86	3.27	8.15	3.96	4.70	3.11
District									
Black students	0.18	0.12	0.13	0.40	0.04	0.01	0.01	0.01	0.05
Hispanic students	0.08	0.09	0.06	0.09	0.24	0.15	0.18	0.17	0.24
Econ disadvantaged students	0.50	0.49	0.42	0.64	0.47	0.44	0.49	0.48	0.46
Special education students	0.13	0.13	0.12	0.13	0.15	0.16	0.16	0.16	0.15
Urban	0.24	0.16	0.21	0.53	0.39	0.00	0.05	0.04	0.42
Suburban/Town	0.58	0.59	0.66	0.45	0.54	0.69	0.66	0.67	0.52
Rural	0.18	0.25	0.13	0.02	0.08	0.31	0.29	0.29	0.05
Outcomes									
Cases per 100K	37.76	31.37	29.67	34.65	9.20	17.41	9.19	10.63	9.05
	(15.98)	(9.77)	(10.65)	(14.18)	(4.62)	(11.13)	(7.76)	(8.97)	(3.83)
Exponential growth	0.42	0.43	0.41	0.42	0.11	0.11	0.07	0.07	0.12
	(0.18)	(0.17)	(0.16)	(0.18)	(0.22)	(0.32)	(0.26)	(0.27)	(0.21)
Doubling time	38.49	46.93	52.71	43.26	100.28	96.52	112.92	110.06	99.20
	(18.42)	(17.73)	(18.22)	(19.07)	(73.00)	(90.10)	(84.23)	(85.17)	(71.55)

Panel C: November

	Michigan				Washington				
	All	In-person	Hybrid	Remote	All	In-person	Hybrid	In-person or Hybrid	Remote
N districts	809	516	161	132	266	34	143	177	89
% districts	100.000	63.782	19.901	16.316	100.000	12.782	53.759	66.541	33.459
% districts, weighted	100.00	55.67	25.73	18.61	100.00	2.62	30.55	33.17	66.83
County									
School/county population ratio	0.15	0.15	0.15	0.15	0.15	0.16	0.17	0.17	0.15
Nursing home residents per 100k	320.11	338.70	301.98	291.79	174.38	214.79	189.73	191.71	168.57
65+ population per 100k	17,565.96	18,192.72	17,051.11	16,293.82	15,800.05	18,146.59	18,279.35	18,268.86	15,037.62
Percent always wears a mask	63.37	61.14	65.81	66.60	69.81	67.46	68.17	68.12	70.57
Share to stay at home	25.32	24.58	25.82	27.60	30.35	29.22	29.84	29.79	30.63
Trump vote share 2016	47.08	50.95	44.44	39.30	40.16	53.23	51.68	51.80	35.60
Religious congregations per 100k	95.44	108.57	77.08	80.33	91.94	127.14	114.63	115.62	81.47
Religious adherents per 1k	424.07	424.57	420.04	429.37	349.75	364.03	362.02	362.18	340.02
Unemployment rate, 2019	4.15	4.19	4.07	4.10	4.50	5.89	5.47	5.51	4.05
Individual poverty rate	15.08	14.81	14.44	16.68	11.74	16.27	14.14	14.31	10.52
Correctional facility	39.80	30.23	49.69	65.15	69.71	43.08	38.85	39.18	84.74
College/University	78.99	72.29	85.71	96.97	93.02	77.95	82.73	82.35	98.27
Lagged cases per 100k	12.36	13.35	11.00	11.25	5.66	10.05	6.66	6.92	5.04
District									
Black students	0.18	0.13	0.12	0.39	0.04	0.01	0.02	0.02	0.05
Hispanic students	0.08	0.08	0.07	0.10	0.24	0.14	0.24	0.23	0.22
Econ disadvantaged students	0.50	0.49	0.42	0.65	0.47	0.44	0.53	0.52	0.42
Special education students	0.13	0.13	0.12	0.14	0.15	0.16	0.16	0.16	0.15
Urban	0.24	0.17	0.19	0.53	0.39	0.22	0.35	0.34	0.42
Suburban/Town	0.58	0.59	0.69	0.42	0.54	0.49	0.49	0.49	0.54
Rural	0.18	0.25	0.13	0.05	0.08	0.29	0.16	0.17	0.04
Outcomes									
Cases per 100K	46.78	48.02	46.29	43.78	24.89	32.73	28.20	28.55	23.08
	(9.65)	(10.10)	(8.97)	(8.41)	(8.83)	(11.38)	(12.87)	(12.80)	(5.10)
Exponential growth	-0.28	-0.28	-0.29	-0.28	-0.22	-0.24	-0.21	-0.21	-0.23
	(0.13)	(0.15)	(0.11)	(0.11)	(0.20)	(0.26)	(0.28)	(0.28)	(0.15)
Doubling time	52.59	51.94	52.45	54.70	44.96	54.42	53.66	53.72	40.65
	(13.52)	(17.04)	(7.35)	(5.89)	(26.34)	(34.85)	(39.36)	(38.97)	(15.30)

NOTE: Modality N's are for number of districts. County variables are county-level characteristics assigned to districts. District variables are means of schools within districts. All means weighted by district size. In-person+hybrid column combines in-person and hybrid columns for Washington. Mutually exclusive categories are either (a) in-person, hybrid, and remote, or (b) in-person+hybrid and remote. A table that includes districts with missing data is included in the appendix. Outcomes include standard deviations in parentheses.

Table 2. Estimated COVID case rates per 100,000 population

	A. Michigan				B. Washington			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-Person	5.271***	0.246	-1.993	-1.642				
	(1.019)	(0.563)	(3.220)	(1.938)				
In-Person and Hybrid					2.715	2.873*	-1.946	4.397
					(1.759)	(1.297)	(1.777)	(4.065)
Hybrid	1.709^{+}	0.294	-3.953	-1.856				
	(0.912)	(0.639)	(2.823)	(2.649)				
Prior month cases	1.035**	0.732*	0.625		1.866*	0.697	0.017	
	(0.375)	(0.344)	(0.566)		(0.735)	(0.425)	(0.342)	
Prior month cases squared	-0.022*	-0.024*	-0.029^{+}		-0.037*	-0.013	0.000	
	(0.011)	(0.010)	(0.017)		(0.015)	(0.008)	(0.007)	
In-Person*Prior month cases			0.198					
			(0.570)					
Hybrid*Prior month cases			0.645					
			(0.531)					
In-Person*Prior month cases squared			0.005					
			(0.017)					
Hybrid*Prior month cases squared			-0.013					
			(0.016)					
(In-Person/Hybrid)*Prior month cases							1.082**	
							(0.384)	
(In-Person/Hybrid)*Prior month cases squared							-0.021*	
							(0.008)	
Percent always wears a mask		-0.528***	-0.517***			0.350**	0.357**	
		(0.108)	(0.108)			(0.116)	(0.115)	
Share to stay at home		-0.331	-0.375			0.063	0.173	
		(0.466)	(0.457)			(0.396)	(0.391)	
Trump vote share 2016		0.270*	0.274*			0.492***	0.479***	
		(0.119)	(0.117)			(0.076)	(0.081)	
Religious congregations per 100k		-0.018	-0.017			-0.019	-0.007	
		(0.022)	(0.022)			(0.031)	(0.031)	
Religious adherents per 1k		0.051**	0.050**			0.075***	0.075***	
		(0.016)	(0.016)			(0.012)	(0.012)	
School to county population ratio		-21.268	-22.470			-1.247**	-1.260***	
		(34.299)	(33.260)			(0.363)	(0.349)	
Nursing home residents per 100k		0.013^{+}	0.012^{+}			0.013^{+}	0.011	
		(0.007)	(0.007)			(0.008)	(0.008)	
65+ population per 100k		-0.000	-0.000			-0.001*	-0.001*	
		(0.000)	(0.000)			(0.000)	(0.000)	
Unemployment rate, 2019		-2.526*	-2.457*			-0.058	0.313	
		(1.250)	(1.232)			(1.135)	(1.140)	
Individual poverty rate		0.247	0.263			0.212	0.150	
		(0.228)	(0.227)			(0.268)	(0.270)	
Underrepresented minority share		0.011	0.010			-0.030	-0.024	
		(0.007)	(0.007)			(0.019)	(0.018)	
Urban		-0.038	0.156			0.464	0.185	
		(0.418)	(0.447)			(0.464)	(0.457)	
Town		-0.483	-0.549			-2.388*	-1.930^{+}	
		(1.459)	(1.457)			(0.921)	(0.956)	
Rural		-1.223	-1.227			-1.791*	-1.759*	
		(0.897)	(0.896)			(0.839)	(0.849)	
Correctional facility		2.833^{+}	2.640			7.723***	7.829***	
		(1.642)	(1.629)			(1.750)	(1.700)	
College/University		-1.429	-1.334			-6.081^{+}	-5.776^{+}	
		(2.190)	(2.103)			(3.089)	(3.086)	
District FE	N	N	N	Y	N	N	N	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2420	2420	2420	2420	552	552	552	552
R^2	0.720	0.814	0.816	0.865	0.700	0.861	0.870	0.929

Notes: Robust standard errors clustered at the county level in parentheses. Regressions weighted by district size. All models include month fixed effects with November as the reference category. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

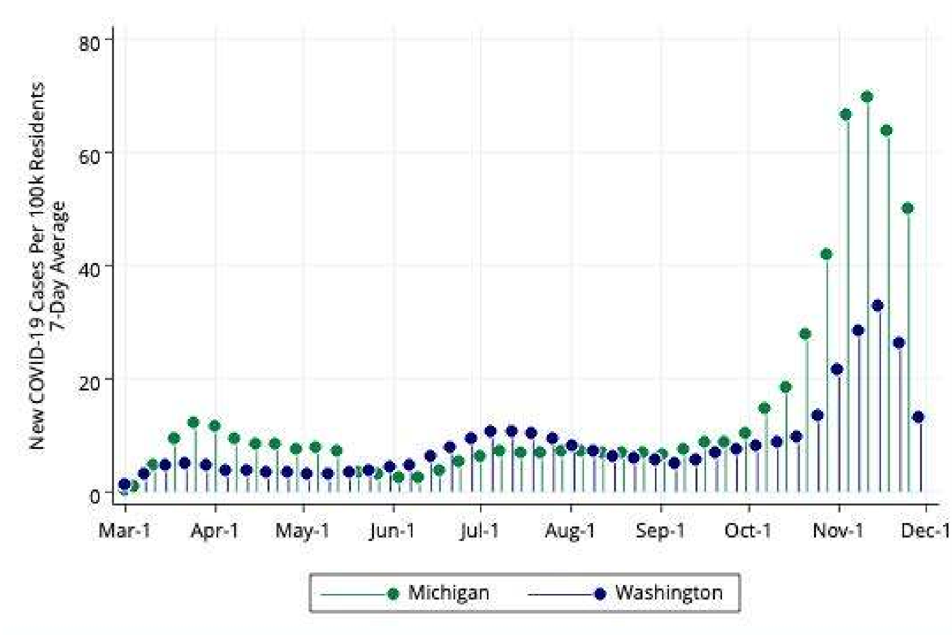
Table 3. Estimated COVID case rates per 100,000 age group population, by age group

	Age 0-19	Age 20-39	Age 40-59	Age 60+
	(1)	(2)	(3)	(4)
Panel A: Michigan				
25th Percentile				
In-Person	-0.211	-1.527	-1.233	-1.973
	(0.756)	(1.723)	(1.364)	(1.230)
Hybrid	-0.391	-1.898	-1.499	-1.154
	(0.640)	(1.297)	(1.018)	(0.942)
50th Percentile				
In-Person	0.080	-0.398	-0.722	-0.976
	(0.377)	(0.959)	(0.715)	(0.671)
Hybrid	0.134	-0.393	-0.329	-0.812
	(0.365)	(0.784)	(0.639)	(0.563)
75th Percentile				
In-Person	0.458	0.893	0.083	0.239
	(0.611)	(1.319)	(0.877)	(0.825)
Hybrid	0.710	1.185	0.929	-0.298
	(0.626)	(1.075)	(1.135)	(1.045)
Panel B: Washington				
25th Percentile				
In-Person and Hybrid	0.348	0.313	-1.304	0.932
	(0.865)	(2.110)	(1.538)	(1.098)
50th Percentile				
In-Person and Hybrid	1.189	1.831	0.244	1.640
	(0.817)	(1.936)	(1.527)	(0.999)
75th Percentile				
In-Person and Hybrid	2.316*	3.877	2.327	2.592*
	(0.946)	(2.254)	(1.933)	(1.084)

NOTE: Robust standard errors clustered at the county level in parentheses. Regressions weighted by district size. All models include month fixed effects with November as the reference category. Separate estimates are for the 25th, 50th, and 75th percentile of pre-existing COVID cases per 100,000 population.
* $p < 0.05$

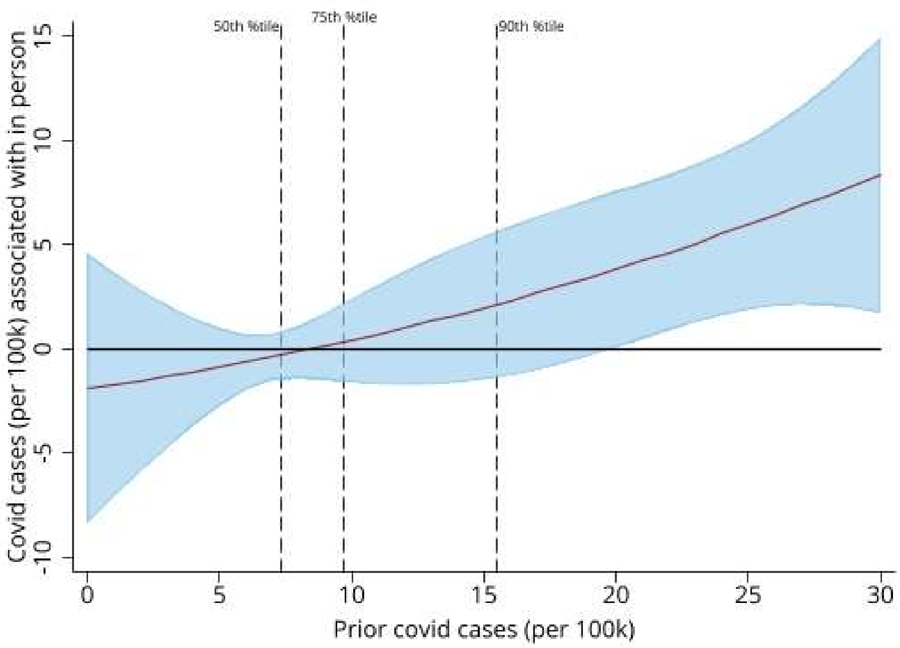
Figures

Figure 1: Statewide Trends in New COVID Cases, Michigan and Washington

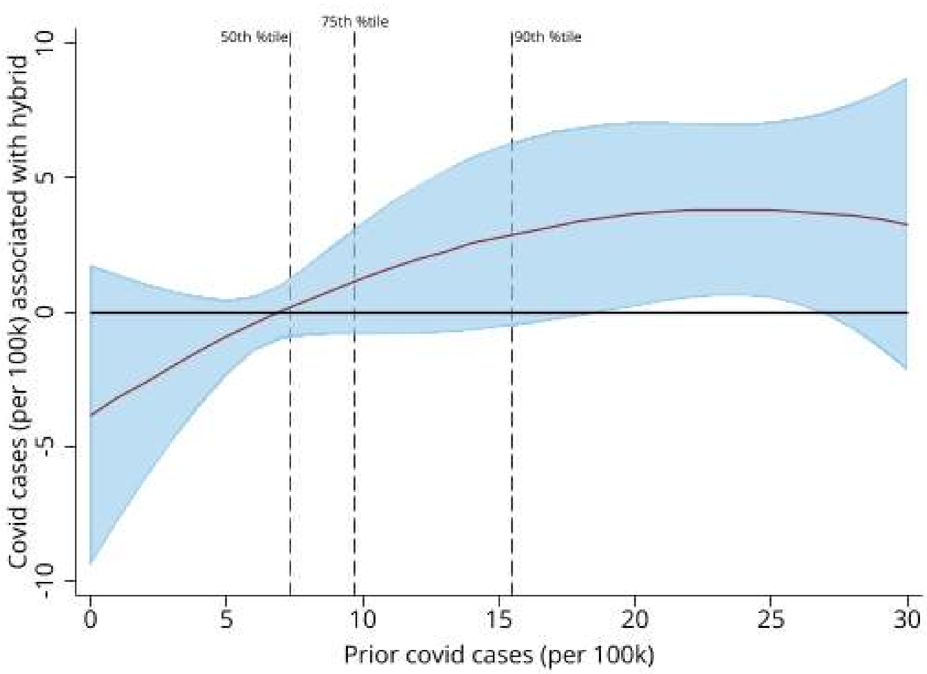


NOTE: Marker heights represent seven-day average daily case rate per 100,000 residents by week.

Figure 2a, b: Marginal predictions of COVID-19 cases per 100,000 by prior cases from modality changes, Michigan



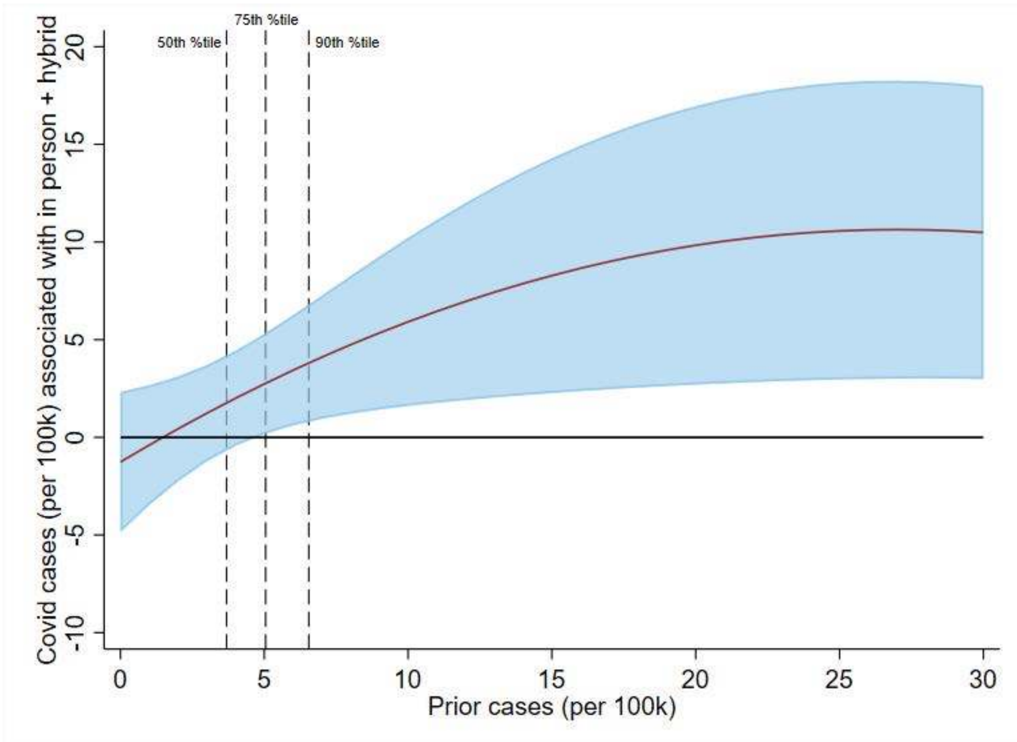
a) All districts in county switch from remote to in-person.



a) All districts in county switch from remote to hybrid.

NOTE: Estimates based on model 3 (without district fixed effects) in Table 2, where school modality is interacted with a quadratic function of COVID case rates in the prior month.

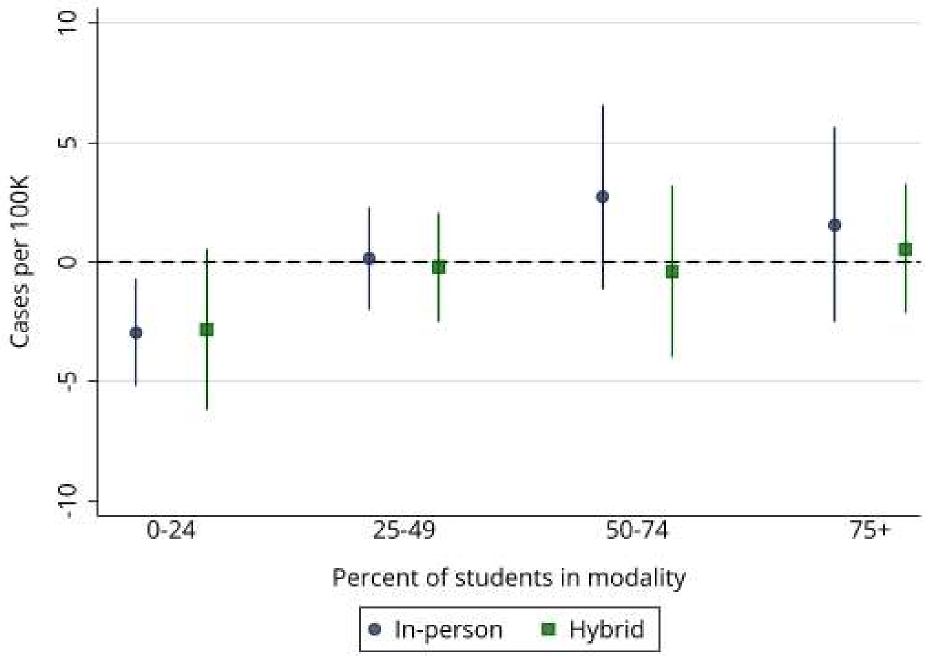
Figure 3: Marginal predictions of COVID-19 cases per 100,000 by prior case from modality changes, Washington



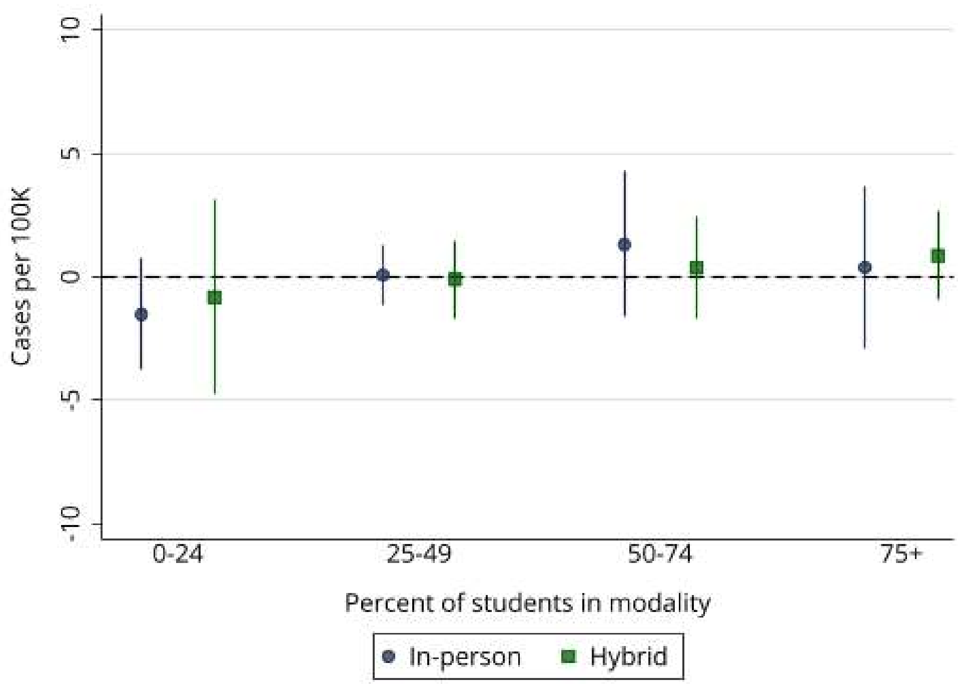
a) All districts in county switch from remote to in-person or hybrid.

NOTE: Estimates based on model 7 (without district fixed effects) in Table 2, where school modality is interacted with a quadratic function of COVID case rates in the prior month.

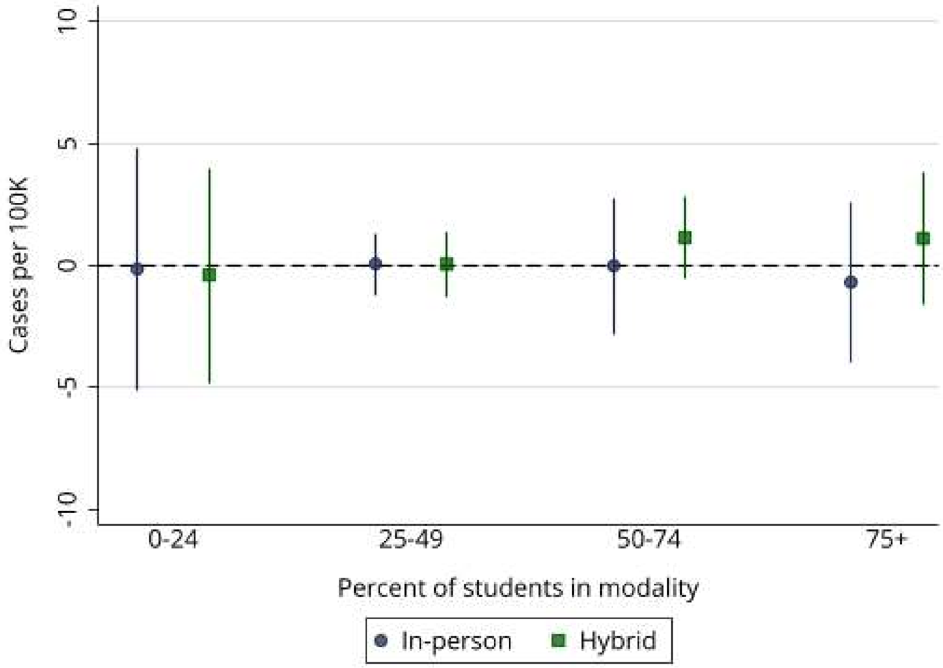
Figure 4a-c: COVID-19 case rates per 100,00 by share of students in modality and prior case rates, Michigan



Panel A. 25th percentile of pre-period COVID-19 rates



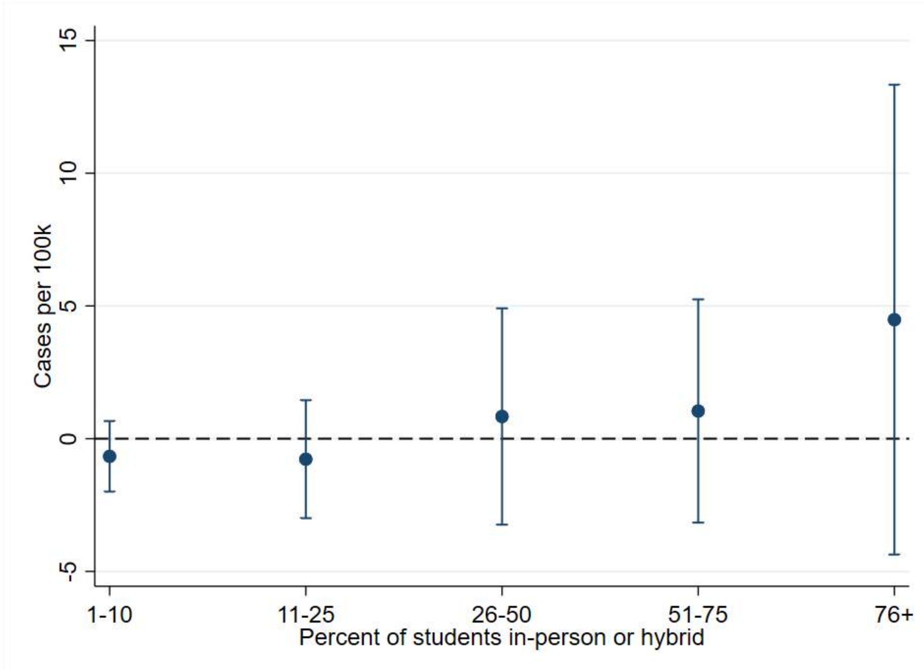
Panel B. 50th percentile of pre-period COVID-19 rates



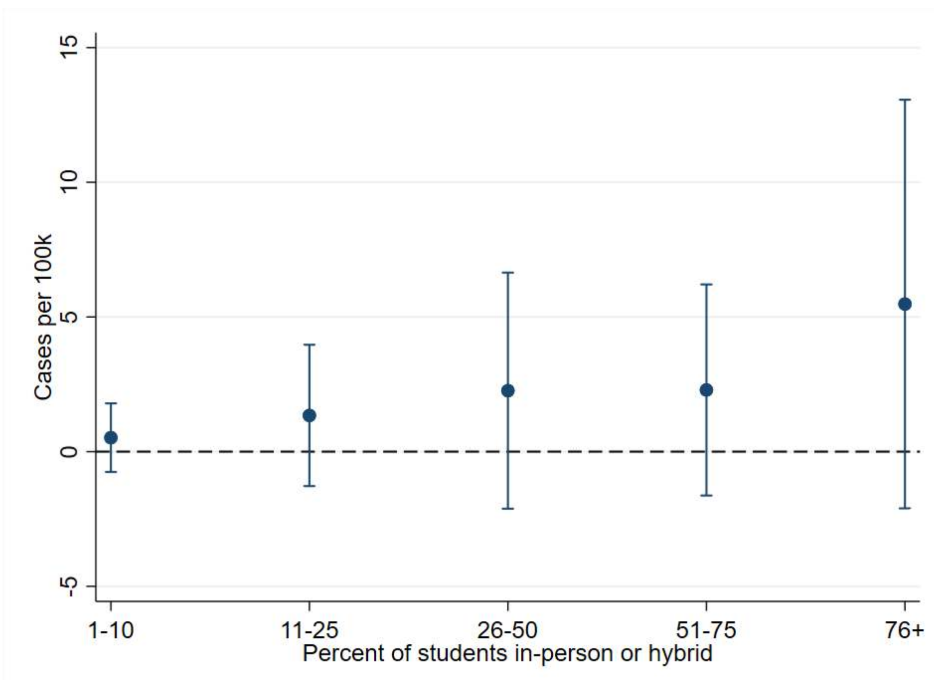
Panel C. 75th percentile of pre-period COVID-19 rates

NOTE: Estimates from models interacting district modality measures with a vector of categorical indicators for the percent of students who are attending schools in a particular modality (represented by x-axis labels). Markers represent point estimates for in-person and hybrid, respectively, and spikes represent 95 percent confidence intervals. Panels are for the 25th, 50th, and 75th percentile, respectively, of lagged case rates.

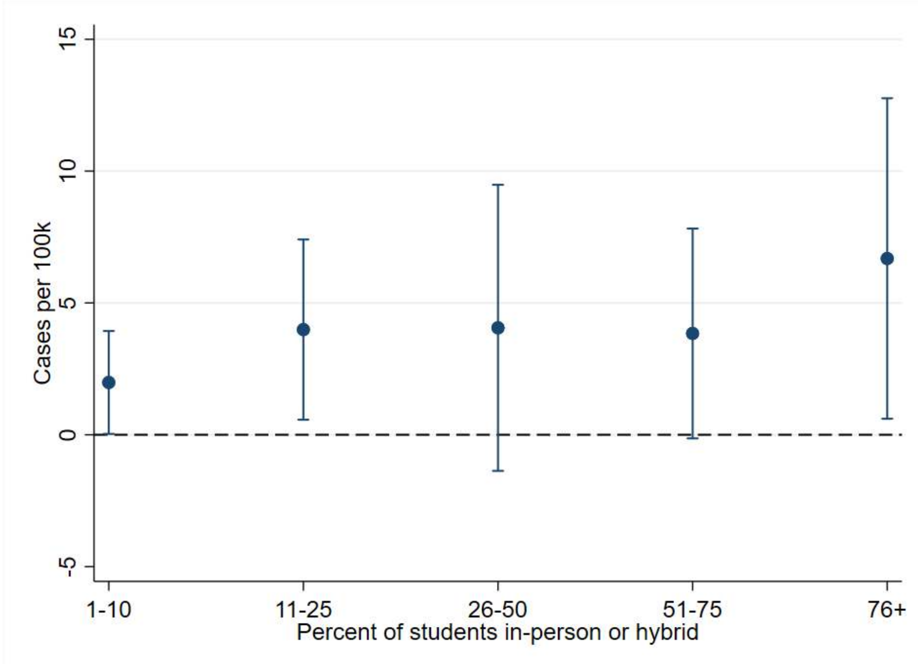
Figure 5a-c: COVID-19 case rates per 100,00 by share of students in modality and prior case rates,, Washington



Panel A. 25th percentile of pre-period COVID-19 rates



Panel B. 50th percentile of pre-period COVID-19 rates



Panel C. 75th percentile of pre-period COVID-19 rates

NOTE: Estimates from models interacting district modality measures with a vector of categorical indicators for the percent of students who are attending schools in a particular modality (represented by x-axis labels). Markers represent point estimates for in-person or hybrid, and spikes represent 95 percent confidence intervals. Panels are for the 25th, 50th, and 75th percentile, respectively, of lagged case rates.

Appendix

Table A1. Summary Statistics by State, Instructional Modality, and Month, Including Districts Missing Modality Data

Panel A: September

	Michigan All	In-person	Hybrid	Remote	No data
N districts	833	472	144	194	23
% districts	100.00	56.66	17.29	23.29	2.76
% districts, weighted	100.00	46.99	16.96	34.59	1.46
County					
School/county population ratio	0.15	0.15	0.15	0.15	0.17
Nursing home residents per 100K	320.11	344.59	303.42	296.19	292.98
65+ population per 100k	17,565.96	18,300.53	16,974.40	16,800.81	18,928.25
Percent always wears a mask	63.37	60.02	64.71	67.23	64.42
Share to stay at home	22.78	24.58	25.82	27.60	23.24
Trump vote share 2016	47.08	51.98	45.35	41.34	45.37
Religious congregations per 100k	95.44	114.32	84.86	74.36	109.93
Religious adherents per 1k	424.07	418.84	414.11	436.68	409.59
Unemployment rate, 2019	4.15	4.22	4.01	4.10	4.49
Individual poverty rate	15.08	14.94	14.71	15.40	16.42
Correctional facility	39.86	30.72	47.22	56.19	39.39
College/University	78.99	70.13	83.33	97.42	81.82
Lagged cases per 100k	6.92	5.92	7.27	8.18	4.49
District					
Black students	0.18	0.13	0.13	0.26	0.25
Hispanic students	0.08	0.09	0.07	0.08	0.09
Econ disadvantaged students	0.50	0.50	0.46	0.52	0.70
Special education students	0.13	0.13	0.12	0.13	0.15
Urban	0.24	0.18	0.20	0.34	0.17
Suburban/Town	0.58	0.53	0.62	0.63	0.62
Rural	0.18	0.29	0.18	0.03	0.21
Outcomes					
Cases per 100k	8.62	9.75	7.84	7.52	7.10
	(6.41)	(8.63)	(3.33)	(2.84)	(4.52)
Exponential growth	0.05	0.02	-0.04	0.02	0.02
	(0.26)	(0.19)	(0.19)	(0.34)	(0.23)
Doubling time	108.07	138.15	153.93	99.78	129.11
	(72.15)	(73.62)	(67.00)	(48.21)	(73.45)

Panel B: October

	Michigan					Washington					
	All	In-person	Hybrid	Remote	No data	All	In-person	Hybrid	In-person +hybrid	Remote	No data
N districts	833	511	162	137	23	295	27	77	104	182	9
% districts	100.00	61.35	19.45	16.45	2.76	100.00	9.15	26.10	35.25	61.695	3.051
% districts, weighted	100.00	55.45	24.69	18.40	1.46	100.00	1.74	8.03	9.76	88.37	1.87
County											
School/county population ratio	0.15	0.15	0.15	0.15	0.17	0.15	0.15	0.15	0.15	0.15	0.17
Nursing home residents per 100K	320.11	340.16	299.28	289.80	292.98	174.38	182.72	186.66	185.96	172.79	189.21
65+ population per 100k	17,565.96	18,177.20	17,061.76	16,292.35	18,928.25	15,800.05	17,974.89	19,938.96	19,589.75	15,342.13	17,659.18
Percent always wears a mask	63.37	61.07	65.76	67.01	64.42	69.81	66.49	67.25	67.11	70.11	69.77
Share to stay at home	25.38	24.58	26.02	27.82	26.18	26.88	27.05	26.59	26.67	26.93	25.83
Trump vote share 2016	47.08	51.10	44.28	38.85	45.37	40.16	52.51	50.35	50.73	38.89	45.03
Religious congregations per 100k	95.44	108.26	78.39	78.51	109.93	91.94	127.48	121.14	122.27	88.42	99.93
Religious adherents per 1k	424.07	423.05	420.20	433.50	409.59	349.75	344.18	332.79	334.81	351.26	356.19
Unemployment rate, 2019	4.15	4.20	4.05	4.08	4.49	4.50	5.69	5.53	5.56	4.36	5.38
Individual poverty rate	15.08	14.83	14.46	16.55	16.42	11.74	15.99	13.58	13.99	11.46	12.98
Correctional facility	39.86	29.94	51.23	62.77	35.90	72.26	66.68	41.06	45.53	75.63	52.82
College/University	78.99	71.82	85.80	97.81	79.49	94.00	76.24	80.26	79.56	95.58	94.75
Lagged cases per 100k	6.04	5.56	7.87	9.33	6.29	3.251	8.146	3.965	4.695	3.111	2.304
District											
Black students	0.18	0.12	0.13	0.40	0.25	0.04	0.01	0.01	0.01	0.05	0.02
Hispanic students	0.08	0.09	0.06	0.09	0.09	0.24	0.15	0.18	0.17	0.24	0.35
Econ disadvantaged students	0.50	0.49	0.42	0.64	0.70	0.47	0.44	0.49	0.48	0.46	0.50
Special education students	0.13	0.13	0.12	0.13	0.15	0.15	0.16	0.16	0.16	0.15	0.16
Urban	0.24	0.16	0.21	0.53	0.17	0.39	0.00	0.05	0.04	0.42	0.49
Suburban/Town	0.58	0.59	0.66	0.45	0.62	0.54	0.69	0.66	0.67	0.52	0.46
Rural	0.18	0.25	0.13	0.02	0.21	0.08	0.31	0.29	0.29	0.05	0.05
Outcomes											
Cases per 100k	34.58	37.76	31.37	29.67	27.67	9.16	17.42	9.19	10.63	9.05	6.90
	(14.16)	(15.98)	(9.77)	(10.65)	(10.17)	(4.60)	(11.13)	(7.76)	(8.97)	(3.83)	(2.49)
Exponential growth	0.42	0.42	0.43	0.41	0.33	0.11	0.11	0.66	0.072	0.12	-0.04
	(0.18)	(0.18)	(0.17)	(0.16)	(0.23)	(0.22)	(0.32)	(0.26)	(0.27)	(0.21)	(0.21)
Doubling time	43.20	38.49	46.93	52.71	37.19	101.01	96.52	112.92	110.06	99.20	139.74
	(19.01)	(18.42)	(17.73)	(18.22)	(9.37)	(74.21)	(90.10)	(84.23)	(85.17)	(71.55)	(122.88)

Panel C: November

	Michigan					Washington					
	All	In-person	Hybrid	Remote	No data	All	In-person	Hybrid	In-person +hybrid	Remote	No data
N districts	833	516	161	132	24	295	34	143	177	89	29
% districts	100.00	61.95	19.33	15.85	2.88	100.00	11.53	48.48	60.00	30.17	9.83
% districts, weighted	100.00	54.84	25.34	18.33	1.48	100.00	2.23	26.05	28.29	56.99	14.72
County											
School/county population ratio	0.15	0.15	0.15	0.15	0.17	0.15	0.16	0.17	0.17	0.15	0.16
Nursing home residents per 100K	320.11	338.70	301.98	291.79	292.82	174.38	214.79	189.73	191.71	168.57	163.59
65+ population per 100k	17,565.96	18,192.72	17,051.11	16,293.82	18,913.26	15,800.05	18,146.59	18,279.35	18,268.86	15,037.62	14,007.09
Percent always wears a mask	63.37	61.14	65.81	66.60	64.25	69.81	67.46	68.17	68.12	70.57	70.14
Share to stay at home	25.28	24.58	25.82	27.60	25.60	30.48	29.22	29.84	29.79	30.63	31.25
Trump vote share 2016	47.08	50.95	44.44	39.30	45.33	40.16	53.23	51.68	51.80	35.60	35.46
Religious congregations per 100k	95.44	108.57	77.08	80.33	109.88	91.94	127.14	114.63	115.62	81.47	86.97
Religious adherents per 1k	424.07	424.57	420.04	429.37	409.34	349.75	364.03	362.02	362.18	340.02	363.53
Unemployment rate, 2019	4.15	4.19	4.07	4.10	4.49	4.50	5.89	5.47	5.51	4.05	4.29
Individual poverty rate	15.08	14.81	14.44	16.68	16.48	11.74	16.27	14.14	14.31	10.52	11.53
Correctional facility	39.86	30.23	49.69	65.15	35.19	72.26	43.08	38.85	39.18	84.74	87.15
College/University	78.99	72.29	85.71	96.97	75.93	94.00	77.95	82.73	82.35	98.27	99.72
Lagged cases per 100k	12.34	13.35	11.00	11.25	10.70	5.79	10.05	6.66	6.92	5.039	6.51
District											
Black students	0.18	0.13	0.12	0.39	0.25	0.04	0.01	0.02	0.02	0.05	0.08
Hispanic students	0.08	0.08	0.07	0.10	0.09	0.24	0.14	0.24	0.23	0.22	0.29
Econ disadvantaged students	0.50	0.49	0.42	0.65	0.70	0.47	0.44	0.53	0.52	0.42	0.53
Special education students	0.13	0.13	0.12	0.14	0.15	0.15	0.16	0.16	0.16	0.15	0.14
Urban	0.24	0.17	0.19	0.53	0.16	0.39	0.22	0.35	0.34	0.42	0.35
Suburban/Town	0.58	0.59	0.69	0.42	0.62	0.54	0.49	0.49	0.49	0.54	0.61
Rural	0.18	0.25	0.13	0.05	0.21	0.08	0.29	0.16	0.17	0.04	0.04
Outcomes											
Cases per 100k	46.72	48.02	46.29	43.78	40.65	25.65	32.73	28.20	28.55	23.08	30.07
	(9.67)	(10.10)	(8.97)	(8.41)	(10.51)	(10.15)	(11.38)	(12.87)	(12.80)	(5.10)	(15.26)
Exponential growth	-0.28	-0.28	-0.29	-0.28	-0.27	-0.22	-0.24	-0.21	-0.21	-0.23	-0.19
	(0.13)	(0.15)	(0.11)	(0.11)	(0.13)	(0.19)	(0.26)	(0.28)	(0.28)	(0.15)	(0.12)
Doubling time	52.51	51.94	52.45	54.70	44.49	44.59	54.42	53.66	53.72	40.65	42.42
	(13.52)	(17.04)	(7.35)	(5.89)	(11.09)	(24.88)	(34.85)	(39.36)	(38.97)	(15.30)	(13.62)

NOTE: Modality N's are for number of districts. County variables are county-level characteristics assigned to districts. District variables are means of schools within districts. All means weighted by district size. In-person+hybrid column combines in-person and hybrid columns for Washington. Outcomes include standard deviations in parentheses.

Table A2: Transition Matrices Showing Changes in District Instructional Modality by Month and State

Panel A. September to October

	Michigan				
October → September ↓	In-person option	Hybrid	Remote only	No data	Total
In-person option	468	4	0	0	472
Hybrid	16	128	0	0	144
Remote only	27	30	137	0	194
No data	0	0	0	23	23
Total	511	162	137	23	833

Panel B. October to November

	Michigan					Washington				
November → October ↓	In-person option	Hybrid	Remote only	No data	Total	In-person option	Hybrid	Remote only	No data	Total
In-person option	499	2	10	0	511	20	3	0	4	27
Hybrid	10	147	5	0	162	4	70	1	2	77
Remote only	7	12	117	1	137	9	69	84	20	182
No data	0	0	0	23	23	1	1	4	3	9
Total	516	161	132	24	833	34	143	89	29	295

NOTE: Rows represent the first month in the table and columns represent the second month in the table.

Table A3. Estimated COVID exponential growth

	A. Michigan			B. Washington		
	(1)	(2)	(3)	(4)	(5)	(6)
In-Person	0.039	-0.001	-0.000			
	(0.024)	(0.013)	(0.061)			
In-Person and Hybrid				-0.007	0.014	0.031
				(0.046)	(0.064)	(0.187)
Hybrid	0.031	0.016	0.028			
	(0.020)	(0.013)	(0.030)			
Percent always wears a mask		-0.000			0.006	
		(0.002)			(0.004)	
Share to stay at home		-0.007			-0.006	
		(0.008)			(0.011)	
Trump vote share 2016		0.004^{+}			0.000	
		(0.002)			(0.003)	
Religious congregations per 100k		-0.001^{+}			-0.002	
		(0.000)			(0.001)	
Religious adherents per 1k		0.000			0.002^{**}	
		(0.000)			(0.001)	
School to county population ratio		1.180^{*}			-0.038^{**}	
		(0.536)			(0.013)	
Nursing home residents per 100k		0.000			0.001^{*}	
		(0.000)			(0.000)	
65+ population per 100k		-0.000			-0.000^{*}	
		(0.000)			(0.000)	
Unemployment rate, 2019		0.027			0.071^{+}	
		(0.024)			(0.037)	
Individual poverty rate		0.003			-0.027^{+}	
		(0.005)			(0.014)	
Underrepresented minority share		0.000			0.000	
		(0.000)			(0.001)	
Urban		0.010			-0.027	
		(0.008)			(0.017)	
Town		0.060^{**}			-0.044	
		(0.022)			(0.036)	
Rural		0.015			-0.024	
		(0.015)			(0.025)	
Correctional facility		0.020			-0.102	
		(0.028)			(0.074)	
College/University		0.008			-0.496^{***}	
		(0.045)			(0.126)	
District FE	N	N	Y	N	N	Y
Month FE	Y	Y	Y	Y	Y	Y
Observations	2420	2420	2420	552	552	552
R^2	0.715	0.740	0.791	0.389	0.444	0.689

NOTE: Robust standard errors clustered at the county level in parentheses. Regressions weighted by district size. All models include month fixed effects with November as the reference category.
$^{+}$ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A4. Estimated COVID doubling time

	A. Michigan			B. Washington		
	(1)	(2)	(3)	(4)	(5)	(6)
In-Person	-23.645***	-5.145+	-14.021			
	(4.717)	(3.012)	(8.586)			
In-Person and Hybrid				12.363	-15.523	-37.546
				(9.871)	(11.467)	(32.534)
Hybrid	-12.027**	-7.412**	-19.447+			
	(4.022)	(2.691)	(10.715)			
Percent always wears a mask		0.678			-0.907	
		(0.576)			(1.234)	
Share to stay at home		6.012**			4.304	
		(2.005)			(4.707)	
Trump vote share 2016		-0.128			-0.904	
		(0.484)			(0.822)	
Religious congregations per 100k		-0.134+			-0.241	
		(0.077)			(0.305)	
Religious adherents per 1k		0.030			-0.029	
		(0.035)			(0.125)	
School to county population ratio		57.606			11.527***	
		(113.421)			(2.663)	
Nursing home residents per 100k		-0.021			-0.080	
		(0.017)			(0.061)	
65+ population per 100k		0.000			0.003	
		(0.001)			(0.002)	
Unemployment rate, 2019		7.331			-3.427	
		(5.634)			(12.844)	
Individual poverty rate		0.383			3.760	
		(1.029)			(2.312)	
Underrepresented minority share		-0.016			0.463*	
		(0.022)			(0.186)	
Urban		0.698			-9.174*	
		(1.991)			(4.382)	
Town		6.468			6.561	
		(4.438)			(7.428)	
Rural		4.166			7.706	
		(2.767)			(6.816)	
Correctional facility		6.634			-50.921**	
		(6.024)			(17.508)	
College/University		-27.926***			4.095	
		(7.297)			(25.821)	
District FE	N	N	Y	N	N	Y
Month FE	Y	Y	Y	Y	Y	Y
Observations	2418	2418	2418	552	552	552
R^2	0.457	0.636	0.703	0.200	0.614	0.803

NOTE: Robust standard errors clustered at the county level in parentheses. Regressions weighted by district size. All models include month fixed effects with November as the reference category.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5. Estimated COVID case rates (unadjusted) using a negative binomial specification

	Michigan				Washington			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-Person	-0.119	0.056	-0.156^{+}	0.060				
	(0.102)	(0.040)	(0.085)	(0.040)				
In-Person and Hybrid					-0.321*	0.087*	-0.054	0.026
					(0.155)	(0.038)	(0.099)	(0.065)
Hybrid	0.031	0.065^{+}	-0.056	0.024				
	(0.075)	(0.036)	(0.094)	(0.051)				
Prior month cases	0.066***	0.010	0.005		0.113***	0.024**	0.023**	
	(0.007)	(0.007)	(0.007)		(0.015)	(0.009)	(0.008)	
Prior month cases squared	-0.000***	-0.000^{+}	-0.000		-0.001***	-0.000^{+}	-0.000*	
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	
In-Person*Prior month cases			0.008**					
			(0.003)					
Hybrid*Prior month cases			0.004					
			(0.003)					
In-Person*Prior month cases squared			-0.000*					
			(0.000)					
Hybrid*Prior month cases squared			-0.000					
			(0.000)					
(In-Person and Hybrid)*Prior month cases							0.016	
							(0.012)	
(In-Person and Hybrid)*Prior month cases squared							-0.000	
							(0.000)	
Percent always wears a mask		-0.020*	-0.019*			0.016	0.015	
		(0.009)	(0.009)			(0.018)	(0.018)	
Share to stay at home		0.052^{+}	0.051^{+}			-0.058	-0.056	
		(0.030)	(0.029)			(0.042)	(0.043)	
Trump vote share 2016		0.002	0.003			0.048***	0.050**	
		(0.009)	(0.009)			(0.015)	(0.015)	
Religious congregations per 100k		-0.011***	-0.011***			-0.015^{+}	-0.015^{+}	
		(0.002)	(0.002)			(0.008)	(0.009)	
Religious adherents per 1k		0.003***	0.003***			0.003	0.003	
		(0.001)	(0.001)			(0.002)	(0.002)	
School to county population ratio		6.003**	5.985**			-0.035	-0.032	
		(2.313)	(2.277)			(0.045)	(0.044)	
Nursing home residents per 100,000		-0.000	-0.000			0.002**	0.002*	
		(0.000)	(0.000)			(0.001)	(0.001)	
65+ population per 100k		-0.000*	-0.000*			-0.000*	-0.000*	
		(0.000)	(0.000)			(0.000)	(0.000)	
Unemployment rate, 2019		-0.109	-0.109			-0.029	-0.036	
		(0.083)	(0.081)			(0.117)	(0.127)	
Individual poverty rate		0.010	0.009			0.002	0.003	
		(0.017)	(0.017)			(0.050)	(0.056)	
Underrepresented minority share		0.002**	0.002**			-0.003	-0.003	
		(0.001)	(0.001)			(0.002)	(0.002)	
Urban		-0.071*	-0.064*			0.022	0.019	
		(0.031)	(0.029)			(0.026)	(0.032)	
Town		-0.204**	-0.193**			-0.059	-0.071	
		(0.063)	(0.062)			(0.063)	(0.081)	
Rural		-0.158**	-0.148**			-0.118^{+}	-0.128	
		(0.049)	(0.049)			(0.065)	(0.085)	
Correctional facility		-0.004	-0.001			0.502**	0.492**	
		(0.101)	(0.099)			(0.189)	(0.188)	
College/University		0.083	0.088			0.125	0.108	
		(0.123)	(0.121)			(0.301)	(0.300)	
County population		0.000***	0.000***			0.000**	0.000***	
		(0.000)	(0.000)			(0.000)	(0.000)	
District FE	N	N	N	Y	N	N	N	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2420	2420	2420	2420	552	552	552	552

NOTE: Robust standard errors clustered at the county level in parentheses. Regressions weighted by district size. All models include month fixed effects with November as the reference category. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6-1. Estimated COVID case rates per 100,000 for 0-19-year-olds

	A. Michigan				B. Washington			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-Person	1.515**	0.465	-0.793	0.392				
	(0.497)	(0.434)	(2.305)	(1.249)				
In-Person and Hybrid					1.212	2.152*	-2.253	3.827
					(1.348)	(1.028)	(1.518)	(3.429)
Hybrid	0.730	0.465	-1.707	-0.197				
	(0.510)	(0.455)	(2.013)	(1.505)				
Prior month cases	0.529*	0.296	0.221		1.550*	1.053*	0.423	
	(0.232)	(0.226)	(0.423)		(0.614)	(0.405)	(0.299)	
Prior month cases squared	-0.013^{+}	-0.012^{+}	-0.014		-0.029*	-0.019**	-0.007	
	(0.007)	(0.007)	(0.012)		(0.012)	(0.007)	(0.005)	
In-Person*Prior month cases			0.123					
			(0.419)					
Hybrid*Prior month cases			0.322					
			(0.376)					
In-Person*Prior month cases squared			0.002					
			(0.013)					
Hybrid*Prior month cases squared			-0.006					
			(0.011)					
(In-Person and Hybrid)*Prior month cases							1.008*	
							(0.383)	
(In-Person and Hybrid)*Prior month cases squared							-0.020**	
							(0.007)	
Percent always wears a mask		-0.336***	-0.331***			0.199^{+}	0.205^{+}	
		(0.079)	(0.079)			(0.109)	(0.107)	
Share to stay at home		-0.731*	-0.753*			0.463^{+}	0.565*	
		(0.305)	(0.300)			(0.271)	(0.268)	
Trump vote share 2016		-0.113	-0.111			0.203**	0.189**	
		(0.080)	(0.078)			(0.068)	(0.068)	
Religious congregations per 100k		-0.023^{+}	-0.022^{+}			-0.024	-0.013	
		(0.013)	(0.013)			(0.043)	(0.045)	
Religious adherents per 1k		0.035**	0.034**			0.030^{+}	0.030^{+}	
		(0.010)	(0.010)			(0.015)	(0.015)	
School to county population ratio		-40.941^{+}	-41.562^{+}			-0.744	-0.759	
		(22.346)	(22.072)			(0.471)	(0.458)	
Nursing home residents per 100k		0.009*	0.009*			0.006	0.004	
		(0.004)	(0.004)			(0.006)	(0.006)	
65+ population per 100k		-0.000	-0.000			-0.000	-0.000	
		(0.000)	(0.000)			(0.000)	(0.000)	
Unemployment rate, 2019		-0.927	-0.891			0.355	0.709	
		(0.849)	(0.840)			(1.176)	(1.145)	
Individual poverty rate		-0.087	-0.079			0.200	0.141	
		(0.153)	(0.153)			(0.379)	(0.375)	
Underrepresented minority share		0.005	0.005			-0.032^{+}	-0.027^{+}	
		(0.004)	(0.004)			(0.016)	(0.015)	
Urban		0.254	0.358			0.637^{+}	0.386	
		(0.289)	(0.316)			(0.357)	(0.338)	
Town		0.140	0.103			-2.428*	-2.026^{+}	
		(1.085)	(1.085)			(0.987)	(1.005)	
Rural		-0.833	-0.839			-2.072**	-2.022**	
		(0.533)	(0.533)			(0.718)	(0.671)	
Correctional facility		2.021^{+}	1.936^{+}			2.893^{+}	2.992^{+}	
		(1.022)	(1.038)			(1.691)	(1.627)	
College/University		-1.973	-1.937			-2.644	-2.352	
		(1.510)	(1.468)			(3.048)	(2.904)	
District FE	N	N	N	Y	N	N	N	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2420	2420	2420	2420	551	551	551	551
R^2	0.631	0.707	0.708	0.786	0.583	0.735	0.753	0.854

NOTE: Robust standard errors clustered at the county level in parentheses. Regressions weighted by district size. All models include month fixed effects with November as the reference category. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6-2. Estimated COVID case rates per 100,000 for 20-39-year-olds

	A. Michigan				B. Washington			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-Person	6.283***	0.552	-4.214	-1.064				
	(1.479)	(0.932)	(4.912)	(2.705)				
In-Person and Hybrid					4.282	3.707	-4.353	6.599
					(2.841)	(2.379)	(3.964)	(8.082)
Hybrid	2.057^{+}	0.385	-5.839	-2.326				
	(1.149)	(0.851)	(3.647)	(3.711)				
Prior month cases	0.891	0.395	-0.094		3.637**	1.681*	0.549	
	(0.603)	(0.503)	(0.919)		(1.278)	(0.808)	(0.627)	
Prior month cases squared	-0.018	-0.018	-0.011		-0.073**	-0.031*	-0.010	
	(0.017)	(0.015)	(0.027)		(0.025)	(0.014)	(0.012)	
In-Person*Prior month cases			0.639					
			(0.875)					
Hybrid*Prior month cases			0.987					
			(0.655)					
In-Person*Prior month cases squared			-0.008					
			(0.027)					
Hybrid*Prior month cases squared			-0.023					
			(0.020)					
(In-Person and Hybrid)*Prior month cases							1.800^{+}	
							(1.013)	
(In-Person and Hybrid)*Prior month cases squared							-0.034^{+}	
							(0.019)	
Percent always wears a mask		-0.594**	-0.579**			0.413^{+}	0.423^{+}	
		(0.190)	(0.191)			(0.232)	(0.239)	
Share to stay at home		-0.599	-0.641			0.504	0.688	
		(0.675)	(0.666)			(0.842)	(0.835)	
Trump vote share 2016		0.342^{+}	0.353*			0.939***	0.916***	
		(0.174)	(0.172)			(0.190)	(0.195)	
Religious congregations per 100k		-0.053	-0.053			-0.090	-0.069	
		(0.033)	(0.033)			(0.089)	(0.094)	
Religious adherents per 1k		0.086***	0.086***			0.107***	0.107***	
		(0.025)	(0.025)			(0.027)	(0.027)	
School to county population ratio		-2.992	-4.769			-1.168	-1.190	
		(59.570)	(58.649)			(0.786)	(0.791)	
Nursing home residents per 100k		0.014	0.013			0.015	0.012	
		(0.009)	(0.009)			(0.015)	(0.016)	
65+ population per 100k		-0.000	-0.000			-0.000	-0.001	
		(0.001)	(0.001)			(0.001)	(0.001)	
Unemployment rate, 2019		-3.167^{+}	-3.086^{+}			-2.197	-1.583	
		(1.806)	(1.801)			(2.397)	(2.520)	
Individual poverty rate		0.413	0.432			0.611	0.509	
		(0.358)	(0.360)			(0.624)	(0.637)	
Underrepresented minority share		0.022^{+}	0.021			-0.046	-0.036	
		(0.013)	(0.013)			(0.039)	(0.040)	
Urban		-0.566	-0.323			0.890	0.421	
		(0.600)	(0.602)			(0.928)	(0.976)	
Town		-0.069	-0.121			-4.737*	-3.964^{+}	
		(2.095)	(2.108)			(1.828)	(1.964)	
Rural		-0.723	-0.701			-3.985*	-3.945*	
		(1.452)	(1.458)			(1.691)	(1.696)	
Correctional facility		1.442	1.367			12.811***	12.988***	
		(2.360)	(2.402)			(3.475)	(3.457)	
College/University		-4.322	-4.300			-11.499^{+}	-10.993^{+}	
		(3.249)	(3.149)			(5.890)	(5.890)	
District FE	N	N	N	Y	N	N	N	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2420	2420	2420	2420	551	551	551	551
R^2	0.724	0.806	0.808	0.864	0.542	0.761	0.773	0.885

NOTE: Robust standard errors clustered at the county level in parentheses. Regressions weighted by district size. All models include month fixed effects with November as the reference category. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6-3. Estimated COVID case rates per 100,000 for 40-59-year-olds

	A. Michigan				B. Washington			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-Person	7.655***	0.411	-1.897	-3.080				
	(1.650)	(0.686)	(3.742)	(2.265)				
In-Person and Hybrid					4.547^{+}	2.109	-6.072*	4.494
					(2.657)	(2.094)	(2.874)	(7.054)
Hybrid	2.344^{+}	0.392	-4.484	-3.380				
	(1.358)	(0.814)	(3.356)	(3.519)				
Prior month cases	1.563**	1.244**	1.309^{+}		2.657*	1.062	-0.094	
	(0.510)	(0.416)	(0.684)		(1.150)	(0.748)	(0.572)	
Prior month cases squared	-0.031*	-0.035**	-0.050*		-0.049*	-0.012	0.011	
	(0.013)	(0.011)	(0.020)		(0.023)	(0.013)	(0.011)	
In-Person*Prior month cases			0.081					
			(0.644)					
Hybrid*Prior month cases			0.738					
			(0.651)					
In-Person*Prior month cases squared			0.015					
			(0.019)					
Hybrid*Prior month cases squared			-0.015					
			(0.020)					
(In-Person and Hybrid)*Prior month cases							1.843*	
							(0.809)	
(In-Person and Hybrid)*Prior month cases squared							-0.035*	
							(0.016)	
Percent always wears a mask		-0.656***	-0.640***			0.578**	0.589**	
		(0.120)	(0.119)			(0.172)	(0.171)	
Share to stay at home		-0.140	-0.219			0.153	0.340	
		(0.612)	(0.595)			(0.729)	(0.730)	
Trump vote share 2016		0.475**	0.479**			0.738***	0.714***	
		(0.152)	(0.150)			(0.152)	(0.153)	
Religious congregations per 100k		-0.016	-0.014			-0.085^{+}	-0.063	
		(0.028)	(0.028)			(0.045)	(0.044)	
Religious adherents per 1k		0.061***	0.059**			0.118***	0.118***	
		(0.018)	(0.017)			(0.019)	(0.019)	
School to county population ratio		12.002	9.979			-1.729**	-1.753**	
		(35.127)	(34.341)			(0.524)	(0.503)	
Nursing home residents per 100k		0.017^{+}	0.017^{+}			0.014	0.011	
		(0.009)	(0.009)			(0.011)	(0.011)	
65+ population per 100k		-0.000	-0.000			-0.001	-0.001	
		(0.000)	(0.000)			(0.000)	(0.000)	
Unemployment rate, 2019		-3.017^{+}	-2.901^{+}			1.488	2.122	
		(1.591)	(1.547)			(1.703)	(1.736)	
Individual poverty rate		0.434	0.461			0.126	0.021	
		(0.308)	(0.306)			(0.373)	(0.374)	
Underrepresented minority share		0.016	0.016			-0.075*	-0.066^{+}	
		(0.010)	(0.010)			(0.036)	(0.035)	
Urban		-0.329	-0.072			1.149	0.677	
		(0.625)	(0.646)			(0.822)	(0.844)	
Town		-0.988	-1.082			-3.974**	-3.202*	
		(1.560)	(1.543)			(1.428)	(1.442)	
Rural		-2.096*	-2.075*			-2.893*	-2.834*	
		(0.998)	(0.987)			(1.275)	(1.255)	
Correctional facility		2.804	2.419			10.717***	10.898***	
		(2.228)	(2.184)			(2.831)	(2.733)	
College/University		-1.252	-1.034			-12.971**	-12.448**	
		(2.625)	(2.548)			(4.338)	(4.193)	
District FE	N	N	N	Y	N	N	N	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2420	2420	2420	2420	551	551	551	551
R^2	0.750	0.844	0.846	0.888	0.527	0.767	0.785	0.871

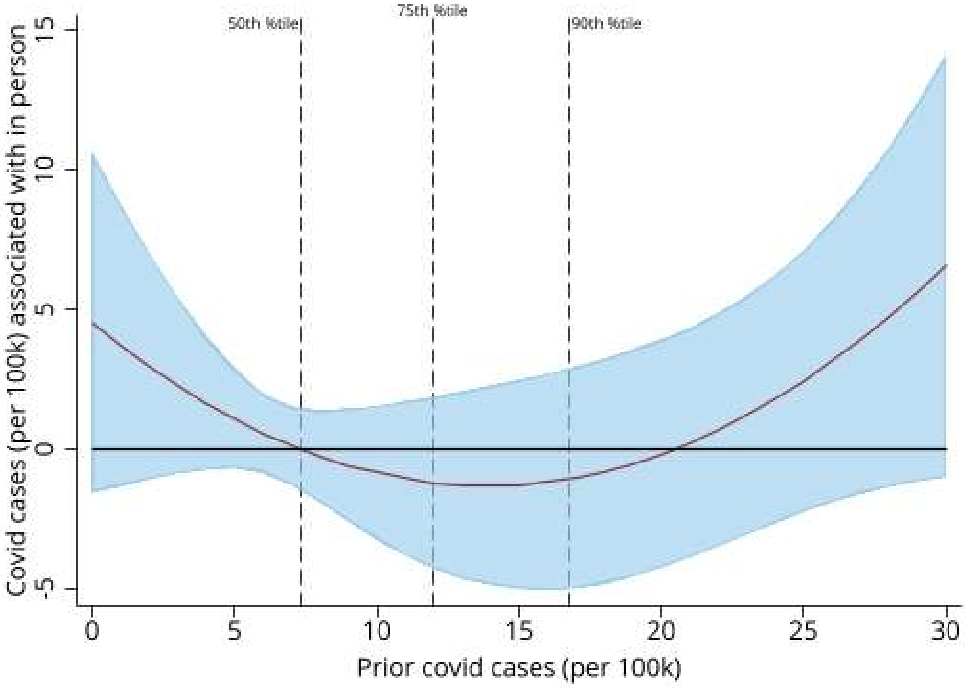
NOTE: Robust standard errors clustered at the county level in parentheses. Regressions weighted by district size. All models include month fixed effects with November as the reference category. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6-4. Estimated COVID case rates per 100,000 for 60+ year-olds

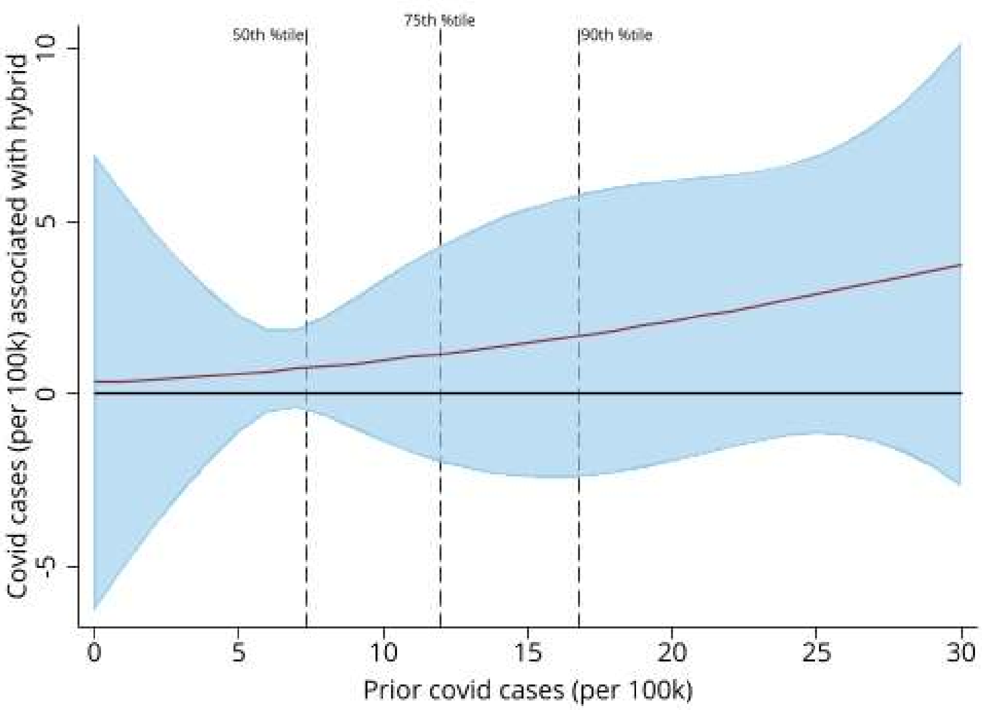
	A. Michigan				B. Washington			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-Person	7.646***	0.063	-4.161	-2.505				
	(1.363)	(0.603)	(3.394)	(1.992)				
In-Person and Hybrid					2.273	2.479*	-1.252	3.909
					(1.732)	(1.186)	(1.919)	(3.740)
Hybrid	1.878^{+}	-0.130	-1.662	-2.469				
	(1.027)	(0.674)	(3.184)	(2.654)				
Prior month cases	1.315**	1.092*	0.822		1.839*	0.548	0.018	
	(0.460)	(0.430)	(0.695)		(0.811)	(0.528)	(0.492)	
Prior month cases squared	-0.028*	-0.032**	-0.034^{+}		-0.029^{+}	-0.000	0.010	
	(0.011)	(0.011)	(0.020)		(0.017)	(0.010)	(0.010)	
In-Person*Prior month cases			0.494					
			(0.597)					
Hybrid*Prior month cases			0.078					
			(0.623)					
In-Person*Prior month cases squared			-0.001					
			(0.019)					
Hybrid*Prior month cases squared			0.008					
			(0.021)					
(In-Person and Hybrid)*Prior month cases							0.845^{+}	
							(0.456)	
(In-Person and Hybrid)*Prior month cases squared							-0.017^{+}	
							(0.009)	
Percent always wears a mask		-0.469***	-0.453***			0.187^{+}	0.192^{+}	
		(0.115)	(0.116)			(0.110)	(0.112)	
Share to stay at home		-0.216	-0.288			0.516	0.602	
		(0.502)	(0.483)			(0.423)	(0.419)	
Trump vote share 2016		0.534***	0.539***			0.543***	0.532***	
		(0.130)	(0.127)			(0.078)	(0.080)	
Religious congregations per 100k		0.005	0.006			-0.039	-0.029	
		(0.023)	(0.023)			(0.034)	(0.034)	
Religious adherents per 1k		0.044**	0.044**			0.059***	0.059***	
		(0.016)	(0.016)			(0.013)	(0.014)	
School to county population ratio		-17.671	-20.297			-0.934**	-0.946**	
		(31.420)	(30.633)			(0.334)	(0.326)	
Nursing home residents per 100k		0.013	0.012			0.022*	0.021*	
		(0.008)	(0.008)			(0.008)	(0.009)	
65+ population per 100k		-0.000	-0.000			-0.001*	-0.001*	
		(0.000)	(0.000)			(0.000)	(0.000)	
Unemployment rate, 2019		-3.479*	-3.354*			0.482	0.775	
		(1.497)	(1.472)			(0.838)	(0.840)	
Individual poverty rate		0.512^{+}	0.527*			-0.198	-0.247	
		(0.266)	(0.263)			(0.247)	(0.256)	
Underrepresented minority share		0.008	0.007			-0.011	-0.006	
		(0.007)	(0.006)			(0.022)	(0.022)	
Urban		0.140	0.369			0.059	-0.155	
		(0.435)	(0.476)			(0.649)	(0.639)	
Town		-0.495	-0.590			-2.426*	-2.078^{+}	
		(1.347)	(1.341)			(1.058)	(1.159)	
Rural		-0.517	-0.511			-0.938	-0.906	
		(0.869)	(0.873)			(0.894)	(0.903)	
Correctional facility		3.651*	3.621*			7.353***	7.436***	
		(1.729)	(1.696)			(1.864)	(1.831)	
College/University		2.830	2.805			-4.233	-3.991	
		(2.538)	(2.437)			(3.030)	(3.074)	
District FE	N	N	N	Y	N	N	N	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2420	2420	2420	2420	551	551	551	551
R^2	0.700	0.820	0.823	0.865	0.534	0.792	0.800	0.873

NOTE: Robust standard errors clustered at the county level in parentheses. Regressions weighted by district size. All models include month fixed effects with November as the reference category. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A1a, b: Marginal predictions of COVID-19 cases per 100,000 by prior case rates excluding September modality, Michigan



a) All districts in county shift from remote to in-person.



b) All districts in county shift from remote to hybrid.

Figure A2: Marginal predictions of COVID-19 cases per 100,000 by prior case rates when combining in-person and hybrid, Michigan

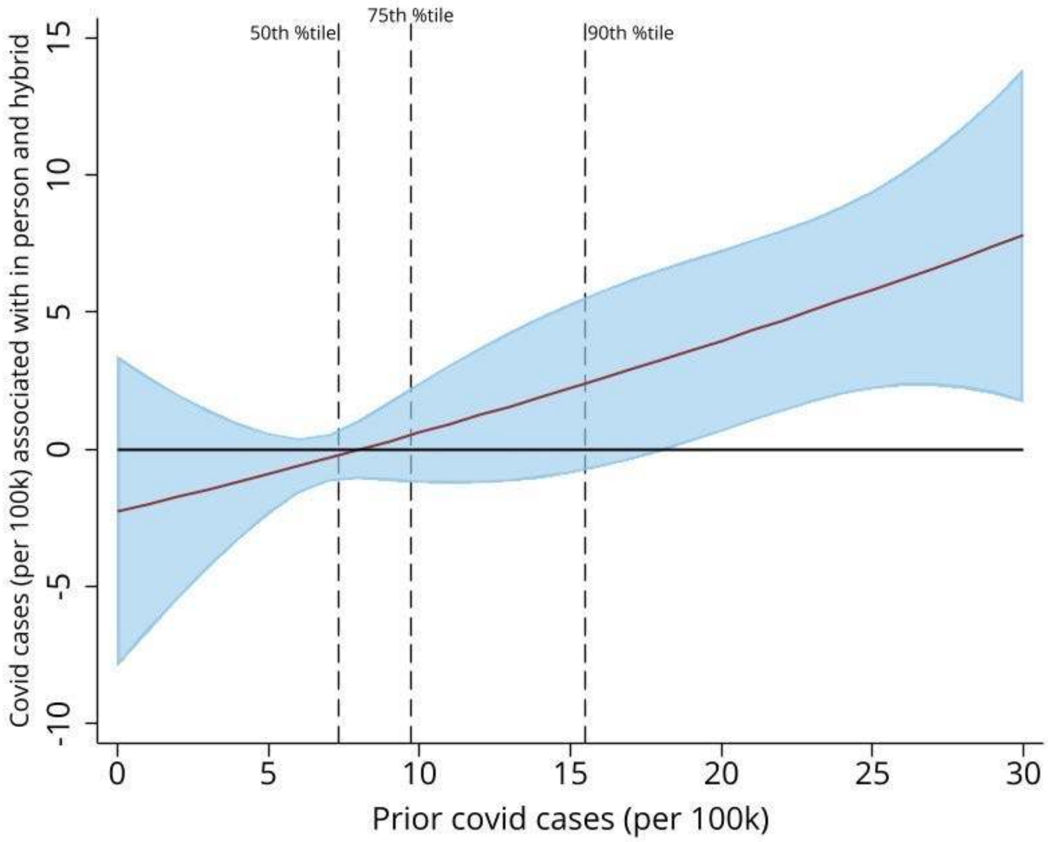
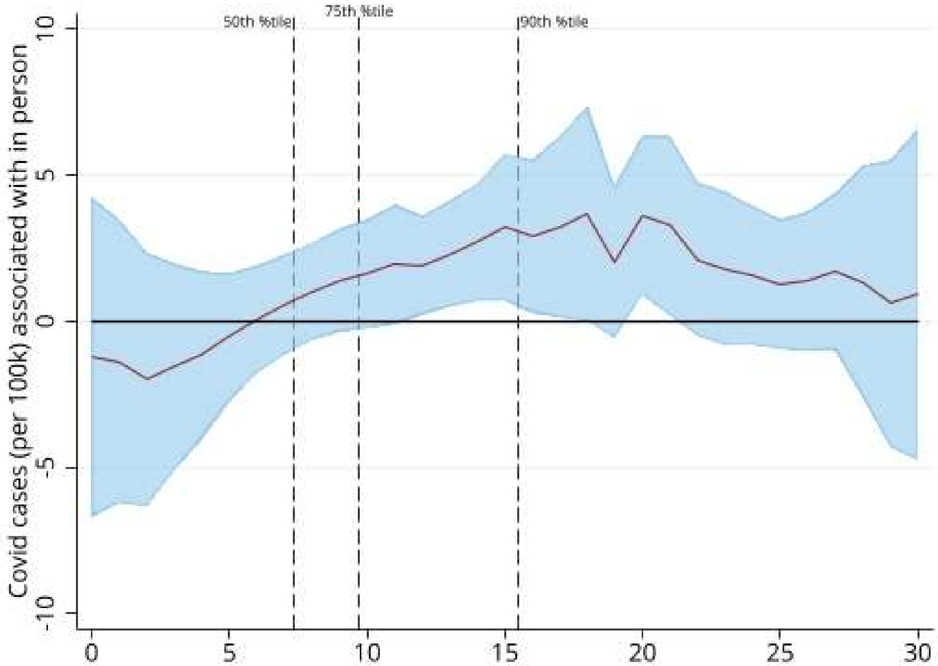
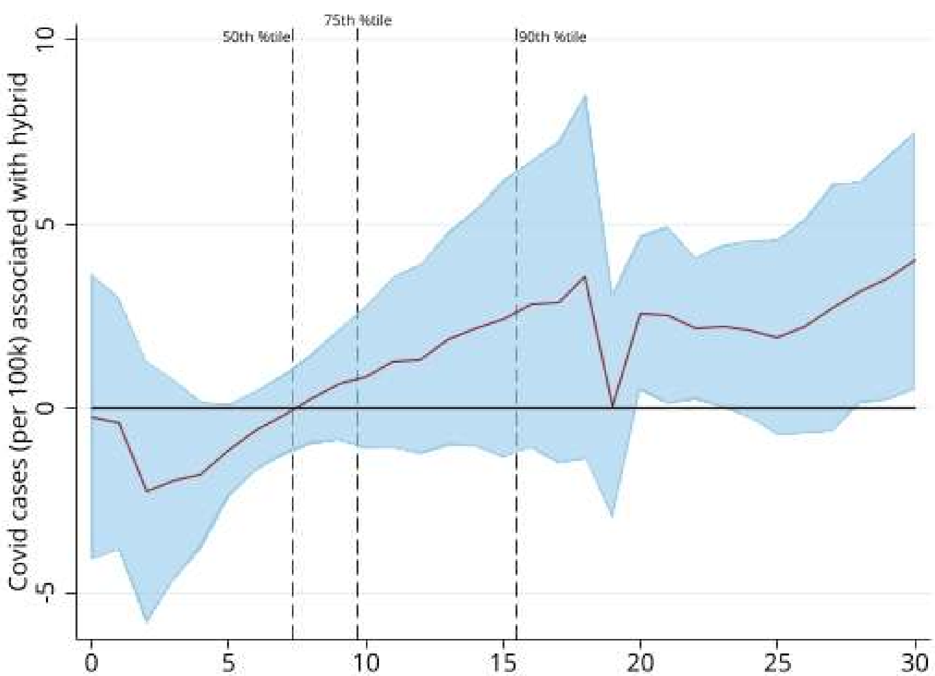


Figure A3a, b: Marginal predictions of COVID-19 cases per 100,000 by prior case rates under complete modality shifts and local linear specification, Michigan

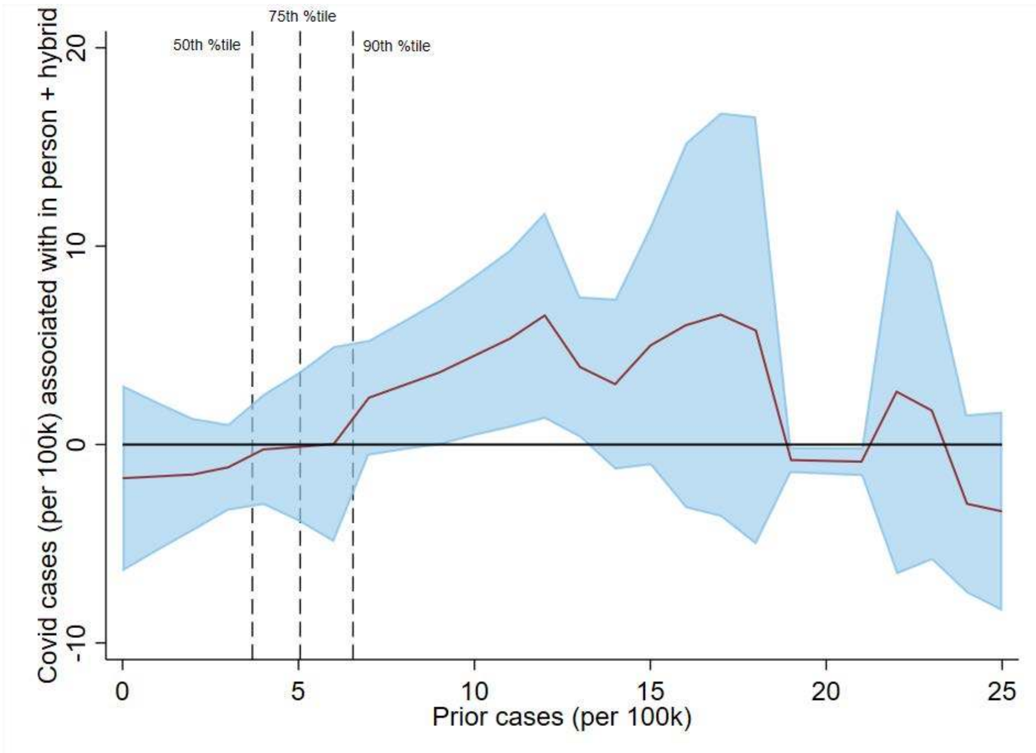


a) All districts in county shift from remote to in-person, 10-case bandwidth



b) All districts in county shift from remote to hybrid, 10-case bandwidth

Figure A4: Marginal predictions of COVID-19 cases per 100,000 by prior case rates local linear specification with a 10-case bandwidth, Washington



All districts in county shift from remote to in-person or hybrid.