



REACH

National Center for
Research on Education
Access and Choice

The Effects of School Reopenings on COVID-19 Hospitalizations

Douglas N. Harris, Tulane University

Engy Ziedan, Tulane University

Susan Hassig, Tulane University

Technical Report
Published January 2021

The Effects of School Reopenings on COVID-19 Hospitalizations

Douglas N. Harris

Engy Ziedan

Susan Hassig

National Center for Research on Education Access and Choice (REACH)

January 4, 2021

Abstract: We provide the first broad-scale evidence regarding the effect of school reopenings on COVID-19 health outcomes. We specifically focus on COVID-19-related hospitalizations, which directly measure the health outcomes of greatest interest and are not subject to the numerous measurement problems that arise with virus positivity rates and contact tracing. We also address selection bias in school reopening decisions by using panel analysis of weekly school reopening and COVID-19 hospitalization data for almost every county in the nation. In addition to fixed effects and matched difference-in-differences methods, we use teacher bargaining power as an instrumental variable. For counties whose pre-opening total new COVID-19 hospitalization rates were below roughly 36-44 per 100,000 population per week (roughly the 75th percentile of counties during the summer), we find no effect of in-person school reopening on COVID-19 hospitalization rates. For these counties, the estimates are robust to alternative school reopening and hospitalization data sources, the addition of controls for general state social distancing policies and college opening modes, and alternative estimation methods. For counties where total baseline new hospitalizations are above the 36-44 new hospitalizations per 100,000 per week, the estimates are inconsistent across methods and are therefore inconclusive. Our work contributes to the ongoing debate on teaching modes during the COVID-19 pandemic and the costs and benefits of remote education.

Acknowledgements: This research was carried out under the auspices of the National Center for Research on Education Access and Choice (REACH) based at Tulane University, which is supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305C100025 to The Administrators of the Tulane Educational Fund. The opinions expressed are those of the authors and do not represent views of the Institute, the U.S. Department of Education, Change Healthcare, or any other organization. For their helpful comments, we thank Sarah Cohodes, Austin Denteh, Dan Goldhaber, Michael Hansen, Scott Imberman, Robert Kaestner, Wei Long, Katharine Strunk, and Jon Valant. We also thank Sumedha Gupta, Chris Marsicano, and Kosali Simon, as well as Burbio, MCH, Change Healthcare, and the COVID-19 research database, a pro-bono cross-industry collaborative <https://covid19researchdatabase.org/>, for access to data and assistance in data cleaning and coding. Olivia Carr and Daniel Oliver provided invaluable research assistance. All remaining errors are those of the authors.

Author Information: Douglas Harris is professor and chair of economics at Tulane and director of REACH (dharris5@tulane.edu). Engy Ziedan is Tulane assistant professor of economics at Tulane (eziedan@tulane.edu). Susan Hassig is associate professor of epidemiology at Tulane (shassig@tulane.edu).

I. Introduction

Since it began to spread in January, COVID-19 has led to 1.7 million deaths worldwide and more than 300,000 in the United States. The health crisis has also precipitated substantial additional economic, social, and health side effects. Economic activity is predicted to decline by \$16 trillion in the U.S. alone (Cutler & Summers, 2020). Bankruptcies, unemployment, and food insecurity are up (Bauer et al., 2020). Mental health is worsening (Czeisler et al., 2020; Pan et al., 2020). People are putting off visits to doctors for non-COVID-19 ailments, potentially creating unintended health outcomes (Ziedan et al. 2020; Mehotra et al. 2020, Skinner et al. 2020).

Another significant effect of the virus has been to keep children, adolescents, and teenagers home from school. By April, more than 1.5 billion children worldwide were no longer in school and 263 million remain so (UNESCO, 2020). The U.S. has closed a larger share of school buildings than other developed countries.¹ More than two-thirds of U.S. students in large districts started the school year fully online (Center for Reinventing Public Education, 2020). While this number gradually dropped to 37 percent, the vast majority of the remainder are still in some form of hybrid learning.

While closing school buildings has been a reasonable reaction to an uncertain and fluid pandemic, the school closures are likely to compound the social and economic crisis in the short-term and the long-term. Remote learning has forced many parents to leave the workforce or work from home while also supporting their children's learning. This has reduced labor force participation and hindered career trajectories, especially among women (Tedeschi, 2020). Even when their parents are helping, children also learn less at home, which will affect their human capital, future productivity, and broader well-being (Hanushek and Woessman, 2020). While data collection during the pandemic has been problematic there are already signs of learning loss and rising achievement gaps (Bacher-Hicks, Goodman, and Mulhern, 2020; Chetty et al., 2020; Kuhfeld et al., 2020).²

When children are home, they are also more likely to experience physical abuse. While the number of reports of abuse have plummeted, this is likely because schools, when operating in-person, are among the primary reporters of abuse to local government agencies (Mathematica, 2020). There are signs that the declining reports of abuse are masking a significant rise in the underlying abuse frequency (Schmidt & Natanson, 2020). Therefore, as we try to grapple with the possible health costs of reopening schools, it is also important to consider the health and other costs to keeping them closed. Having children in school in-person has important benefits.

¹ <https://en.unesco.org/covid19/educationresponse>

² The Kuhfeld et al. (2020) study provides a seemingly more positive picture than the other two listed above, but the Kuhfeld et al. study also reports a 25 percent drop in the share of students tested in participating schools and a 50 percent drop in the share of schools participating at all. The authors attempt to simulate the effects of the former, but do not address the latter form of selection bias, so their results likely under-state learning losses.

The extent of this trade-off between the costs and benefits of reopening schools depends on how the virus spreads, the measures that schools take to reopen safely, and the kinds of social interactions in-person schooling replaces. Schools are supervised environments whose leaders are usually actively engaged with public health officials. When students are at home, in contrast, there may be less supervision, depending on home circumstances. So, while the number of social interactions is higher in schools, the effect on COVID-19 spread may be offset, at least in part, by higher safety of those interactions.

Partly for these reasons, some experts have suggested that reopening schools to in-person instruction would create limited increase in SARS-CoV2, the virus that leads to COVID-19 and its associated health ailments (e.g., American Association of Pediatrics, 2020; Oster, 2020). School-age children seem less likely to transmit the virus (Viner et al., 2020) or to suffer mortality (Laxminarayan et al., 2020). Unfortunately, the idea that it might be safe to reopen schools is based on limited evidence (Goldstein, 2020). The problem is that the data likely miss the vast majority of infections, especially among children, and even the infections we do observe are a function of self-selection.³ Also, the rate of COVID-19 testing is likely to change when schools reopen in-person. First, schools may be more likely open in-person where testing capacity is increasing or expected to increase in the near future. Also, when one person in a school population tests positive, school policies may require that the infected person and their close contacts test negative before re-entering school, increasing the frequency of COVID-19 testing. These factors make it difficult to determine whether any changes in the positivity rate after school reopening reflect changes in actual virus transmission or changes in the testing regimes, which may be unrelated to virus transmission.

Contact tracing is also based on virus testing and therefore suffers from similar problems.⁴ A few studies in the U.S. have found limited spread from children (e.g., Hobbs et al., 2020),⁵ but a virus “outbreak” is unlikely to be detected given the infrequency of testing. If an outbreak did become apparent, rare and selective testing makes it difficult to attribute this to schools as opposed to other places where social interaction occurs. In short, contact tracing might not show when schools are actually spreading the virus; and contact tracing might suggest an

³ It is unclear how many people have been tested. The CDC has reported 84 million tests (<https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covidview/index.html>), but an unknown share of these come from the same people receiving multiple tests (e.g., some college students and workers are being tested on a monthly or even weekly basis). Even if each test were from a different person, this would mean only one-quarter of the population has ever been tested.

⁴ An exception is Sweden where researchers were able to link individual students and teachers to one another, students to their parents, and teachers to their partners/spouses, an elaborate form of contact tracing that is without precedent in the U.S. (Vlachos et al., 2020). These authors also rely on the fact that upper secondary schools remained under remote instruction and lower secondary went back to in-person, creating exogenous variation in social distancing and potential virus exposure. This research suggests that school reopenings did increase SARS-CoV2 spread from students to their parents (odds ratio: 1.15) and from teachers to their partners (odds ratio: 2.01).

⁵ There are also two additional studies from the UK (Forbes et al., 2020; Ismail et al., 2020).

outbreak from schools even when the outbreak sources lay elsewhere.⁶ In any event, those few contact tracing studies that can be informative about school spread fall almost entirely outside the United States.⁷

A final limitation of analyses based on COVID-19 testing cannot provide evidence on what ultimately matters: health outcomes. We are left to assume that the effect on transmission, as reflected in the (imperfect) positivity rates, translates directly into negative symptoms, but there are good reasons to expect this not to be the case. For example, families may have more lax social distancing rules for their children if they are unlikely to come in contact with their grandparents or other older adults, reducing the extent to which the positivity rate translates into negative health outcomes.

In this study, we provide the first evidence of the effects of school reopenings on health outcomes, i.e., without relying on the positivity rate. Specifically, we focus on the effects of school reopenings on rates of *hospitalizations for COVID-19-related diagnoses that include almost all counties in the nation*. Our focus on hospitalizations is important because it gets us much closer to the outcomes of greatest importance--actual sickness. In addition, the validity and reliability of this measure is not likely to be affected by whether schools reopen. Unlike the positivity rate, which is likely to change after schools reopen regardless of school spread effects, hospitals are not likely to change their rate of illness reporting because schools reopen.⁸

Our specific health outcome measure is the number of hospitalizations that involve a COVID-19 diagnosis, using two data sources: health insurance claims data provided by the organization Change Healthcare and recently released data from the U.S. Department of Health and Human Services (HHS) data from essentially all U.S. hospitals. The former include diagnosis codes for each individual patient, along with the admission date and other information that allow us to identify the county of residence of the patient (3-digit zip code of the patient's home residence), from January through the end of October, providing ample time for effects to emerge after school reopenings, even if, as we expect, the hospitalizations are delayed by transmission time and virus incubation. The new HHS data do not begin until the end of July but they include more fine-grained 5-digit zip code location data (using the location of the hospital rather than the patient).

The other key type of data involves the date and form of school reopening. We use data from three sources—the trade publication *Education Week* and two private companies, Burbio

⁶ To be clear, contact tracing can still be a useful tool for schools trying to contain the virus. As we show later, reopening schools is likely to spread the virus when there is more of the virus in the community, regardless of the source.

⁷ The Viner et al. (2020) meta-analysis included 16 studies, including six from China, three from the U.S., and single studies from various other countries. The study focused on contact tracing studies addressed these concerns by focusing just on those contact tracing studies that involved fairly universal testing and tracing. The results of these more credible studies suggest that the “attack rate” (i.e., the probability of infection when being in contact with an infected person) was consistently lower in children compared with both adolescents, who in turn had lower attack rates than adults (Viner et al., 2020). However, this does not tell us whether schools are spreading the virus.

⁸ As discussed later, we only study in-patient cases and hospitals might not admit patients when hospitals are already near capacity, but the share of hospitals reaching that capacity has been very low.

and MCH Strategic Data—regarding the date and mode of school reopening (fully in-person, fully remote, and hybrid). Each of these data sources has advantages and disadvantages; however, they generally yield similar conclusions when we apply the analysis with each one separately.

We analyze these county-by-week panel data in a generalized difference-in-differences framework that incorporates both propensity score matching and instrumental variables estimation. Specifically, we regress the number of COVID-19 hospitalizations on measures of the instructional mode of school reopening, variables capturing state social distancing guidelines, college reopening dates and modes, and county-level fixed effects. Both the school reopening and hospitalizations are at the county-by-week level, allowing us to observe changes in hospitalizations each week after schools reopened (up to 6 weeks post-treatment).

Even with the above rich set of controls, it is possible that school reopening decisions are related to factors that also affect hospitalizations in other ways; therefore, we also use teacher bargaining power as an instrumental variable (IV) in the fixed effect analyses. School districts with more bargaining power are less likely to open in person (Hartney & Finger, 2020). Our results from the first stage IV estimation confirm this. Also, there are few reasons to expect that teacher unions affect hospitalizations through any other channel, especially not in a way that coincides with the timing of school reopening.

Using these methods, we see no indication that in-person school reopenings have increased COVID-19 hospitalizations in the counties below 36-44 new COVID-19 hospitalizations per 100,000 population per week (this is roughly the 75 percent of U.S. counties as of October, the most recent month of data available). Neither the levels nor the trends change in any direction when schools open in this group, even as far as 6 weeks after schools reopened. In fact, we often see precise estimates suggesting *declines* in hospitalizations in these low-baseline COVID-19 counties; and we pass parallel trends tests from roughly 6 weeks prior to school reopening up to the reopening dates (with some non-parallel trends in the early summer weeks). The results are also robust to the inclusion of time-varying state social distancing policies, college reopening timing and mode, the use of alternative school reopening data sets (Burbio versus MCH), and different estimation strategies. Our main results focus on the Change Healthcare data because of the larger number of periods, but the results are also robust to the use of the new HHS data.

In the counties with higher pre-opening COVID-19-hospitalization rates, however, the results are inconclusive. While we still sometimes see evidence of reduced hospitalizations, the estimates also sometimes suggest the opposite. This possibility of increased hospitalizations is consistent with the idea that social interaction creates more negative health outcomes when there is more of the virus to be spread, perhaps despite careful school safety measures. In these cases, it could still be appropriate to reopen schools, because of the negative effects on students and parents from keeping schools closed (see above), but there may be more of a trade-off. Opening schools in these high-COVID-19 locations might spread the virus, but improve other health outcomes for students and their families in other ways (e.g., reduced abuse and mental illness).

Our method is similar to one in Germany (Isphording, Lipfert, & Pestel, 2020), which found that school reopening reduced SARS-CoV2 transmission. The authors explain that the drop is possible because schools instituted strict protocols that quarantine students who tested positive. This threat, combined with strong messages sent by educators to encourage safe behaviors, may have led students to be more careful in social distancing outside of school, leading to the net drop in transmissions.⁹ Also, we have to consider the counterfactual of what students would have been doing in the absence of going to school in-person. In-person schooling, under supervision of safety-trained educators, might replace unsupervised, unsafe group activities outside of school. Our study is also similar to a study in progress using data from Michigan and Washington (Goldhaber et al., 2020). However, these studies both rely on the positivity rate.

The inadequacies with the positivity rate suggest that additional research is necessary to provide a complete picture of the effects of school reopening on SARS-CoV2 transmission and COVID-19 health outcomes. In Section II, we summarize more of what is known about the factors affecting school reopenings and SARS-CoV2 transmission. Section III describes our data in more detail. We discuss our identification strategy in section IV and finally, in section V, present our results. Important considerations for interpreting these findings can be found at the end of section V and in section VI.

II. Prior Research on School Reopenings and COVID-19

At least two strands of research inform the interpretation of results regarding the effects of school reopening on COVID-19 transmission. First, we discuss what is known about the extent and type of school reopenings and the factors affecting these decisions. We also include information on college reopenings, as these are potential confounders in our analyses. This discussion also helps us understand the data generating process and identify appropriate identification strategies.

Second, we consider what is known about how COVID-19 typically spreads in the population. This is important particularly for determining how we set up and interpret our econometric model, i.e., how the length of the virus incubation period and development of symptoms affect the expected lag between school reopenings and hospitalizations.

II.A. School and College Reopening Rates, Modes, and Predictors

Several ongoing data collection efforts focus on analysis of the reopening of urban schools. The Center for Reinventing Public Education (CRPE, 2020), tracking 106 mostly large urban districts, shows a gradual decline in the percentage of districts operating with fully remote instruction. CRPE projected that, by the end of October, 37 percent of schools would be fully

⁹ The study in Germany only covered a three-week post-opening time period (less than half as our study); however, virus transmission and incubation do normally occur within this time frame.

remote (down from 76 on September 7). This is offset by a similar rise in the share of districts reporting “phased reopening.” The number fully or mainly in-person has stayed relatively steady at 18-19 percent. Similarly, in another survey of the 50 largest districts, the *Washington Post* reported that 24 districts reported “in-person classes for large groups of students” and another 11 planned to do so in the forthcoming weeks.¹⁰

Schools vary widely in their approach to reopening. Almost all reports, for example, indicate that districts allowing students back in-person at all bring back elementary age students first, and fewer high school students. Reopening decisions have also been driven by state policies. The states of Arkansas, Florida, Iowa, and Texas have required public schools to give parents the option for in-person instruction. Rhode Island and some other states have also placed strong pressure on districts to offer in-person options.

Others have studied the factors affecting state policies as well as more localized school reopening decisions. Perhaps surprisingly, the COVID-19 positivity rate has not been the strongest predictor of reopenings; instead, the strongest predictor is the political persuasion of the local population (Hartney & Finger, 2020; Valant, 2020). School reopening became a polarizing issue as President Trump and Secretary DeVos placed considerable public pressure on schools to reopen in-person. As a result, even after controlling for other demographic differences, those areas with strong Trump support were much more likely to offer in-person options (Hartney and Finger, 2020; Valant, 2020).

Hartney and Finger (2020) also report a positive association between the number of private schools located in the district and reopening in-person. Private schools were under much more pressure to reopen because of their nearly complete dependence on tuition revenue; this might also be why they reopened faster than public schools in the spring (Harris et al., 2020). Traditional public schools may have worried that they would lose enrollments to private schools if they opened too slowly.

Teacher union power is another factor and one that figures prominently in the analysis that follows. The Hartney and Finger (2020) study also concluded there was a role for teacher unions, but had to base this conclusion on district size as a proxy for union power. This is problematic given the other ways in which district size might affect school reopening that the study did not account for. Nevertheless, as we show later, actual data on unionization intensity reinforces that this was a strong predictor of school reopening mode.

Understanding the factors determining school reopening decisions is important to estimating the effects of these policy changes. In particular, we can expect teacher unionization to have minimal impact on the rate of COVID-19 hospitalization aside from its effects on school reopening mode. This creates a natural instrumental variable. Political persuasion and the number of private schools, in contrast, are likely to directly affect hospitalizations, e.g., political persuasion likely affected mask-wearing and social distancing and private schools, especially those that reopened in-person, could spread the virus on their own, independent of the opening

¹⁰ https://www.washingtonpost.com/education/school-districts-reopening-coronavirus/2020/10/19/3791c952-0ffb-11eb-8074-0e943a91bf08_story.html

decisions of traditional public schools. We discuss our use of teacher unionization as an instrumental variable later, in section III.

Another factor that could affect SARS-CoV2 transmission and hospitalization is college reopening. Like private K-12 schools, most colleges (even ostensibly public ones) are heavily dependent on tuition, fees, and room and board for their financial survival. However, colleges are apt to spread viruses, especially in residential colleges where students come from a distance and live in dormitories or other group housing. Students are likely to bring the virus to campus with them, to spread the virus in dorms and social settings, and then to bring the virus back home during breaks and vacations. Multiple studies have shown increased COVID-19 positivity of college-age adults and in the general population living near colleges (Anderson et al., 2020; Salvatore et al., 2020).

For this reason, it is important to account for the potential effects of in-person opening of colleges as we consider how school reopenings affect health outcomes. The instrumental variables method largely addresses this possibility (see below). However, we also test the robustness of our IV estimates by: (a) including time-varying college reopening mode in our models; and (b) estimating the first stage of the IV model regression where we attempt to predict the county's college reopening mode (hybrid/in-person) using the county's K-12 teacher union power.

II.B. SARS-CoV2 Infection and Relation to COVID-19 Hospitalizations

One challenge of the pandemic has been tracking its expansion. We have a number of tools in use to meet this challenge, but each has distinct shortcomings. To understand this, we need to start with how SARS-CoV2 progresses in human hosts and the opportunities provided for detection or diagnosis of the infection.

We all share a vulnerability for infection upon exposure to the virus. When a human is exposed to any viral pathogen, the immune system reacts by a number of pathways, including one which produces potential markers of infection, antibodies. These antibodies have not been a reliable tool for the identification of persons actively infected with SARS-CoV2.

While the virus is replicating in the human host, it may be unrecognized, and an infected person can transmit the infection to others. This infectious phase is when viral detection diagnostic methods become useful and tracking of active human infections is possible. In the case of SARS-CoV2, the time needed to reach a detectable level of virus in a human host can range from 1-14 days, with most individuals reaching a detectable viral load around 4-7 days after an infection event. Recent research indicates that 97 percent of infected persons will have a detectable viral load by day 11 post-infection (Wiersinga, et al. 2020). While the virus is replicating, the body's immune system is mounting its response which will, within roughly 2 weeks, contain the infection, and disrupt further replication as well as the potential for transmission to others. Given these constraints, timing of viral detection tests is critical to the

detection of the active infections which drive expansion of the pandemic, and significantly limits the accuracy of virus tests in delineating viral expansion in populations (CDC, 2020).

Given the issues with antibody and virus tests, our ability to accurately assess current levels of actively infected persons is not robust. Implementation of testing efforts is not consistent across communities, nor even over time within communities. There are many reasons for this heterogeneity, ranging from availability of test kits and personnel to administer them, willingness of persons to participate in voluntary testing programs, and support for large-scale testing efforts by some local, state and federal governments. The selection processes inherent in this heterogeneity complicates interpretation of test results, expressed as case counts, cases per population, and/or test positivity (the number of positive tests/tests performed). At any point in time, we must assume that the cases detected are an underestimate (of unknown magnitude) of the actual number of persons infected, which provides an incomplete picture of the expansion of the pandemic.

Another approach is to track clinical, symptomatic disease as a key health outcome. The SARS-CoV2 virus appears to cause some form of clinical illness (COVID-19) in 60-70 percent of infected persons, with a substantial percentage of those ill persons experiencing very mild, and potentially unrecognized or discounted disease, which may not be captured in any medical interaction (Wiersinga et al., 2020). It is also a lagging indicator, as persons with SARS-CoV2 may develop serious disease requiring hospitalization anywhere from 1-4 weeks post infection (Wiersinga et al, 2020). Given that symptoms of infection generally occur 4-7 days after exposure, if school reopening increased infections leading to hospitalizations, we would expect to see a rise in COVID-19 hospitalizations 2-5 weeks after schools reopened, if schools are spreading the virus.

Accessing medical care for symptomatic disease, and especially hospitalization for serious illness, which constitutes an estimated 5-10 percent of SARS-CoV2 infections, appears to be one of the most stable and reliable measures we have available to track the clinical impact of SARS-CoV2 (Wiersinga et al., 2020). Persons experiencing shortness of breath, and other debilitating symptoms will seek care out of necessity, even if they might normally have a variety of barriers limiting their interaction with healthcare. Since there appears to be less selection bias in hospitalizations compared with positivity rates and related measures, we focus our analysis on COVID-19 hospitalizations, allowing for a 2-5 week, or longer, lag to capture the effects of not only initial infection and disease associated with school opening, but also the effects of subsequent generations of infection which may be produced.

III. Data

We study the effects of school reopening on hospitalizations for COVID-related diagnoses at the county level. Three key variables drive the analysis: the timing and mode of school reopening, teacher unionization (the instrumental variable), and hospitalizations. We discuss these below in turn.

III.A. School Reopening Data

There are three data sets on school reopenings that are at least partially publicly available that include large national samples of school districts: *Education Week*, Burbio, and MCH Strategic Data. All three collected data on the date of reopening and the instructional mode: fully in-person, fully remote, and hybrid. These data sources have not provided clear definitions about the precise distinctions between these categories or how they were operationalized.

The trade publication, *Education Week*, began collecting data on school reopenings from school websites in the summer for 907 of the nation's largest districts. This constitutes roughly seven percent of districts but a much larger share of the nation's public school students. While not a random sample, *Education Week* also sought at least five districts per state, since many states do not have large districts by national standards. Nevertheless, the relatively small, non-representative sample is problematic. For this reason, we include *Education Week* data for some descriptive analysis, but do not include it in our main analyses.

The private company, Burbio, also collected data from school websites, but from a larger sample of 1,200 districts, again mostly larger districts. Burbio aggregated these data up to the county level. The least populous counties, which account for 25 of the student population, are imputed from other nearby counties. Finally, MCH collected data primarily by calling essentially all school districts in the United States by phone.¹¹

Table 1 shows the percentage of schools opened in instructional mode, according to each data source. The figures vary across sources. For example, the percent in-person ranges from 19 percent in MCH to 43 percent in Burbio and the percent remote varies from 24 percent in MCH to 49 percent in *Education Week*. This is no doubt partly a function of the differences in samples, e.g., *Education Week*'s sample is more heavily urban, which likely explains why more districts are labeled remote.

The differences in school reopening modes across data sources are also likely partly due to the ambiguous (and generally undefined) nature of the "hybrid" mode. This category may include districts where elementary schools reopened partially in-person, but where other schools remained fully remote; or it might include districts where elementary schools were fully in-person but secondary schools were fully-remote; and districts where all schools opened to partially-in-person instruction. Those creating the data could have used different definitions and

¹¹ MCH also did some web scraping (later verified by phone calling) and sent surveys to some districts.

coding procedures, which, in any event, are not available. As a further check, note that Burbio reports 35 percent of districts being fully remote as compared with 42 by the Center for Reinventing Publication (2020).

The three data sources have greater overlap in the opening dates, however. For example, 95 percent of the 907 *Education Week* districts are listed as having opened in the same week as the same set in MCH. (The overlap is somewhat lower in the Burbio data.). Nevertheless, given the differences in definitions and/or coding of instructional mode, we use both Burbio and MCH in most of the main analyses. (The *Education Week* data provide too few observations and are used for diagnostic purposes.)

One challenge in understanding the extent of in-person instruction is that many schools are allowing students to continue learning remotely even when the schools are officially “fully in-person.” One of the few studies to differentiate the two is from Michigan where a detailed analysis of district plans found that 16 percent of districts gave a hybrid *option*, while only 14 percent were remote only (Education Policy Innovation Collaborative, 2020). Also, 53 percent of students had an in-person option, but, again, a much smaller share was likely actually attending in person, especially on a full-time basis. This highlights an important distinction between school reopening *policies* regarding instructional modes and what students’ *experiences*.¹²

None of the three data sources explicitly include charter or private schools. However, note that nearly half of charter schools are authorized by traditional public school districts and likely followed the districts reopening plans. Private schools are not obligated to follow district reopening policies, but these constitute fewer than 10 percent of all elementary and secondary schools and an even smaller percentage of the U.S. school-age population; therefore, this is unlikely to affect our results.¹³

While the Burbio and MCH collected data on a continuous basis and therefore have information about changes in reopening status, we focus our analysis only on the initial fall reopening and do not attempt to account for changes in instructional mode over time. This is for two main reasons. First, the data on the timing of those changes is likely less accurate than the initial reopening; Burbio and MCH began collecting data before schools reopened and had many weeks to reach schools and collect data before any changes occurred. However, the situation became more fluid after the first month or so of the semester and the rate of data collection may

¹² Given that many schools are offering the option of reopening, surveys of parents might seem to be a better source of the extent of in-person instruction. However, we are not aware of good estimates. Since early August, the U.S. Census has been collecting biweekly survey data on the percentage of students attending school to varying extents. Nationally, as of October 14-26, 82 percent of families report remote instruction. Unfortunately, the Census survey items do not distinguish fully remote learning and hybrid (i.e., the combination of in-person and remote), which is problematic since other evidence suggests that these are the two most common categories.

¹³ Even aside from the small number of charter and private schools, their omission does not affect the results if they opened either: (a) in the same fashion as nearby traditional public schools we observe; or (b) they opened differently than traditional public schools but in a way that is similar across counties within states (more on this later). Other data suggest that these schools did open faster in the spring (Harris et al., 2020) and anecdotal evidence suggests they opened in-person more commonly this fall as well

not have kept up with the changes. Second, the 2-5 week lag between exposure to infected individuals and potential hospitalizations brings us near the end of our panel; therefore, we cannot even attempt to estimate effects for changes in opening status that occurred after September. Third, even if we had more recent data, any subsequent changes likely involve endogeneity in the dynamics of school reopening that would be difficult to account for in any empirical analysis.

To test whether the focus on just initial reopening is likely to affect our results, we created a transition matrix, which shows the percent of districts that initially opened in which mode in the fall (time t) and the mode shown in the data as of October 10 using MCH data (see Appendix Table 1). The results suggest that two-thirds of districts were still in the same mode as of October 10. This reinforces the usefulness of focusing identification just on the initial reopening period. This is the time period where the data are most accurate and stable and where we can cleanly identify effects.

The Burbio and MCH data are at the county and district level, respectively. As discussed below, we can also convert the hospitalization data to the county level (weighting by district enrollment) therefore the county is the main unit of analysis in the study.¹⁴

III.B. Teacher Bargaining Power

For the instrumental variables analyses, we use data on teacher unionization from the 1999-2000 public use Schools and Staffing Survey (SASS) from the National Center for Education Statistics of the U.S. Department of Education. The SASS is collected on a nationally representative sample of teachers and administrators periodically. The data include information for 4,690 school districts, or a bit more than one-third of the total. Like the other education data in this study, the unionization data are aggregated to the county level; we use the (weighted) average of the available districts to represent the county as a whole. This yields data for 1,854 counties of the roughly 3,000 counties in the U.S.

There are newer waves of the SASS, but the use of these older data is necessary to allow the linkage to hospitalization data.¹⁵ Some changes in teacher unionization have occurred since 2000 as some states reduced the power of teacher unions; however, there is little reason to expect that this would affect our results. The 2000-public-use and 2011-restricted-use SASS data sets are correlated at +0.80 on the teacher bargaining power variables.

The SASS reports two types of teacher unionization: collective bargaining and meet and confer. The former means that the district administration is obligated to bargain with the union, while the latter means that district administration has volunteered to confer with teachers over issues similar to those that are the subject of collective bargaining, even though such agreements

¹⁴ School districts almost always fall within a single county. In some cases, especially in the South, the county and district are coterminous.

¹⁵ The restricted use SASS data cannot be moved from the secure computers; the same was true of the hospitalization data. Using the public use SASS allowed us to move the data into the hospitalization files.

are not legally binding as contracts. These two teacher bargaining variables are therefore ordinal, with collective bargaining at one end, no teacher agreements at the other end, and meet and confer providing a middle ground of teacher bargaining power.

Some of the variation in teacher bargaining power is at the state level as some states bar collective bargaining for public employees. However, all but nine states have some meet and confer districts and, in states where collective bargaining is allowed, the teachers in some districts have not voted for collective bargaining. This creates variation within states that allows us to keep all states in the analysis and still use state fixed effects, which are helpful for absorbing the influence of time-invariant factors such as unobserved state policies and political orientation.

Table 2 reports each state's legal status of unions, the number of total school districts in the state, the number of districts for which we have SASS bargaining power data, and the shares of those districts that are labeled as collective bargaining and meet and confer. As expected, we see zero or near-zero numbers of districts reporting collective bargaining in the states where it is barred. This reinforces the validity of the data.

One limitation, however, is that only roughly half the states have much variation in teacher bargaining power, which is necessary to use these variables as instruments in models with state fixed effects. Also, the states with the most variation in bargaining power tend to have small populations and be located in the South and Plains states.¹⁶ Since COVID-19 spread is thought to be biologically universal, we do not expect this to influence the general findings, but the differences in results could reflect effect heterogeneity, which we test for.

III.C. Hospitalization Data

We use two sources of hospitalization data. First, we use medical claims data from Change Healthcare with approval from the COVID-19 Research Database.¹⁷ We also use nationwide facility-level data from the U.S. Department of Health and Human services (HHS).

Change Healthcare is the nation's largest claims clearinghouse with a network of 900,000 providers and 5,500 hospitals across the country, processing nearly 55 percent of all commercial claims (including Medicaid Managed Care and Medicare Advantage, but not Medicare FFS) in the U.S for nearly 170,000,000 unique individuals. Change Healthcare provided us with de-identified claims within days after claim processing. We were not provided with all claims in Change Healthcare's database. Instead, we received a longitudinal dataset of claims for individuals ever diagnosed with COVID-19. Specifically, we received all in-patient claims for any patient ever observed with a COVID-19 diagnosis using the International Classification of

¹⁶ There are 19 states that have between 10 and 90 percent in either the collective bargaining and meet and confer categories. These are (alphabetically): Alabama, Alaska, Arizona, Colorado, Idaho, Kansas, Kentucky, Louisiana, Missouri, Montana, New Mexico, North Dakota, Oklahoma, South Dakota, Tennessee, Utah, Virginia, West Virginia, and Wyoming.

¹⁷ <https://covid19researchdatabase.org/>

Diseases (ICD) codes: U07.1 and U07.2.¹⁸ We observe the entire record for those patients pre- and post-the COVID-19 diagnosis.

From this subsample, we count only inpatient hospitalizations (including through emergency rooms) with diagnoses of COVID-19 *or* COVID-19 related symptoms.¹⁹ The resulting sample is 660,000 COVID-19 hospital admissions to the inpatient setting or the emergency room between January 2020 and October 2020.²⁰ For this group, we observe the patient's admission date, discharge date, diagnosis, facility type of admission (inpatient, outpatient, ER), gender, 3-digit zip code of patient's residence, year of birth and a de-identified token that allows us to link the patient's records over time. (We do not observe information on race/ethnicity.)

To give an example, consider a patient who tests positive for COVID-19 in March 2020 (ICD -U07xx) and is therefore observed in our subsample. Subsequently, in September 2020, she was hospitalized for a bladder infection. We do not count this encounter as a COVID-19 hospitalization because bladder infections are not COVID-19-related. Now, consider a patient who is diagnosed with COVID-19 (ICD U07xx) and subsequently admitted for Acute Respiratory Distress Syndrome (eg: ICD J80); we count this as a COVID-19 related admission (even if the inpatient admission did not explicitly state a COVID-19 ICD-10 code).

Since we received data at the 3-digit zip code, we generate county-level data, by aggregating the 3-digit zip code level data to the county level. Specifically, to convert to counties, the 3-digit zip codes were first converted to five-digit zip codes by distributing the share of hospitalizations across the appropriate zip codes based on population proportions. This assumes that the distribution of hospitalizations follows the same distribution as the population. Zip codes were then converted to counties using a zip code-county crosswalk provided by the Department of Housing and Urban Development.²¹

We summarize the trend in COVID-19 hospitalizations in our data in Figure 1A. These data highlight the steep changes in hospitalizations. The hospitalization rate peaks in week 42 (mid-October) at 15 hospitalizations per 100,000 in the population. While not shown, this trend reflects a heavily skewed distribution, with most counties having zero hospitalizations and some have more than a thousand. (As these are per 100,000 in the population, they account for wide variation in county population size.)

In addition, on Dec 7th, 2020, HHS released nationwide hospitalization data that was collected by Teletracking (a third-party contractor). This dataset includes capacity reporting from

¹⁸ We also received outpatient and prescription drugs information, but we do not utilize these data in the current analyses.

¹⁹ Specifically, we use codes: using 10 ICD codes (U07xx, R50xx, R05xx, R06xx, J18xx, J17XX, J96XX, J80XX, J12XX, J20XX, J40XX, J22XX, J98XX, Z03.818, Z20XX, Z11XX. These codes were obtained following CDC covid19 coding guidelines <https://www.cdc.gov/nchs/data/icd/COVID-19-guidelines-final.pdf>

²⁰ The January 2020 data includes admissions for symptoms related to Covid-19 even if Covid-19 was not explicitly stated at time of admission.

²¹ This approach has been used before for example when studying the distribution of opioid prescriptions across counties from 3-digit zip code data from the Drug Enforcement Agency (Kaestner and Ziedan 2020, among others).

individual hospitals in 2,200 counties. Specifically, the data report weekly counts of confirmed and suspected COVID-19 admissions at the hospital level starting from the week of July 31st 2020. The term “suspected” is defined as a person who is being managed as though he/she has COVID-19 because of signs and symptoms suggestive of COVID-19 as described by CDC’s guidance, but does not have a laboratory positive COVID-19 test result. This may include patients who have not been tested or those with pending test results and patients with negative test results.

Figure 1B presents nationwide trends in suspected, confirmed and total (suspected plus confirmed) admissions over time from the HHS facility-level data. Until week 42, the number of hospitalizations for COVID-19 suspected cases surpassed the number of hospitalizations for COVID-19 confirmed cases. After week 42, the number of hospitalizations per 100k for confirmed COVID-19 cases surpasses the suspected per 100k admissions. This pattern may be due to increases in testing availability and turnaround time. Since the Change Healthcare COVID-19 admissions are for those with positive COVID-19 tests, the counts per 100k from Change Healthcare (Figure 1A) are most comparable to the counts of confirmed cases in Figure 1B. Also, the number of hospitalizations (per 100k) at any given time may be higher in the HHS data because our insured sample, which excludes Medicare Fee for Service patients, is younger and likely less likely to become symptomatic than the overall population.

Both data sets are useful for purposes of this analysis as they both include large and consistent samples of institutions (insurers and hospitals, respectively). However, the Change Healthcare data come with three advantages that lead us to focus on these in our main results. First, the Change Healthcare data start on January 1st 2020 and provide a longer time series with which to test for parallel trends. In contrast, the HHS data start on August 1, within four weeks of the start date of 57 percent of school districts.²²

In addition, the Change Healthcare data provide much more detail regarding patient diagnoses and allow us to define cases ourselves in a standardized way. In contrast, the HHS data rely on the somewhat amorphous notion of “suspected” cases; more generally, the HHS data rely more on the reporting discretion of hospitals than the Change Healthcare data.

Finally, the Change Healthcare data map COVID-19 hospitalizations to the residence of the *patient*, which is likely closer to the point of virus transmission (from school reopenings or otherwise). In contrast, the HHS data use the location of the *hospital*. This could be a particular issue in rural areas where hospitals may not be located nearby. Also, patients may have to travel to more distant hospitals when they get sick if nearby ones are already full, or if more distant hospitals have better health care and public health services generally for COVID-19; this capacity to deal with the virus could affect the virus’s spread, creating an endogeneity problem. For these reasons, we rely on the Change Healthcare in most of our analyses.

²² We observed 2,400 counties with school reopening dates in Burbio. Of them, 1,372 (57%) had opened their school district(s) by August 30th 2020. Similarly, of 8,283 school districts in the MCH data 4,762 (57.4%) opened by August 30th, 2020.

Even with the richness of the individual-level claims from Change Healthcare, these data also come with concerns about generalizability, changing samples, and measurement error. As noted above, one potential problem is school reopenings might affect the insured differently from the uninsured. Also, the percent of the population insured may have changed as insurance coverage was dropped as a result of unemployment and the general economic slowdown, which could occur differentially across counties in ways that are correlated with school reopenings. That said, one recent report estimated that losses of employer-based coverage will be lower than some expect across the last three quarters of 2020 because employment losses have been disproportionately concentrated among workers who did not have access to employer-based coverage before the pandemic (Karpman & Zuckerman, 2020).²³ Also, those who did lose employer-sponsored insurance are eligible for ACA assistance either through Medicaid or subsidized marketplace coverage (Kaiser Family Foundation, 2020). Since our data include Medicaid Managed Care claims cleared by Change Healthcare, we are less concerned with changes in the proportion of individuals moving from employer-sponsored insurance to Medicaid coverage. In addition, Medicaid Managed care is a much larger group than Medicaid Fee for Service (approximately 69 percent of Medicaid insured individuals are in Medicaid Managed Care²⁴). Further, even unemployment, insurance loss, and the mode of school reopening were all correlated, this is still unlikely to bias our results unless the decline in insurance coverage happened to coincide with the precise *timing* of school reopenings.

A final limitation of the Change Healthcare data is that they have 3-digit zip code (of the patient), which is less precise than the HHS's 5-digit zip code (of the hospital). As described above, some 3-digit zip codes are larger than counties, which required us to make assumptions about how many occurred in each county, in order to link to the school reopening data. Given these limitations, we also re-run our main analyses using the HHS data.

Overall, we view the Change Healthcare data as valid and reliable for purposes of understanding the effects of school reopenings. They provide a large and consistent sample covering half the U.S. population and provide more detail about patient symptoms and diagnoses, as well as patients' home addresses. Also, the main limitations noted above seem likely to introduce only measurement and not bias our results. Nevertheless, we estimate our main results using both data sets.

III.D. Other Data

While the primary data sources pertain to school reopenings, teacher bargaining power, and hospitalizations, several other data sources provide useful covariates and allow for additional diagnostics of the main data sources.

²³ Link here https://www.urban.org/sites/default/files/publication/102552/changes-in-health-insurance-coverage-due-to-the-covid-19-recession_4.pdf

²⁴ <https://www.kff.org/medicaid/issue-brief/10-things-to-know-about-medicare-managed-care/#:~:text=Managed%20care%20plays%20a%20key,the%20fiscal%20implications%20for%20states.>

We merged the school reopening data with school district information from the National Longitudinal School Database (NLS), which includes all available federal education data from the Common Core of Data (CCD) and district-level Census data. Most importantly, the NLS includes the county in which the school district is located, allowing us to merge the school reopening data with the health data (more on this below). In addition, the Census data in the NLS allow us to create useful variates and variables for effect heterogeneity analysis.

We use the Device Exposure Index (DEX) from PlaceIQ to measure social distancing. The DEX index quantifies the exposure of devices to each other within venues. For a smartphone whose “home” is in a given county, the DEX indicates how many distinct devices also visited in any of the commercial venues that the device visited in a given day. Other studies have also used the DEX to study social mobility and distancing (Couture et al. 2020; Gupta et al. 2020; Painter and Qiu 2020; Nguyen et al. 2020). To be clear, we use the DEX only to gauge the relationship between our instrument and social distancing, since school reopenings are not the only factor affecting distancing and therefore hospitalizations. This variable is only for diagnostic purposes to better understand the instrumental variable.

We also collected data on general state COVID-19 reopenings. Many states have responded to the COVID-19 pandemic by enacting a variety of laws and policies related to limiting the spread of the associated virus and ensuring that healthcare resources are freed to absorb COVID-19 patients. To characterize state policies, we reviewed the range of policies and dates of implementation used in prior studies (see Gupta et al. (2020a) and from institutions tracking multiple sources for state policy dates such as the Urban institute²⁵ and Boston University.²⁶ To accurately identify the implementation date of a policy and to classify in a parsimonious way main elements of a state’s policy response, we focused on those that could potentially affect COVID-19 hospitalizations through social interaction and mobility. Based on our review, we chose the following policy measures: stay at home orders, non-essential business closures, non-essential business reopening, restaurant closures, restaurant reopenings, mask mandates and resumption of religious gatherings. Our list is not exhaustive of all state policies. For example, we did not include in our models the date the states closed or reopened bars explicitly, since most restaurants and bars resumed operations within the same week and if not restaurants reopened first. Appendix Figure 6 summarizes the percent of states that had those various general opening policies. These stabilized at the time that schools were reopened (see the 33rd week). So, while we control for these policies, there is little reason to think that changes in state (or local policies) had an influence on the before-and-after periods of greatest relevance in this analysis.

Finally, we analyzed data on the timing and mode of reopening of colleges from the College Crisis Initiative (<https://collegecrisis.org/>). We received instruction modes for 2,984

²⁵ <https://www.urban.org/policy-centers/health-policy-center/projects/covid-19-resource-tracker-guide-state-and-local-responses>

²⁶ <https://www.bu.edu/sph/news/articles/2020/tracking-covid-19-policies/>

colleges. These data cover mostly large higher education institutions in the United States and identify whether a college opened mostly in-person, hybrid or remotely. Of that sample we received dates of reopening for 1,430 colleges. These data are similar to the school reopening data, so we observe the date and mode of reopening. We aggregate this information to the county level and create a time varying indicator in our DD models for whether the county has a college that opened in-person or in hybrid mode at week t . If a county does not have a college present, and to avoid dropping counties without colleges, we assume that variable is constantly zero. We incorporate these data into our models and test the robustness of our estimates when including college reopening information. We also estimate a “placebo” first stage where we test whether teachers’ K-12 union power can predict college reopening mode (see additional discussion below).

IV. Econometric Framework

IV.A. Generalized Difference-in-Differences

To estimate the total effect of school reopenings, we begin with a generalized difference-in-differences event study model. This method is particularly useful in the present context given the (likely) delay in effects on hospitalizations. Specifically, we estimate:

$$Y_{ct} = \sum_{r=-10}^6 [\alpha_r \cdot \mathbf{1}(r = t) + \beta_t (InPerson_{cr} \cdot \mathbf{1}(r = t))] + \theta X_{st} + \lambda_c + \tau_t + \varepsilon_{ct} \quad (1)$$

where Y_{ct} is the number of COVID-19 hospitalizations in county c at time/week t . $InPerson_{cr}$ is the county’s share of students allowed to attend in-person at time t , which is zero prior to reopening and $0 \leq InPerson_{cr} \leq 1$ afterwards. This variable combines fully in-person (with a weight of 1) and hybrid instruction (with a weight of 0.5), under the assumption that hybrid means that half of students are in the building on any given day (fully remote is coded as zero). Since the data are initially at the district level, the county-level $InPerson_{cr}$ variable is weighted across districts by enrollment.

The term $\mathbf{1}(r = t)$ is an indicator for each week. Equation (1) includes a vector of these indicators as well as their interactions with $InPerson_{cr}$. The vector of coefficients β_t are the “effects” in each week. If there is little selection in instructional mode, then hospitalizations prior to reopening should not differ systematically with $InPerson_{cr}$, and thus β_t should be close to zero for all $t < 0$. Equation (1) also includes county fixed effects λ_c and time fixed effects τ_t . (We do not include state fixed effects explicitly as time-constant state factors are absorbed in the county fixed effects.) The term ε_{ct} is a white noise error term.

Estimating the post school reopening β_t via OLS, however, would likely yield biased estimates of the effects. School districts, as described in section II, decide to open schools in-person for a variety of political, economic, health, social and other reasons, some of which are likely unobservable. For example, a district might open because district officials are aware of

new communitywide policies being put in place to improve COVID-19 safety, which might be implemented at the same time that schools open. In this example, if the additional safety measures succeed in reducing COVID-19 spread, then the point estimates for β_t would be downwardly biased because we would falsely attribute to school reopening any reduction in hospitalizations due to the extra (unobserved) safety precautions. Alternatively, schools might decide to open because their hospitalizations rates are idiosyncratically low, a form of regression to the mean, that would upwardly bias the estimates.

The first step we take to address this endogeneity problem is to control for time-varying factors that we expect to influence hospitalizations, reflected in X_{st} in equation (1). This vector primarily includes state policies pertaining to COVID-19, such as the opening of bars and restaurants, allowing religious gatherings to resume and mandating mask-wearing. Note, too, that the county-level fixed effects account for all time-invariant county (and state) characteristics, including political orientation. In some models, we also add time-varying county-level factors especially college reopenings. (To address the possibility that factors like political orientation might also affect the *trend* in hospitalizations, we also include robustness checks that include control for week linear trends interacted with pre-opening state characteristics.)

We label equation (1) above as the fixed effects (FE) method because, as in a standard FE model, the treatment variable $InPerson_c$ is continuous. Another common method is to estimate a more standard difference-in-differences (DD) event study model, comparing counties that have any positive share of in-person instruction according to the index where $SomeInPerson_c = 1$ when $InPerson_c > 0$ and zero otherwise. Specifically, we estimate:

$$Y_{ct} = \sum_{r=-10}^6 [\alpha_t \cdot \mathbf{1}(r = t) + \beta_t (SomeInPerson_{cr} \cdot \mathbf{1}(r = t))] + \theta X_{st} + \lambda_c + \tau_t + \varepsilon_{ct} \quad (2)$$

Similar to equation (1), $SomeInPerson_{cr}$ is zero for both control and treatment in the pre-treatment weeks, so that the β_t in those weeks reflect the differences between those counties that eventually have some in person and those that do not.

The effect estimates in (1) and (2) have slightly different interpretations. In the FE/equation (1), the post-treatment β_t is the effect of going from no in-person instruction to completely in-person instruction, while in the DD/equation (2), it is the effect of being in the treatment group relative to the control group. We therefore expect the latter coefficients to be smaller in magnitude, though they can be scaled up, multiplying by the inverted treatment group mean to obtain a similar interpretation.

An advantage of the DD analysis over the FE is that it can be readily with propensity score matching (PSM). It is helpful to couple DD and PSM when the DD by itself does not yield a parallel trend before schools open. The PSM-DD makes it more plausible that the comparison and treatment groups would have followed the same pattern in the absence of treatment. This type of model has been analyzed before in Smith and Todd (2005), Stuart et al. (2014), Bell et al. (2020), and Friedson et al. (2020).

IV. B. Instrumental Variables

The longitudinal nature of the data allows us to account for time-invariant factors affecting hospitalizations and the control variables allow us to account for some time-varying factors, such as state policies and college reopenings. However, they may still be insufficient if school reopening policy adoption is endogenous with respect to unobserved, time-varying factors. We therefore also estimate IV versions of the above models that use teacher bargaining power as the instrument (see section II.C.). We begin with a first stage equation:

$$InPerson_c = \alpha + \phi_1 CollectiveBarg_c + \phi_2 MeetConfer_c + \gamma_s + \varepsilon_{cs} \quad (3)$$

where $InPerson_c$ is the share of schools in county c that initially opened in a given instructional mode, $CollectiveBarg_c$ is the county's share of districts with collective bargaining contracts and $MeetConfer_c$ is the county's share of districts with meet and confer agreements (all three are enrollment-weighted). The term γ_s is a state fixed effect.

Using a two-stage least squares (2SLS) framework, we predict the teaching mode from (3) and test that teacher bargaining power really does predict instructional mode. These results are shown in Table 3. Both teacher bargaining variables clearly predict opening mode, in the expected way, especially with our index that combines fully in-person and hybrid into a single index (see the far-right column). We report the F -statistic from a test of joint significance of both instruments (excluding the state fixed effects). The results are stronger in the MCH data (F -statistic of 6.38). The instrument is weak with the Burbio data (F -statistic of 2.14). These results reinforce the prior findings of Hartney and Finger (2020), though we have a more direct measure of teacher unionization than their study.

Finally, we use (1) to predict school reopening, yielding the variable $In\widehat{Person}_{cr}$, and obtain the IV estimates for the FE model as follows:

$$Y_{ct} = \alpha + \sum_{t=-10}^6 [\alpha_t \cdot \mathbf{1}(r = t) + \beta_t (In\widehat{Person}_{cr} \cdot \mathbf{1}(r = t))] + \theta X_{st} + \lambda_c + \tau_t + \varepsilon_{ct} \quad (4)$$

Note that $In\widehat{Person}_{cr}$ is time-varying in the sense that it is fixed at zero until the time that schools reopen. This implies further that we are taking the mode of opening as endogenous, but still assuming the timing of reopening is exogenous.

Setting aside for the moment the potential weak instrument problem, the FE-IV meets the exclusion restriction so long as teacher unionization does not influence the form of school reopening *in ways that coincide with the timing of school reopening*. This last highlighted phrase is important because it shows the benefit of combining IV with panel analysis. Suppose, for example, that teacher unionization is correlated with county-level *non-education* unionization, which, in turn, could affect the reopening and distancing in other kinds of businesses and

organizations.²⁷ For this to bias our estimates the effect of non-schooling unions would also have to coincide with school reopenings. This seems unlikely given that non-schooling organizations (private businesses, government agencies, etc.) generally operate continuously, year-round. Such an effect is not likely to coincide with school reopening, so the longitudinal nature of the analysis (specifically controlling for the summer hospitalization rates) addresses the potential bias.

A more viable threat is that teacher unionization might affect not just whether schools reopen but how. For example, anecdotal evidence suggests that, among those unionized districts that do open at least partially in-person, unions bargain for stricter social distancing rules, which could affect the implementation of school reopening in ways that are unobserved. In this respect, we can think of the mode of reopening as two-dimensional, reflecting both the number of students (and school staff) in person and the rules associated with within-school interactions. The instrument might be valid on the first dimension but not the second, which is largely unobserved. Despite this potential issue, and the possible weak instrument problem, the IV provides a useful additional check on our results.

Another potential concern is college reopenings, which have received considerable press attention. This might violate the exclusion restriction assumption in the sense that colleges do tend to open at roughly the same time as schools. However, this is unlikely to create bias since it is not obvious that teacher unionization should influence college reopenings. We test whether teacher union power can predict college opening mode by reestimating the first-stage equation with college reopening as the dependent variable. Appendix Table 5 presents these estimates. We find no evidence that teacher union power predicts college opening mode; the F -statistic is 0.8 and all estimates are insignificant.

We provide further visual evidence for the IV in the appendix. Appendix Figure 1 shows that teacher bargaining power is largely uncorrelated with baseline (January 2020 to July 2020) hospitalizations. Also, Appendix Figure 2 shows that the trends in DEX social mobility (see section III.D.) are parallel in the low- and high-teacher bargaining power counties,²⁸ providing visual evidence that the exclusion restriction is likely met, i.e., teacher unionization is not correlated with trends in mobility over time.

²⁷ This is plausible because, for example, the American Federation of Teachers also represents nurses and other kinds of workers outside the school sector.

²⁸ This is based on the DEX index, which measures the number of cell phones that are near each phone when the phone is away from its “home base.” The vertical grey bar in the graph indicates the start of COVID-19 precautions and the general economic shutdown. One trend line is for counties with 50 percent or more collective bargaining and the other is for those with less than 50 percent collective bargaining.

V. Results

We begin by reporting the FE model from equation (1) using only the Change Healthcare data and then proceed to the difference-in-differences (DD) and the preferred models: PSM-DD and the FE-IV model. Note that across all the models, the point estimates are generally imprecise when we estimate at the week level.²⁹ For this reason, we also estimate models that bin weeks to increase statistical power while maintaining some flexibility in the functional form. Specifically, we combine weeks into three periods: far before reopening/early summer (t-10 to t-5), near reopening/late summer (t-4 to t+1), and the post-reopening period (t+2 to t+6). Our conclusions are based mainly on these three-period estimates. We report each of these various specifications first for MCH and then Burbio school reopening data.

For all the models, we also report two functional forms where the dependent variable is either hospitalizations per 100,000 county residents or the natural log of total hospitalizations.³⁰ The appropriate model depends on the underlying structural relationship between school reopenings and hospitalizations, which is not known. As robustness checks, we also estimate inverse hyperbolic sign (IHS) instead of $\log(Y+1)$ and estimate Poisson regression to address the statistical issues with count data. The results using the HHS data are reported toward the end.

Before moving to the estimates, we briefly discuss whether we have sufficient statistical power to detect a population level effect. There are roughly 53 million K-12 students and 5 million school staff in the United States. If we add in their immediate family members, then there are roughly 175.8 million people directly connected to schools (roughly half the U.S. population).³¹ While it is difficult to identify a specific plausible effect from these numbers, the fact that such a large share of the population comes in regular contact with schools, students, school staff suggests that reopening schools could increase COVID-19 hospitalizations by 50 percent or more, if schools were active virus spreaders. Below, we compare this with the minimum detectable effects of the analysis.

²⁹ The imprecision is for several reasons: (a) the dependent variable frequently 0 especially when analyzing the data at the week level; (b) likely measurement error in the treatment variable; (c) the county-level fixed effects (with county clustering); (d) the IV, which reduces power in itself and, in this case, reduces the sample size; and (e) the importance of the dynamic pattern of effects and the lags, which require us to report the results at small time intervals; this results in a large number of 0s at the county-by-week level.

³⁰ Since there is a large number of zeros, we transform this to $\log(Y+1)$. We also estimated models where we transformed the dependent variable using the inverse hyperbolic sine (IHS). The two methods produce extremely close results. See Appendix Table 2 and Appendix Table 3 where we compare the $\log(Y+1)$ versus IHS models for propensity score matching DD and IV estimates.

³¹ This number accounts for the fact that many students are in the same households with one another. To avoid double-counting, we specifically assume that one-third of the 53 million are siblings of one of the others in that count. Also, note that 69 percent of children are in two-parent households, so the average number of parents in the household for the average student is 1.7. We further assume that the average student has 0.5 non-school-age siblings at home and, finally, that the average school staff member lives in a household with two other non-school people. This yields:
 $(53 \times 0.33 \times 0.5) + (53 \times 0.33)(1.7 + 0.5) + (53 \times 0.67)(1 + 1.7 + 0.5) + (5 \times 3) = 8.7 + 38.5 + 113.6 + 15 = 175.8$ million.

V.A. Fixed Effects and Difference-in-Differences Results

This section focuses on the FE and DD results. We initially report these without the IV or PSM, respectively, so that we can show later how these adjustments affect the results. The week-by-week FE and DD results are shown in Figures 2A and 2B. A concern in these figures is the lack of parallel pre-trends, particularly in the weeks immediately before school reopening. This is not surprising given the noisiness of the weekly measures and the fact that we would expect policy decisions regarding instructional modality to be partly driven by the pre-opening COVID-19 hospitalizations rate. For this reason, we draw no conclusions here and move on to the more precise three-period estimates.

Half of the three-period estimates, shown in Table 4, still show issues with parallel pre-trends. Two of the post-opening estimates are positive (one significant) and two are negative, but these clearly differ between hospitalizations/100k and the log specification, which is suggestive of effect heterogeneity. Since the effects appear negative in the log specifications, it could be that the effects are especially small in counties with few total COVID-19 cases, where a small increase in the total would yield large percentage increases.

Therefore, in Table 5A (MCH) and 5B (Burbio), we break these into four subgroups based on the pre-opening hospitalization rate from March through July: counties with no more than one hospitalization/100k at baseline (57 percent of counties) followed by the 58th-75th percentile, 76th-90th percentile, and greater than the 90th percentile. (We do not use quartiles or similar equal-sized groups because this would be misleading with our skewed of baseline hospitalizations.)

Table 5A and 5B both show that the one positive and significant average treatment effect estimate (from Table 4) is coming from the counties above the 75th percentile on baseline hospitalizations. For example, the largest point estimates suggest possible increases in hospitalization of 3.5 percent (though these are insignificant). This pattern shows up with both Burbio and MCH and in both the hospitalizations/100k and most of the log specifications. Stratification on the baseline hospitalizations also largely addresses the pre-trend problem (in all but three of the 16 subgroup estimates). In short, we see no evidence of increased COVID-19 hospitalizations in the vast majority of counties, but possible increases in counties with high baseline hospitalization rates.

We also present DD estimates by individual weeks (not binned) for these four subgroups. Appendix Figures 4A and 4B present the log and per 100k DD-event study estimates using MCH data while Appendix Figures 4C and 4D does the same using the Burbio data. Again, we find evidence of balance on pre-trends (especially within 5 weeks prior to reopening and onward) for counties in the lower 75th percentile of baseline hospitalizations. Counties in the top 25th percentile of baseline hospitalizations have erratic pre-trends and therefore inconclusive increases in hospitalization rates.

Another way to address the pre-trends problem is through the PSM-DD (Table 6). This method eliminates the pre-trend problem even without stratifying, as shown in the top panel. The

bottom panels of Table 6 combine stratification with PSM. All eight of the estimates for groups below the 75th percentile show negative (but insignificant) point estimates. Likewise, all eight of the estimates are positive above the 75th percentile and three are precisely estimated. The estimates from MCH for the top groups are statistically significant in the post-reopening period. For counties in the 75th to 90th percentile, COVID-19 hospitalizations per 100k increased by 2 percent (0.260/13) in the 6 weeks post reopening. Similarly, counties above the 90th percentile show a 1.8 percent increase in hospitalizations per 100k (1.52/82).

Recall, however, that these models do not account for possible endogeneity based on time-varying, unobserved factors. For this reason, we turn to instrumental variables estimation.

V.B. Instrumental Variables Results

Figures 3A, 3B, 4A, and 4B report coefficients from the FE-IV by week. We note that the results have flat pre-trends (up to 10 weeks prior to reopening), except above the 90th percentile, which makes us more cautious about the results for that group. From the lead coefficients (post school reopening), we see no visual evidence of increased hospitalizations. Starting from the earliest possible time that hospitalizations could increase ($t+2$), the estimates generally decline afterwards and none are statistically higher than the $t=0$ or $t+1$ periods.

Table 7 reports the three-period FE-IV results for MCH and Burbio and with both logs and hospitalizations/100k. Across all the estimates in Table 7, the only coefficient indicating increased hospitalizations is with the MCH data with hospitalizations/100k. However, even in that case, the parallel trends test fails and the pre-trend estimate is larger than the post-opening coefficient. Using the MCH data, the vast majority of effect estimates are statistically insignificant and are arguably small in absolute value. When we use the Burbio data, we have better balance on pre-trends and find no increases in hospitalizations for counties below the 75th percentile and *decreases* in hospitalizations above the 75th percentile.

One reason why the results might be less indicative of increased hospitalizations in the FE-IV, compared with the PSM-DD, is the previously mentioned concern that teacher unions not only reduce the probability of reopening, but work to improve the safety of reopenings, in order to protect their members and students, which in turn could reduce the extent of COVID-19 spread and the number of hospitalizations. For this reason, we are cautious in interpreting these results by themselves as evidence that school reopenings do not increase hospitalizations for any group of counties.³²

The results are consistent, however, for counties up to the 75th percentile of baseline hospitalizations. These results remain generally consistent across the PSM-DD and FE-IV and

³² One way to overcome this is to estimate the reduced form effect of teacher union power on hospitalizations which would encompass both the mechanisms related to opening mode or safety protocols when opening in-person/hybrid instruction. For a sample of all counties (not stratified) we estimated event study reduced form regressions of the effect of teacher unions on hospitalizations and found no statistically significant effect in the pre 10 week period or the post 6 week period. Those estimates are available upon request.

across functional forms (log versus hospitalizations) and data sources (MCH versus Burbio). None of our estimates with parallel pre-trends suggest any evidence of increased hospitalizations.

V.C. Additional Robustness Checks

This section focuses on three additional robustness checks: switching from Change Healthcare to HHS data on hospitalizations, adding college reopenings, and switching from OLS to Poisson (count data) estimation.

We reestimated the main models (DD³³ and FE-IV) using the HHS data as shown in Appendix Figures 7-12. Note that we report slightly different percentiles of the baseline hospitalization rate because there are somewhat fewer counties with zero hospitalizations in the HHS data (50 percent versus 57 percent); the groupings are otherwise the same as before. Also, we report these only as weekly event studies; the limited number of pre-opening weeks make it more difficult to create three logical groupings.

The general pattern of results is very similar to the Change Healthcare data. In only one of 14 graphs (Burbio data and hospitalizations per 100k below the 50th percentile) do we see any evidence of increased hospitalizations below the 75th percentile of the baseline hospitalization rate. Also, as before, we do see multiple graphs where there are signs of increased hospitalizations above the 75th percentile, as well as graphs indicating flat or declining effects.

Also, one potential threat to identification is that colleges may open at roughly the same time as schools and this, in turn, might affect hospitalizations independently of school reopenings. The FE-IV at least partially addresses this because there is little reason to expect teacher unions to affect college reopening decisions, especially after accounting for county fixed effects. (College towns have different political orientations, but this should be time constant.)

We tested the robustness of the PSM-DD model and the FE-IV model to include time varying controls for college reopening in in-person or hybrid mode. Appendix Table 5 presents a comparison between our main PSM-DD model in Table 6 and an alternative model that adds a time varying hybrid/in-person college reopening indicator in the county. The estimates are very similar both in magnitude and sign. Similarly, Appendix Table 6 presents the main IV estimates in Table 7 for all counties and compares the point estimates to an alternative model that adds the college reopening time-varying indicator. The results are robust to this addition to the earlier models.

Finally, given the large share of observations with zero COVID-19 hospitalizations, we also reestimated our main models using count data methods, i.e. Poisson regression. The results, shown in Appendix Tables 7 and 8, provide qualitatively similar results to the PSM-DD and FE-IV per 100k estimates to those from a count Poisson regression of total hospitalizations in a county week.

³³ We focus on the DD instead of the PSM-DD because of the difficulty of matching on fewer pre-trend periods. Also, the pre-trends are generally flatter with the HHS data.

VI. Conclusions

This study provides the first evidence regarding the effects of in-person school reopenings on COVID-19 health outcomes. In doing so, it avoids the problems with all past studies on the topic, which have been forced to rely on virus positive rates that are subject to infrequent and unsystematic testing. The errors in COVID-19 positivity rates are also confounded with school reopenings because schools may open because of anticipated, unobserved changes in public health practices and the frequency of testing may change as a direct result of school reopenings. COVID-19 hospitalizations do not suffer from these problems and they focus our attention on what matters most: health outcomes.

Our results suggest that school reopenings have not increased COVID-19 hospitalizations, especially for the 75 percent of counties that had the lowest baseline hospitalizations. This conclusion is robust to a wide variety of estimation methods: Burbio versus MCH data, hospitalizations/100k versus logs, PSM-DD versus FE-IV, OLS versus Poisson regression, and limited covariates versus extensive ones, including state social distancing policies and college reopenings.

To develop policy relevant thresholds, we used the HHS data, which reflect the entire population (not just those with insurance) and reflect the data that public health officials can access as they advise school leaders. Using these data, we see no effects below *36-44 new COVID-19 hospitalizations per 100,000 population per week*. Also, note that some counties are much larger than others, which is why we report on a per 100,000 basis. More than 40 U.S. counties have populations over one million residents and, in these counties, the threshold involves at least 360-440 new COVID-19 hospitalizations per week.

The results for high-baseline-hospitalization counties are inconclusive because of failed parallel trends tests and inconsistent results across specifications. There are reasons to expect that opening schools in-person under such conditions would be more likely to spread the virus and negative health outcomes because there is more of the virus to spread in those cases. This theory is consistent, for example, with the findings of Goldhaber et al. (2020). While they were forced to use the COVID-19 positivity rate, they found that the rate increases in locations where the baseline rate was relatively high.

The interpretation and policy implications of these results may be less straightforward than they seem, however. First, recall that most schools that are offering in-person instruction are also giving families the option of remote instruction and many families are taking advantage of this. This means that what we are actually estimating is the effect of the *policy* of sending all children back in-person, not the effect of actually having all students in school buildings as they were prior to the crisis. So, even if these results were taken literally, they do not mean that sending all children back to school in-person, even in low-baseline-hospitalization counties, would be safe. Rather, what we are capturing is the effect of the policy of allowing all students to return, with the option to remain remote that many families would evidently opt for.

Second, opening safely and in-person creates considerable difficulty for schools. When schools are fully in-person, they can operate as before (but with additional safety measures). When they operate fully remotely, they can send everyone home and use as many online tools as their Broadband access and technologies allow. But when some students are home and others are remote at the same time, this creates new problems. Anecdotally, teachers tend to focus on students who are there in-person, which undermines the remote experience. Also, many teachers have to stand in front of their computers so that others can see them at home on Zoom, which, in addition to the challenges of communicating with masks on, undermines the in-person experience. Anecdotally, these challenges have led even more students to opt out of in-person.

Third, these coefficients capture both the direct effects of school reopenings themselves (i.e., getting in a school bus and/or going into a school building and spreading the virus) and several closely related indirect effects. School reopenings might increase social interaction among children outside of school (e.g., sleepovers, playdates, and additional shopping for school clothes that require trips to the mall) and induce more parents to go to work in-person. As noted with respect to the similar study in Germany (Isphording, Lipfert, & Pestel, 2020), however, there may also be indirect effects that reduce COVID-19 transmission (e.g., educators sending stern messages about social distancing and students being more reluctant to engage in their non-school social interactions in order to avoid exclusion from school activities because of quarantines). As a practical matter, we cannot separate the direct effects from the indirect effects, though this is not problematic since we view the total effect as the parameter of interest for policy purposes; the indirect effects are likely to accompany most forms of school reopening, especially in the current U.S. policy environment.

Fourth, reopening schools affects different groups in different ways. One of the main reasons that more schools have not opened in-person (or allowed that option) is that teachers and other school staff are sometimes in risk categories and have been understandably concerned about their health. While our hospitalization results do include school staff, we cannot separate out the effects for this group from the general population. It is theoretically possible that opening schools increases negative health outcomes for school staff even if not for others. The only scenario we can envision in which this is possible is that school staff spread the virus to one another, but that students do not spread it amongst themselves. If students were the main drivers of transmission then it would spread both to school staff and to parents, resulting in an increase in hospitalizations that we do not see here (in the bottom 75 percent). In addition, there are different implications across racial groups. African Americans have suffered disproportionate health consequences. The potential trade-offs across all of these various groups are important to remember.

The underlying assumption of COVID-19 school decision-making has been that opening up schools to in-person instruction would benefit students and parents in many ways, but at a cost of spreading the virus and harming teachers and the community as a whole. While we find evidence that this trade-off exists in counties with already high virus transmission, we do not find evidence of such a trade-off for the majority of school districts, based on the summer COVID-19

numbers. This is important for policymakers to consider as they make decisions this spring and in future virus events.

References

Andersen, Martin S., Ana I. Bento, Anirban Basu, Chris Marsicano, and Kosali Simon (2020). College Openings, Mobility, and the Incidence of COVID-19 Cases. *medRxiv*
doi: <https://doi.org/10.1101/2020.09.22.20196048>

Bacher-Hicks, Andrew, Joshua Goodman, and Christine Mulhern (2020). What Google Search Data Reveals About Learning During the Pandemic. *Education Next*.
<https://www.educationnext.org/google-search-data-reveals-about-learning-pandemic/>

Bauer, Lauren, Kristen Broady, Wendy Edelberg, and Jimmy O'Donnell (2020). Ten Facts about COVID-19 and the U.S. Economy. [https://www.brookings.edu/research/ten-facts-about-covid-19-and-the-u-s-economy/#:~:text=The%20COVID%2D19%20crisis%20also,\(U.S.%20Census%20Bureau%202020a\).](https://www.brookings.edu/research/ten-facts-about-covid-19-and-the-u-s-economy/#:~:text=The%20COVID%2D19%20crisis%20also,(U.S.%20Census%20Bureau%202020a).)

Bell, S. A., Klasa, K., Iwashyna, T. J., Norton, E. C., & Davis, M. A. (2020). Long-term healthcare provider availability following large-scale hurricanes: A difference-in-differences study. *PloS one*, 15(11), e0242823.

Center for Reinventing Public Education (2020). Fall 2020: The State of School Reopening. <https://www.crpe.org/current-research/covid-19-school-closures>.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Michael Stepner, and the Opportunity Insights Team (2020). The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data. https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf

Clarke, D. and Kathya Tapia Schythe (2020). *Implementing the Panel Event Study*. IZA DP No. 13524. IZA Institute of Labor Economics. <http://ftp.iza.org/dp13524.pdf>.

Couture, V., J. Dingel, A. Green, J. Handbury, and K. Williams (2020). Location Exposure Index Based on PlaceIQ Data. <https://github.com/COVIDExposureIndices/COVIDExposureIndices/blob/master/documentation/LEX.pdf>

Cutler DM, Summers LH. The COVID-19 Pandemic and the \$16 Trillion Virus. *JAMA*. 2020;324(15):1495–1496. doi:10.1001/jama.2020.19759.

Czeisler MÉ , Lane RI, Petrosky E, et al. Mental Health, Substance Use, and Suicidal Ideation During the COVID-19 Pandemic — United States, June 24–30, 2020. *MMWR Morb Mortal Wkly Rep* 2020;69:1049–1057. DOI: <http://dx.doi.org/10.15585/mmwr.mm6932a1>

Education Policy Innovation Collaborative (2020). Instructional Delivery Under Michigan Districts' Extended Continuity of Learning Plans. East Lansing, MI: Michigan State University. <https://epicedpolicy.org/wp-content/uploads/2020/11/EPIC-ECOL-Report-November-2020.pdf>.

Forbes, Harriet, Caroline E Morton, Seb Bacon, Helen I McDonald, Caroline Minassian, Jeremy P Brown, Christopher T Rentsch, Rohini Mathur, Anna Schultze, Nicholas J DeVito, Brian MacKenna, William J Hulme, Richard Croker, Alex J Walker, Elizabeth J Williamson, Chris Bates, Amir Mehrkar, Helen J Curtis, David Evans, Kevin Wing, Peter Inglesby, Henry Drysdale, Angel YS Wong, Jonathan Cockburn, Robert McManus, John Parry, Frank Hester, Sam Harper, Ian J Douglas, Liam Smeeth, Stephen JW Evans, Krishnan Bhaskaran, Rosalind M Eggo, Ben Goldacre, Laurie A Tomlinson. Association between living with children and outcomes from COVID-19: an OpenSAFELY cohort study of 12 million adults in England. medRxiv doi: <https://doi.org/10.1101/2020.11.01.20222315>

Friedson, A. I., McNichols, D., Sabia, J. J., & Dave, D. (2020). Shelter-in-place orders and public health: evidence from California during the COVID-19 pandemic. *Journal of Policy Analysis and Management*.

Goldhaber, Dan, Scott Imberman, Katharine Strunk, Bryant Hopkins, Nate Brown, Erica Harbatkin, and Tara Kilbride (2020). *To What Extent Does In-Person Schooling Contribute to the Spread of COVID-19? Evidence from Michigan and Washington*. Michigan State University: Education Policy Innovation Collaborative. <https://epicedpolicy.org/does-in-person-schooling-contribute-to-the-spread-of-covid-19/>

Hanushek, Eric A. and Ludger Woessmann (2020). The Economic Impacts of Learning Losses. Organization for Economic Development and Cooperation. <http://www.oecd.org/education/The-economic-impacts-of-coronavirus-covid-19-learning-losses.pdf>.

Gupta, S., L. Montenegro, T. D. Nguyen, F. L. Rojas, I. M. Schmutte, K. I. Simon, B. A. Weinberg, and C. Wing (2020). Effects of social distancing policy on labor market outcomes. NBER Working Paper .

Hartney, Michael and Finger (2020). Politics, Markets, and Pandemics: Public Education's Response to COVID-19. EdWorkingPaper 20-304. Brown University: Annenberg Institute. <https://www.edworkingpapers.com/sites/default/files/ai20-304.pdf>

Havers FP, Reed C, Lim T, Montgomery JM, Llena JD, et al. (2020). Seroprevalence of Antibodies to SARS-CoV-2 in 10 Sites in the United States, March 23-May 12, 2020. JAMA Intern Med. doi:10.1001/jamainternmed.2020.4130 Isphording, Ingo E., Marc Lipfert, and Nico Pestel (2020). School Re-Openings after Summer Breaks in Germany Did Not Increase SARS-CoV-2 Cases. IZA DP No. 13790.

Hobbs, Charlotte V., Lora M. Martin, Sara S. Kim, Brian M. Kirmse, Lisa Haynie, Sarah McGraw, Paul Byers, Kathryn G. Taylor, Manish M. Patel, Brendan Flannery. (2020). Factors Associated with Positive SARS-CoV-2 Test Results in Outpatient Health Facilities and Emergency Departments Among Children and Adolescents Aged <18 Years — Mississippi, September–November 2020. CDC Weekly 69(50);1925-1929.

Ismail, Sharif A, Vanessa Saliba, Jamie Lopez Bernal, Mary E Ramsay, Shamez N Ladhani (2020). SARS-CoV-2 infection and transmission in educational settings: a prospective, cross-sectional analysis of infection clusters and outbreaks in England
Published: December 08, 2020 DOI: [https://doi.org/10.1016/S1473-3099\(20\)30882-3](https://doi.org/10.1016/S1473-3099(20)30882-3)

Karpman, Michael and Stephen Zuckerman (2020). *ACA Offers Protection as the COVID-19 Pandemic Erodes Employer Health Insurance Coverage*. Washington, DC: Urban Institute. https://www.urban.org/sites/default/files/103181/aca-offers-protection-as-the-covid-19-pandemic-erodes-employer-health-insurance-coverage_0.pdf

Kaufman, Brystana G., Rebecca Whitaker, Nirosha Mahendraratnam, Valerie A. Smith, and Mark B. McClellan (2020). Comparing Associations of State Reopening Strategies with COVID-19 Burden. *Journal of General Internal Medicine*.
<https://link.springer.com/article/10.1007/s11606-020-06277-0>

Kuhfeld, Megan, Beth Tarasawa, Angela Johnson, Erik Ruzek, and Karyn Lewis. Learning during COVID-19: Initial findings on students' reading and math achievement and growth. Portland, OR: NWEA. <https://www.nwea.org/research/publication/learning-during-covid-19-initial-findings-on-students-reading-and-math-achievement-and-growth/>

Laxminarayan, Ramanan, Brian Wahl, Shankar Reddy Dudala, K. Gopal, Chandra Mohan, S. Neelima, K. S. Jawahar Reddy, J. Radhakrishnan, Joseph A. Lewnard (2020). Epidemiology and transmission dynamics of COVID-19 in two Indian states. *Science* 370(6517).

Mathematica (2020). Using Data to Identify Changes in Child Welfare Referrals and Screening in the Era of COVID-19. <https://www.mathematica.org/events/using-data-to-assess-changes-in-child-welfare-screenings-and-referrals-in-the-era-of-covid-19>

McDermott, Daniel, Cynthia Cox, Robin Rudowitz, and Rachel Garfield (2020). How Has the Pandemic Affected Health Coverage in the U.S.? Kaiser Family Foundation. <https://www.kff.org/policy-watch/how-has-the-pandemic-affected-health-coverage-in-the-u-s/>

Neelima, S., K. S. Jawahar Reddy, J. Radhakrishnan, and Joseph A. Lewnard (2020). Epidemiology and transmission dynamics of COVID-19 in two Indian states. *Science* 370, 691–697.

Neidhofer, Claudio and Guido Neidhofer (2020). The Effectiveness of School Closures and Other Pre-Lockdown COVID-19 Mitigation Strategies in Argentina, Italy, and South Korea. Working paper.

Nguyen, T. D., S. Gupta, M. Andersen, A. Bento, K. I. Simon, and C. Wing (2020). Impacts of state reopening policy on human mobility. NBER Working Paper .

Oster, E. (2020). Schools Aren't Superspreaders. *The Atlantic*. <https://www.theatlantic.com/ideas/archive/2020/10/schools-arent-superspreaders/616669/>

Painter, M. and T. Qiu (2020). Political beliefs affect compliance with covid-19 social distancing orders. Available at SSRN 3569098 .

Pan, Kuan-Yu, Almar A L Kok, Merijn Eikelenboom, Melany Horsfall, Frederike Jörg, Rob A Luteijn, Didi Rhebergen, Patricia van Oppen, Erik J Giltay*, Brenda W J H Penninx* (2020). The mental health impact of the COVID-19 pandemic on people with and without depressive, anxiety, or obsessive-compulsive disorders: a longitudinal study of three Dutch case-control cohorts. *The Lancet*. [https://doi.org/10.1016/S2215-0366\(20\)30491-0](https://doi.org/10.1016/S2215-0366(20)30491-0).

Salvatore, Phillip P., Erisa Sula, Jayme P. Coyle, Elise Caruso, Amanda R. Smith, Rebecca S. Levine, Brittney N. Baack, Roger Mir, Edward R. Lockhart, Tejpratap S.P. Tiwari; Deborah L. Dee, Tegan K. Boehmer, Brendan R. Jackson, Achuyt Bhattarai, Erisa Sula, Jayme P. Coyle, Elise Caruso, Amanda R. Smith, Rebecca S. Levine, Brittney N. Baack, Roger Mir, Edward R. Lockhart, Tejpratap S.P. Tiwari, Deborah L. Dee, Tegan K. Boehmer, Brendan R. Jackson, Achuyt Bhattarai (2020). Recent Increase in COVID-19 Cases Reported Among Adults Aged 18–22 Years — United States, May 31–September 5, 2020. *CDC Weekly* 69(39);1419–1424

Schmidt, Samantha and Hannah Natanson (2020). With kids stuck at home, ER doctors see more severe cases of child abuse. *Washington Post*.

<https://www.washingtonpost.com/education/2020/04/30/child-abuse-reports-coronavirus/>

Smith, J.A., & Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators?. *Journal of econometrics*, 125(1-2), 305-353.

Stuart, E. A., Huskamp, H. A., Duckworth, K., Simmons, J., Song, Z., Chernew, M. E., & Barry, C. L. (2014). Using propensity scores in difference-in-differences models to estimate the effects of a policy change. *Health Services and Outcomes Research Methodology*, 14(4), 166-182.

Tedeschi, Ernie (2020). The Mystery of How Many Mothers Have Left Work Because of School Closings. *New York Times*. October 29. <https://www.nytimes.com/2020/10/29/upshot/mothers-leaving-jobs-pandemic.html>

UNESCO (2020). One in every five children, adolescents and youth is out of school worldwide. <https://en.unesco.org/news/one-every-five-children-adolescents-and-youth-out-school-worldwide#:~:text=According%20to%20data%20from%20the,over%20the%20past%20five%20years.>

U.S. Census Bureau (2020). Household Pulse Survey. <https://www.census.gov/data/tables/2020/demo/hhp/hhp17.html>

U.S. Center for Disease Control. Overview of Testing for SARS-CoV2 (COVID-19). Updated Oct 21, 2020 <https://www.cdc.gov/coronavirus/2019-ncov/hcp/testing-overview.html#previous> accessed 12/1/2020.

Valant, Jon (2020). School reopening plans linked to politics rather than public health. Washington, DC: Brookings Institution. <https://www.brookings.edu/blog/brown-center-chalkboard/2020/07/29/school-reopening-plans-linked-to-politics-rather-than-public-health/>

Viner, Russell M., Oliver T. Mytton, Chris Bonell, G. J. Melendez-Torres, Joseph Ward, Lee Hudson, Claire Waddington, James Thomas, Simon Russell, Fiona van der Klis, Archana Koirala, Shamez Ladhani, Jasmina Panovska-Griffiths, Nicholas G. Davies, Robert Booy, Rosalind M. Eggo (2020). Susceptibility to SARS-CoV-2 Infection Among Children and Adolescents Compared With Adults: A Systematic Review and Meta-analysis. *JAMA Pediatrics*.

Vlachos, Jonas and Edvin Hertegård, Helena Svaleryd (2020). School closures and SARS-CoV-2. Evidence from Sweden's partial school closure. Working paper. <https://doi.org/10.1101/2020.10.13.20211359>.

Wiersinga WJ, Rhodes A, Cheng AC, Peacock SJ, Prescott HC. Pathophysiology, Transmission, Diagnosis, and Treatment of Coronavirus Disease 2019 (COVID-19): A Review. *JAMA*. 2020; 324(8):782–793. doi:10.1001/jama.2020.12839 *JAMA*. Published online May 6, 2020. doi:10.1001/jama.2020.8259 <https://jamanetwork.com/journals/jama/fullarticle/2768391>

Williamson, E.J., Walker, A.J., Bhaskaran, K. *et al.* Factors associated with COVID-19-related death using OpenSAFELY. *Nature* 584, 430–436 (2020). <https://doi.org/10.1038/s41586-020-2521-4>

Ziedan, Engy, Kosali I. Simon & Coady Wing (2020). Effects of State COVID-19 Closure Policy on NON-COVID-19 Health Care Utilization. NBER Working Paper 27621. Cambridge, MA; National Bureau of Economic Research

Table 1 Percent in Districts in each Instructional Mode by Source

Source	In-Person	Remote	Hybrid	Other	Undecided
MCH	19.13%	24.10%	54.70%	2.06%	-
EdWeek	24.15%	48.73%	27.12%	-	-
Burbio	42.51%	34.48%	22.82%	-	0.19%

Notes: These data reflect the percentage of districts reporting each mode of instruction at the start of the school year. For Education Week and MCH, the data were provided at the district level and we report them this way (unweighted by enrollment size). For Burbio, the data were provided at the county level and the figures reflect the percent of students.

Table 2 Collective Bargaining Descriptive Statistics

State	State Bargaining Legal Status	# Total Districts	# Districts w/ Bargaining Info	% Collective Bargaining	% Meet and Confer
Alabama	illegal	138	85	1.18	17.65
Alaska	required	54	39	89.74	7.69
Arizona	illegal	664	82	3.66	56.10
Arkansas	permissible	278	90	4.44	4.44
California	required	1096	248	93.95	2.42
Colorado	permissible	186	75	33.33	29.33
Connecticut	required	199	64	98.44	0.00
Delaware	required	43	15	93.33	6.67
District of Columbia	required	61	1	100.00	0.00
Florida	required	73	48	97.92	2.08
Georgia	illegal	212	91	0.00	3.30
Hawaii	required	1	1	100.00	0.00
Idaho	required	159	70	71.43	20.00
Illinois	required	952	122	96.72	0.00
Indiana	required	409	106	99.06	0.94
Iowa	required	333	108	98.15	0.93
Kansas	required	289	111	73.87	20.72
Kentucky	permissible	176	88	10.23	12.50
Louisiana	permissible	200	56	10.71	1.79
Maine	required	209	61	96.72	1.64
Maryland	required	25	17	100.00	0.00
Massachusetts	required	407	92	98.91	0.00
Michigan	required	889	140	97.86	1.43
Minnesota	required	528	110	94.55	4.55
Mississippi	permissible	156	94	0.00	2.13
Missouri	required	565	116	2.59	33.62
Montana	required	400	111	84.68	3.60
Nebraska	required	270	78	91.03	8.97
Nevada	required	20	14	92.86	7.14
New Hampshire	required	189	65	96.92	3.08
New Jersey	required	676	125	99.20	0.80
New Mexico	required	150	52	38.46	3.85
New York	required	1042	165	98.79	0.61
North Carolina	illegal	293	71	0.00	2.82
North Dakota	permissible	223	77	64.94	19.48
Ohio	required	1009	129	96.90	0.00
Oklahoma	required	543	200	41.50	8.50
Oregon	required	199	77	97.40	2.60
Pennsylvania	required	754	126	98.41	1.59
Rhode Island	required	60	26	100.00	0.00
South Carolina	illegal	98	53	0.00	0.00
South Dakota	required	152	85	61.18	23.53
Tennessee	permissible*	147	79	67.09	7.59
Texas	illegal	1203	276	0.36	4.35
Utah	permissible	154	32	40.63	50.00
Vermont	required	187	49	95.92	2.04

Virginia	illegal	205	71	0.00	15.49
Washington	required	319	111	98.20	1.80
West Virginia	permissible	56	47	0.00	10.64
Wisconsin	required	447	131	95.42	2.29
Wyoming	permissible	61	39	12.82	28.21

Notes: These data describe teacher bargaining power by state. “State Bargaining Legal Status” comes from the National Council for Teacher Quality (<https://www.nctq.org/contract-database/collectiveBargaining>) which has several options: “required” means districts must collectively bargain when teachers vote to do so; “permissible” means that districts may choose to collectively bargain if teachers vote for it; and “illegal” means that collective bargaining is not allowed. (Tennessee is distinctive with its “collaborative conferencing” and we place this in the permissible category.) The last two columns come from the 2000 public-use Schools and Staffing Survey from the U.S. Department of Education. “% Collective bargaining” is the percent of districts that report in the SASS that they collectively bargain, meaning there is a legally binding contract (unweighted by enrollment size) and “% Meet and confer” is the percent of districts that report meet and confer arrangement, which are not contracts and are more akin to Memoranda of Understanding (MOU).

Table 3 – First Stage Estimates of the Effect of Unions on School Opening Modality

Panel A. MCH	Online (1)	In Person (2)	Hybrid/In person (3)
Share of Collective Bargaining Union	0.180** (0.074)	-0.112*** (0.028)	-0.121*** (0.040)
Share of Meet and Confer Union	0.196** (0.084)	-0.0757*** (0.028)	-0.131*** (0.046)
P-value for Joint Significance	0.011	0.000	0.001
F-statistic for Joint Significance	4.49	8.47	6.38
Mean Dep Variable	0.165	0.201	0.473
Number of Obsv. (counties)	1827	1827	1827
adj. R-sq	0.434	0.173	0.327
Panel B. Burbio	Online (1)	In Person (2)	Hybrid/In person (3)
Share of Collective Bargaining Union	0.151*** (0.053)	-0.054 (0.054)	-0.104** (0.052)
Share of Meet and Confer Union	0.069 (0.064)	0.022 (0.0518)	-0.0234 (0.054)
P-value for Joint Significance	0.015	0.473	0.117
F-statistic for Joint Significance	4.23	0.75	2.14
Mean Dep Variable	0.371	0.375	0.502
Number of Obsv. (counties)	1725	1725	1725
adj. R-sq	0.496	0.363	0.426

Notes – The level of observation is the county. Table 3 reports estimates of equation (3), a regression of the share of students in online only, in person only, or hybrid/in-person combined on two measures of teacher unionization (see notes to Table 2 for details). Hybrid/in-person is defined as the share of students in-person + 0.5 times the share of students in hybrid. Panel A uses school reopening data from MCH. Panel B.uses school reopening data from Burbio. All regressions include state fixed effects and county population weights. We report the *p*-value and *F*-statistic of joint significance of both union coefficients (excluding state fixed effects). Standard errors of estimates are constructed using robust-cluster methods allowing for non-independence of observations within a county. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.001 < p\text{-value} \leq 0.01$.

Table 4 – Difference in Differences and Fixed Effects Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020)

	Per 100K Hospitalizations				Log Total Hospitalizations			
	MCH FE	MCH DD	Burbio FE	Burbio DD	MCH FE	MCH DD	Burbio FE	Burbio DD
Share In-Person/Hybrid x T-10 to T-5	-0.986*	-0.0401	-0.823*	-0.354*	-0.0091	-0.114***	-0.0354	-0.0170
	(0.429)	(0.195)	(0.335)	(0.164)	(0.0412)	(0.0322)	(0.0209)	(0.0187)
Share In-Person/Hybrid x T+2 to T+6	0.207	0.420**	0.148	0.146	-0.0128	-0.0254	-0.0172	-0.0113
	(0.240)	(0.147)	(0.162)	(0.111)	(0.0273)	(0.0263)	(0.0216)	(0.0192)
Mean Dependent Var	7.88	7.88	8.62	8.62				
Number of Observations	51575	51575	61860	61860	51575	51575	61860	61860

Notes – The regression only includes the 10 weeks prior to school reopening and the 6 weeks after school reopening for each county. We divide this period into 3 groups: period 1 (weeks -10 to -5), period 2 (weeks -4 to +1) is the omitted category, and period 3 (weeks +2 to +6). The unit of observation is the county-week. All regressions include state fixed effects, county fixed effects, calendar week fixed effects and controls for state time varying covid-19 policies. Standard errors are clustered by county and all estimates are weighted by the county population. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.001 < p\text{-value} \leq 0.01$

Table 5A– Difference in Differences Estimates the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020) by Baseline Hospitalizations (March to July 2020) MCH

	Per 100K Hospitalizations					Log Total Hospitalizations				
	All	<57th	58 th to 75 th	75 th to 90 th	>90 th	All	<57th	58 th to 75 th	75 th to 90 th	>90 th
Share In-Person/Hybrid x T-10 to T-5	-0.0401 (0.195)	0.015 (0.009)	0.082 (0.065)	0.294 (0.196)	2.080* (0.907)	-0.114*** (0.0322)	0.0003 (0.0005)	-0.011 (0.032)	-0.014 (0.046)	0.051 (0.047)
Share In-Person/Hybrid x T+2 to T+6	0.420** (0.147)	-0.006 (0.003)	0.021 (0.041)	0.374** (0.116)	1.348* (0.519)	-0.0254 (0.0263)	-0.0002 (0.0002)	-0.012 (0.021)	0.036 (0.038)	0.035 (0.049)
Mean Dependent Var	7.88	0.42	0.54	14.54	61.29					
Number of Observations	51575	29528	14756	8043	4062	51575	29528	14756	8043	4062

Notes – The regression only includes the 10 weeks prior to school reopening and the 6 weeks after school reopening for each county. We divide this period into 3 groups: period 1 (weeks -10 to -5), period 2 (weeks -4 to +1) is the omitted category, and period 3 (weeks +2 to +6). The unit of observation is the county-week.

All regressions include state fixed effects, county fixed effects, calendar week fixed effects and controls for state time varying covid-19 policies. Standard errors are clustered by county and all estimates are weighted by the county population. For each outcome variable, log hospitalizations or per 100k hospitalizations, we present estimates for 5 samples. First, we show estimates for all counties which instruction modality information. Second, we present estimates for counties in the bottom 57th percentile, 58th to 75th percentile, 75th to 90th and 90th plus of baseline log hospitalizations (March 2020 to July 2020). ** indicates 0.01 < p-value ≤ 0.05, *** indicates 0.001 < p-value ≤ 0.01

Table 5B – Difference in Differences the Hybrid/In-Person Teaching on Covid19 Hospitalizations
(January to October 2020) by Baseline Hospitalizations (March to July 2020) Burbio

	Per 100K Hospitalizations					Log Total Hospitalizations				
	All	<57th	58 th to 75 th	75 th to 90 th	>90 th	All	<57th	58 th to 75 th	75 th to 90 th	>90 th
Share In-Person/Hybrid x T-10 to T-5	-0.354*	0.002	0.031	-0.653***	-0.303	-0.017	0.0002	-0.002	-0.104*	-0.030
	(0.164)	(0.008)	(0.036)	(0.176)	(0.817)	(0.019)	(0.0003)	(0.002)	(0.041)	(0.037)
Share In-Person/Hybrid x T+2 to T+6	0.146	-0.002	-0.014	0.150	0.415	-0.011	-0.0004	0.001	0.032	-0.042
	(0.111)	(0.002)	(0.012)	(0.143)	(0.376)	(0.019)	(0.00003)	(0.003)	(0.040)	(0.050)
Mean Dependent Var	8.62	0.61	0.94	12.88	86.54					
Number of Observations	61860	36190	10991	9646	5033	61860	36190	10991	9646	5033

Notes: See notes to Table X. This table is the same except we use the Burbio data to identify school reopenings. ** indicates 0.01 < p-value <=0.05, *** indicates 0.001< p-value <=0.01

Table 6 – Propensity Score Matching Difference in Differences Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020)

	Per 100K		Log Total Hospitalizations	
Panel A. All Counties	MCH	Burbio	MCH	Burbio
Share In-Person/Hybrid x T-10 to T-5	-0.078 (0.252)	-0.250 (0.229)	-0.063 (0.035)	0.012 (0.024)
Share In-Person/Hybrid x T+2 to T+6	0.295 (0.187)	0.133 (0.114)	-0.019 (0.028)	-0.005 (0.016)
Mean Dependent Var	7.24	9.79		
Number of Observations	51,274	59,452	51,274	59,452
Panel B: <57th Percentile	MCH	Burbio	MCH	Burbio
Share In-Person/Hybrid x T-10 to T-5	0.0133 (0.007)	-0.001 (0.005)	0.001 (0.0004)	0.0001 (0.0005)
Share In-Person/Hybrid x T+2 to T+6	-0.010* (0.005)	-0.005 (0.004)	-0.0005 (0.0003)	-0.0001 (0.0001)
Mean Dependent Var	0.411	1.11		
Number of Observations	29,939	35,135	29,939	35,135
Panel C: 58th – 75th Percentile	MCH	Burbio	MCH	Burbio
Share In-Person/Hybrid x T-10 to T-5	0.026 (0.031)	0.018 (0.053)	-0.001 (0.005)	0.003 (0.003)
Share In-Person/Hybrid x T+2 to T+6	-0.006 (0.015)	-0.049 (0.029)	-0.002 (0.003)	-0.002 (0.002)
Mean Dependent Var	1.512	0.75		
Number of Observations	3,494	11,252	3,494	11,252

Panel D: 76th - 90th Percentile	MCH	Burbio	MCH	Burbio
Share In-Person/Hybrid x T-10 to T-5	-0.015 (0.136)	-0.319 (0.185)	-0.061 (0.040)	-0.051 (0.053)
Share In-Person/Hybrid x T+2 to T+6	0.263** (0.086)	0.281 (0.159)	0.079* (0.035)	0.039 (0.038)
Mean Dependent Var	13.52	14.61		
Number of Observations	6,481	8,313	6,481	8,313
Panel E: > 90th Percentile	MCH	Burbio	MCH	Burbio
Share In-Person/Hybrid x T-10 to T-5	1.385 (1.311)	-0.724 (0.808)	0.048 (0.043)	0.024 (0.046)
Share In-Person/Hybrid x T+2 to T+6	1.513* (0.690)	0.648 (0.423)	0.005 (0.047)	0.007 (0.056)
Mean Dependent Var	82.58	81.63		
Number of Observations	4,594	4,738	4,594	4,738

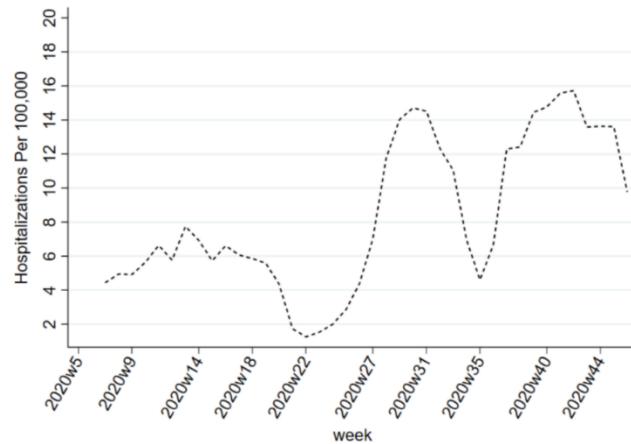
Notes – The regression only includes the 10 weeks prior to school reopening and the 6 weeks after school reopening for each county. We divide this period into 3 groups: period 1 (weeks -10 to -5), period 2 (weeks -4 to +1) is the omitted category, and period 3 (weeks +2 to +6). The unit of observation is the county-week. We first estimate propensity scores using a one period logistic regression. We then weight the DD regression by the interaction of the county population and the inverse probability weight (IPW). All regressions include state fixed effects, county fixed effects, calendar week fixed effects and controls for state time varying covid-19 policies. Standard errors are clustered by county and all estimates are weighted by the county population. For each outcome variable, log hospitalizations or per 100k hospitalizations, we present estimates for 5 samples. First, we show estimates for all counties which instruction modality information. Second, we present estimates for counties in the bottom 57th percentile, 58th to 75th percentile, 75th to 90th and 90th plus of baseline log hospitalizations (March 2020 to July 2020). ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.001 < p\text{-value} \leq 0.01$

Table 7 – IV Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020) by Baseline Hospitalizations (March to July 2020)

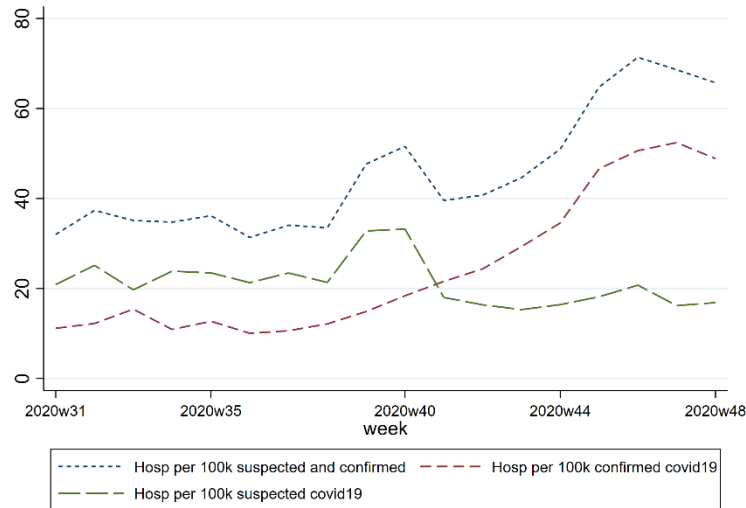
	Per 100K Hospitalizations					Log Total Hospitalizations				
Panel A: MCH	All	<57 th	58 th to 75 th	75 th to 90 th	>90 th	All	<57 th	58 th to 75 th	75 th to 90 th	>90 th
Share In-Person/Hybrid x T-10 to T-5	-0.180 (0.687)	-0.003 (0.005)	0.128 (0.125)	-0.085 (0.508)	8.618*** (2.197)	-0.184*** (0.072)	-0.0001 (0.0003)	0.007 (0.010)	0.131 (0.168)	-0.005 (0.124)
Share In-Person/Hybrid x T+2 to T+6	0.329 (0.539)	0.002 (0.004)	0.058 (0.072)	0.191 (0.455)	5.767*** (1.718)	-0.207** (0.084)	0.0001 (0.0004)	-0.008 (0.006)	0.049 (0.129)	0.041 (0.153)
Mean Dependent Var	9.46	0.007	0.309	10.54	70.19					
Number of Observations	30,815	17,730	6070	4271	2744	30,815	17,730	6070	4271	2744
Panel B: Burbio	All	<57 th	58 th to 75 th	75 th to 90 th	>90 th	All	<57 th	58 th to 75 th	75 th to 90 th	>90 th
Share In-Person/Hybrid x T-10 to T-5	0.564 (0.873)	0.004 (0.006)	-0.058 (0.101)	-0.269 (0.807)	3.862 (3.164)	-0.016 (0.095)	-0.0001 (0.0002)	-0.025 (0.013)	0.114 (0.195)	-0.212 (0.170)
Share In-Person/Hybrid x T+2 to T+6	-0.886 (0.457)	-0.022 (0.018)	-0.110** (0.057)	-1.312** (0.582)	-3.302 (1.942)	-0.091 (0.084)	-0.0006 (0.0005)	-0.009 (0.009)	-0.572*** (0.190)	-0.250 (0.152)
Mean Dependent Var	6.39	0.05	0.21	29.41	87.13					
Number of Observations	27,604	15,432	5,222	4496	2454	27,604	15,432	5,222	4496	2454

Notes – The regression only includes the 10 weeks prior to school reopening and the 6 weeks after school reopening for each county. We divide this period into 3 groups: period 1 (weeks -10 to -5), period 2 (weeks -4 to +1) is the omitted category, and period 3 (weeks +2 to +6). The unit of observation is the county-week. The first stage is estimated from a one-period county level model of share in hybrid/in person on share of teachers in collective bargaining and share of teachers in meet and confer unions, and state fixed effects (see first stage in Table 3). Accordingly, the second stage estimates the effect of predicted share of students in hybrid/in person X post-school reopening periods on hospitalizations, state fixed effects, county fixed effects, calendar week fixed effects and controls for state time varying covid-19 policies. Standard errors are clustered by county and obtained for the aggregate effect using block bootstrap (500 replications). For each outcome variable, log hospitalizations or per 100k hospitalizations, we present estimates for 3 samples. First, we show estimates for all counties which have union information, hospitalizations data, and share of students in hybrid/in person learning. Second, we present estimates for counties in the bottom 90th percentile of baseline log hospitalizations (March 2020 to July 2020). Finally, we present estimates for counties in the top 10th percentile of baseline log hospitalizations. ** indicates 0.01 < p-value <=0.05, *** indicates 0.001 < p-value <=0.01

Figure 1- Covid-19 Hospitalizations Per 100k From Claims



Change Health Claims

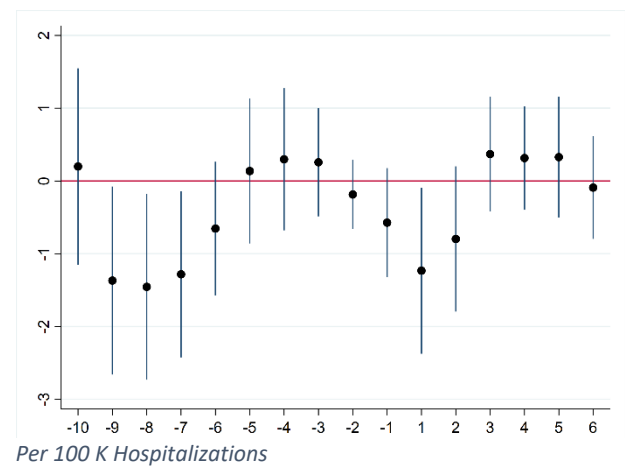
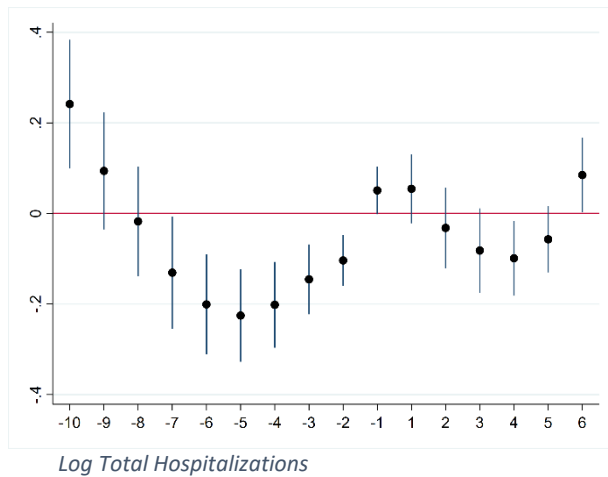


HHS Data Released Dec 7th, 2020

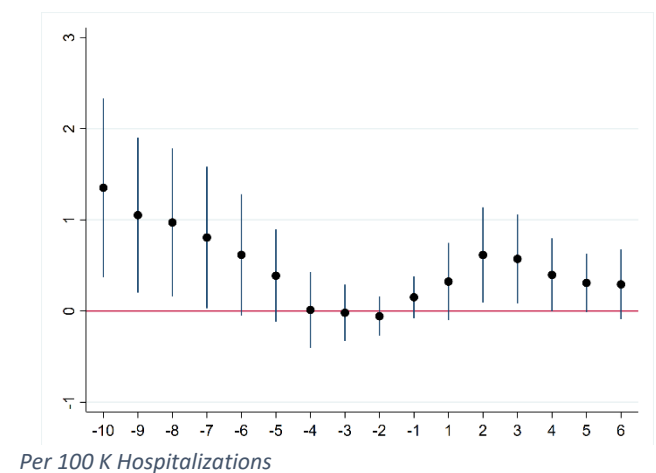
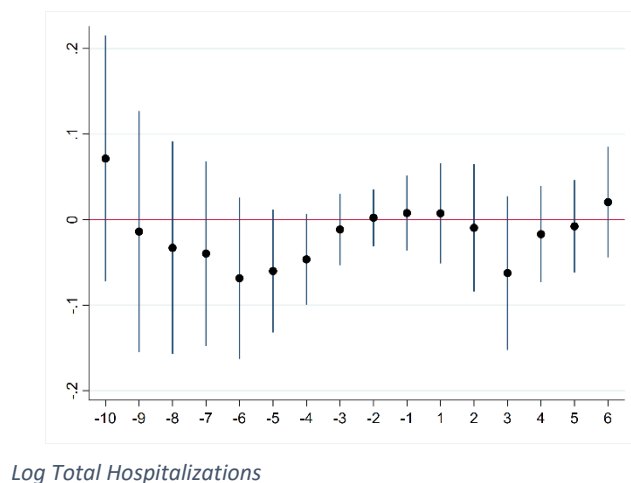
Notes - Figure1(i) presents the trend in hospitalizations per 100K from Change Healthcare claims data. Figure 1 (ii) presents trends in hospitalizations per 100k from data released by the Department of Health and Human Services on Dec 7th, 2020. The data is a nationwide dataset of the number of admissions for covid-19 confirmed and suspected cases at the facility level. The HHS data published begins on week 31 of 2002 (week of July 31st) and is updated daily. The term “suspected” is defined as a person who is being managed as though he/she has COVID19 because of signs and symptoms suggestive of COVID-19 as described by CDC’s Guidance but does not have a laboratory positive COVID19 test result. This may include patients who have not been tested or those with pending test results. The count may also include patients with negative test results but whom continue to show signs/symptoms suggestive of COVID-19.

Figure 2A – Fixed Effects and DD Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020) using MCH

i. Fixed Effects (Continuous Share In-Person/Hybrid)



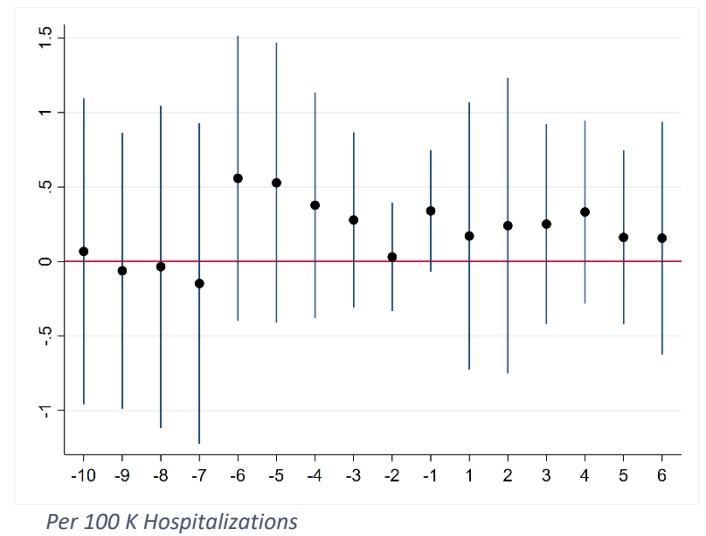
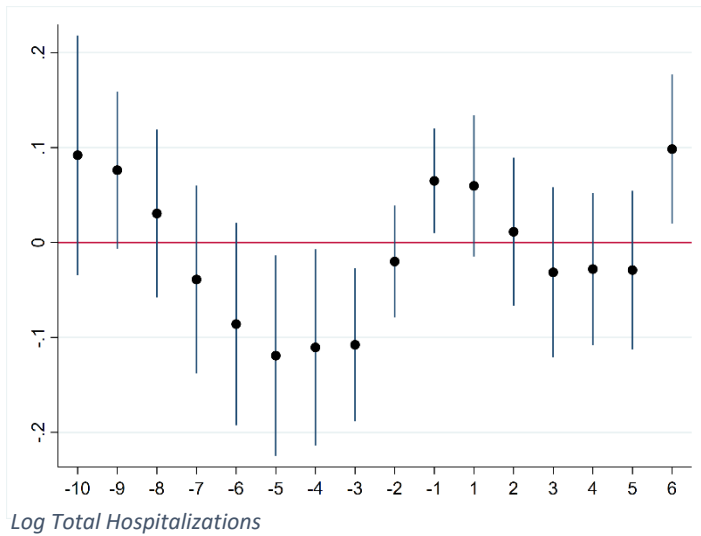
ii. DD (Yes/No Teaching In-Person/Hybrid)



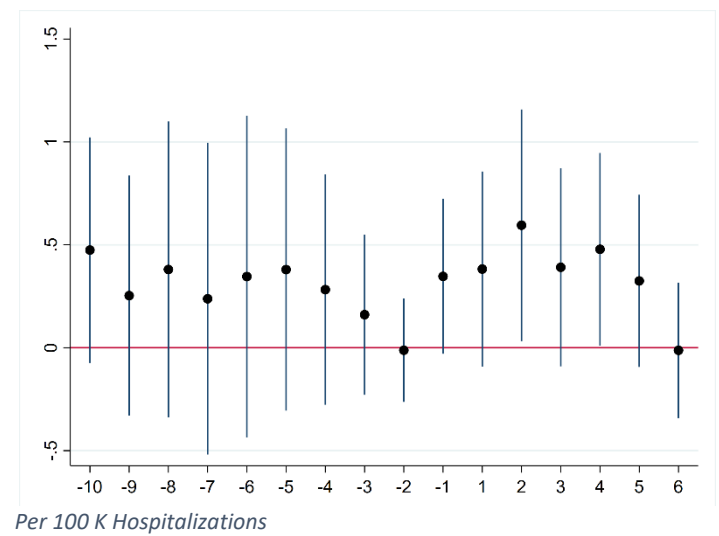
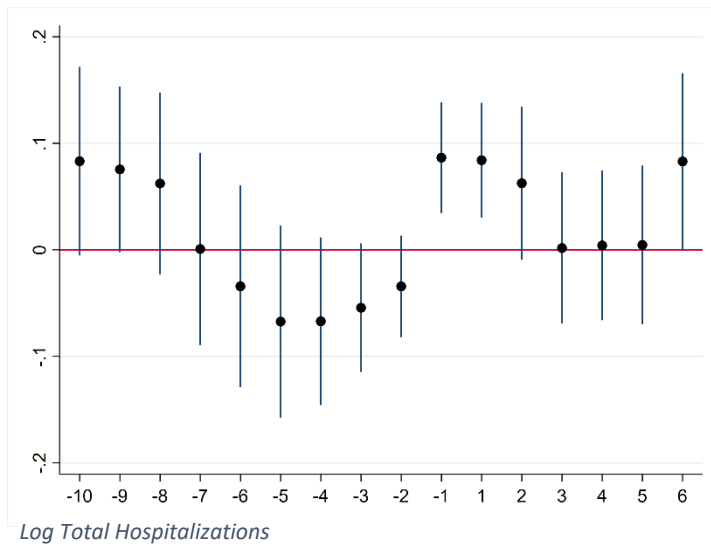
Notes: The level of observation is the county-week. We include all counties for which data on instruction modality was reported from MCH (2404 counties). The first panel (i) presents estimates from a regression of hospitalizations on indicator variables for weeks pre- and post-school reopening interacted with the share of students in in-person/hybrid instruction (FE Model). The second panel (ii) presents estimates from a regression of hospitalizations on indicator variables for weeks pre- and post-school reopening interacted with and indicator (0/1) for whether a county has any districts fully in-person (DD Model). All regressions include county fixed effects, state time varying controls for COVID-19 policies. Estimates are weighted by the county population. N=109,908 and mean hospitalizations per 100K = 7.71.

Figure 2B – Fixed Effects and DD Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020) using Burbio

(i) Fixed Effects (Continuous Share In-Person/Hybrid)

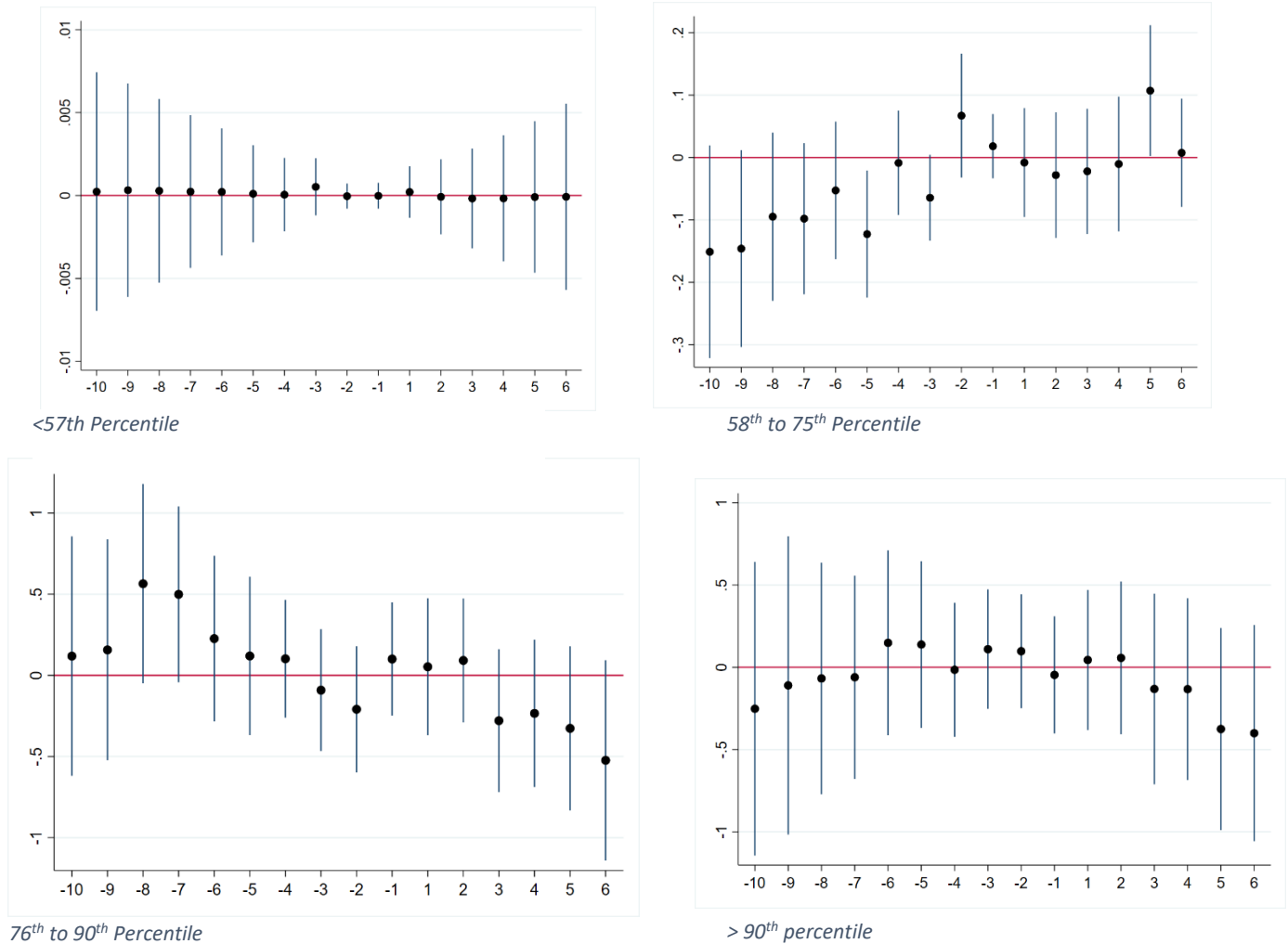


(ii) DD (Yes/No Teaching In-Person/Hybrid)



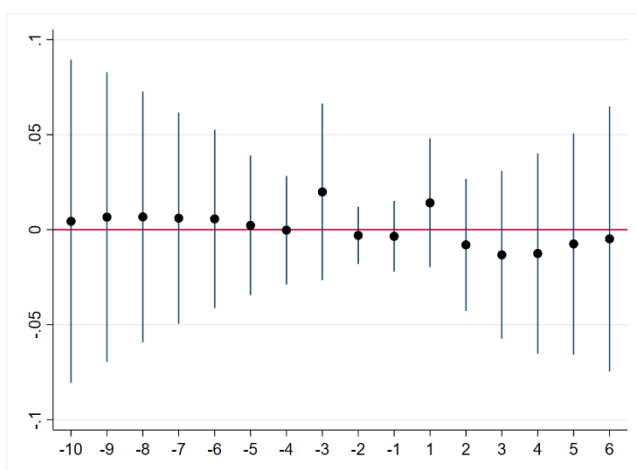
Notes – See notes to Table 2A. This table is the same except for the use of the Burbio data. N=103,415 and mean hospitalizations per 100K=6.69.

Figure 3A– IV-Event Study Coefficients for the effect of Share hybrid/in-person on Log Total Covid19 Hospitalizations (MCH)

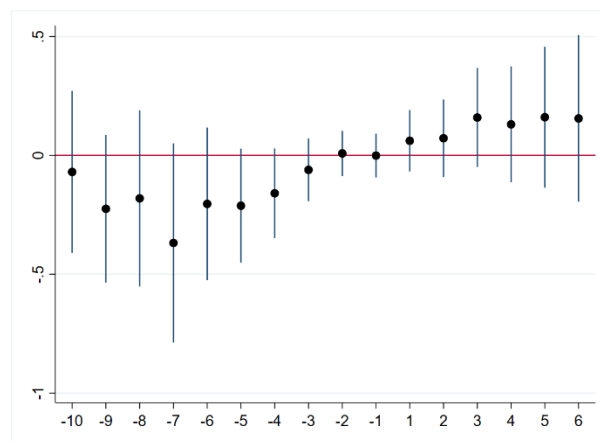


Notes - The unit of observation is the county-week. The figure presents IV coefficients for 10 weeks pre through 6 weeks post school reopening. The first stage is estimated from a one period county level model of share in hybrid/in person on share of teachers in collective bargaining and share of teachers in meet and confer unions, and state fixed effects (see first stage in Table 3). Accordingly, the second stage estimates the effect of predicted share of students in hybrid/in person X post-school reopening periods on hospitalizations, county fixed effects, calendar week fixed effects and controls for state time varying COVID-19 policies. Standard errors are clustered by county and obtained for the aggregate effect using block bootstrap (500 replications). We present estimates for 3 samples. First, we show estimates for all 1807 counties which have union information, hospitalizations data, and share of students in hybrid/in person learning. Second, we present estimates for counties in the bottom 90th percentile of baseline log hospitalizations (Feb to July 2020). Finally, we present estimates for counties in the top 10th percentile of baseline log hospitalizations. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.01 \leq p\text{-value} < 0.001$.

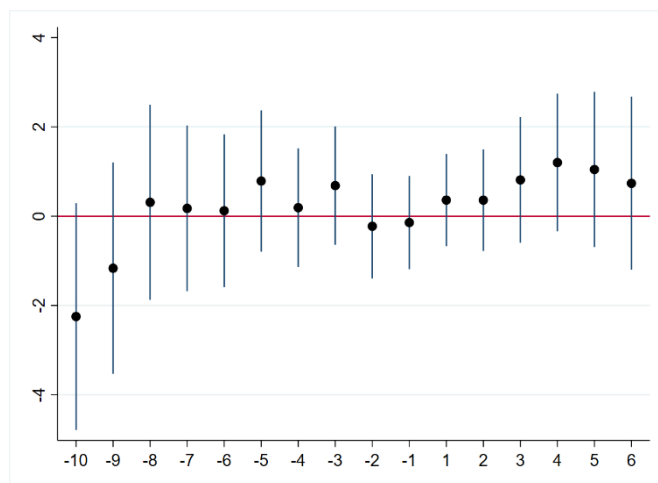
Figure 3B– IV -Event Study Coefficients for the effect of Share hybrid / In-person on Per 100K Covid19 Hospitalizations (MCH)



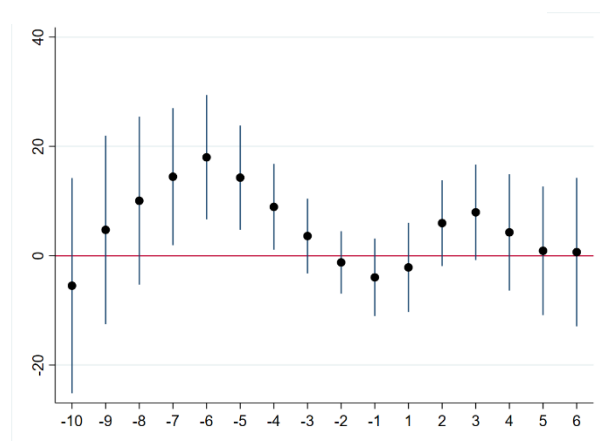
<57th Percentile



58th to 75th Percentile



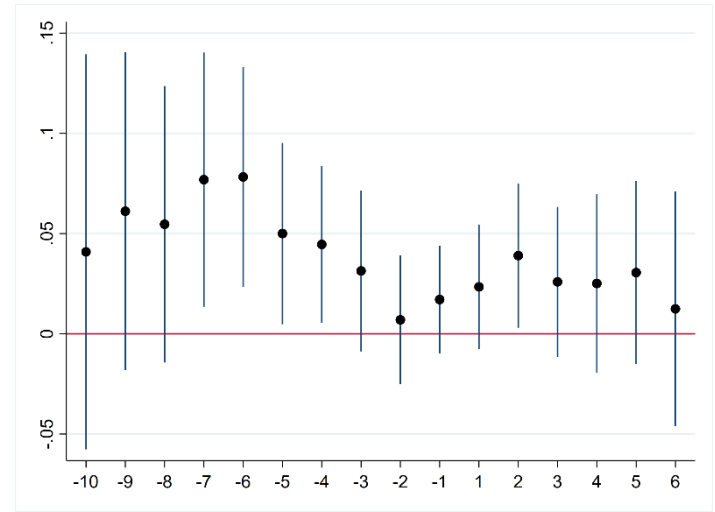
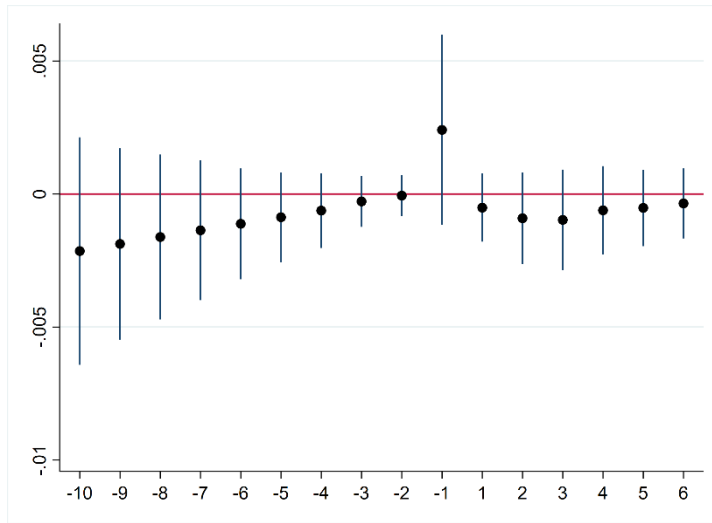
76th to 90th Percentile



> 90th percentile

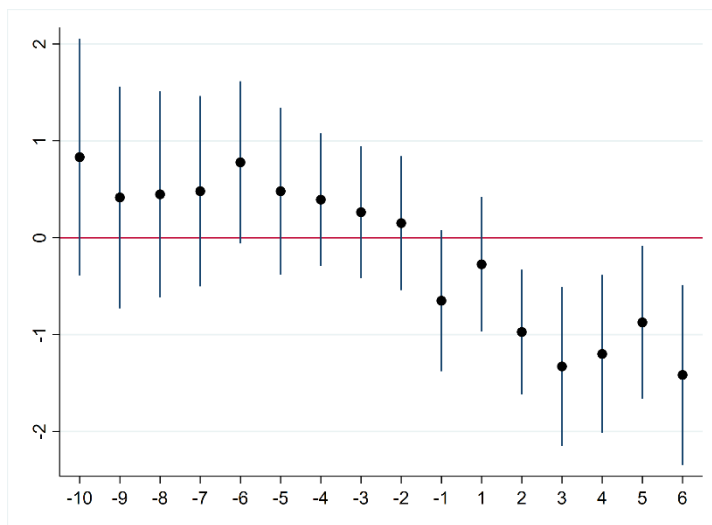
Notes – See notes to Figure 3A. These are the same except Figure 3B uses Per 100K as the outcome variable. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.01 \leq p\text{-value} < 0.001$.

Figure 3C: IV-Event Study Coefficients for the Effect of Share Hybrid/In-person on Log Total Hospitalizations (Burbio)

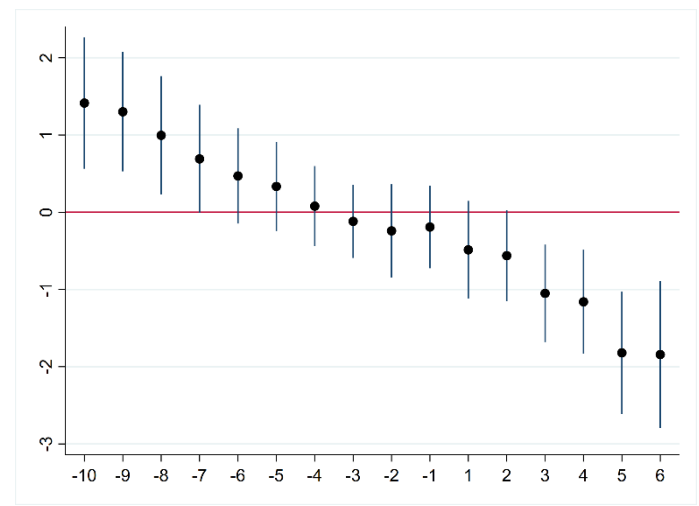


<57th Percentile

<58th to 75th Percentile



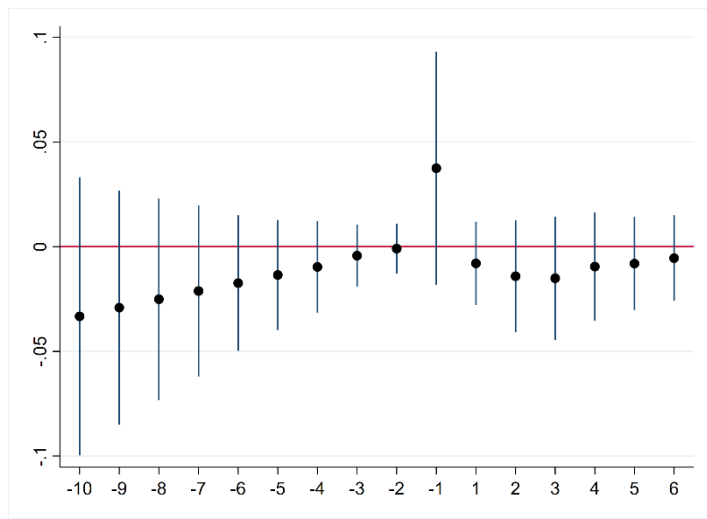
76th to 90th percentile



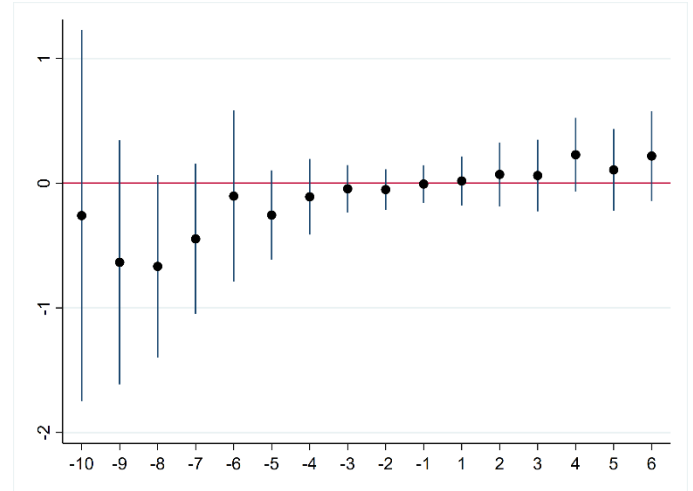
>90th percentile

Notes: See notes to Figure 3A. Figure 3C is the same except this figure uses the burbio data. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.01 \leq p\text{-value} < 0.001$.

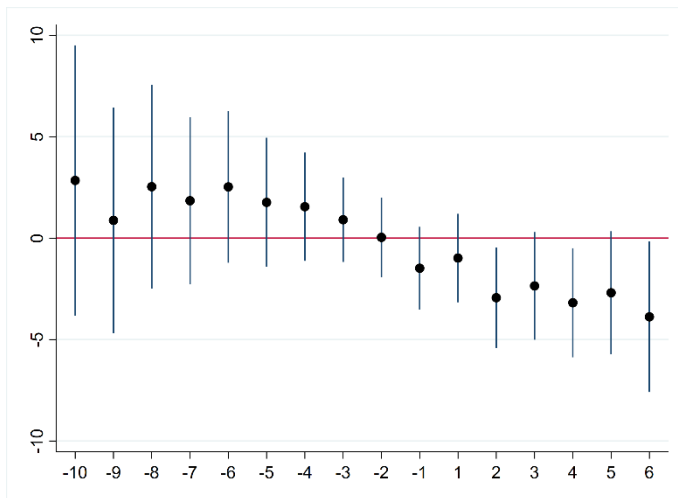
Figure 3D– IV -Event Study Coefficients for the effect of Share hybrid / In-person on Per 100K Hospitalizations (Burbio)



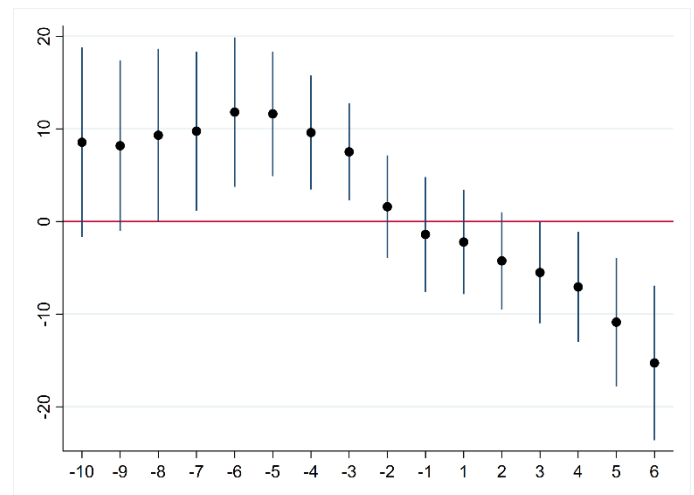
<57th Percentile



58th – 75th Percentile



76th to 90th percentile



> 90th percentile

Notes: See notes to Figure 3B. Figure 3D is the same except this figure uses the burbio data. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.01 \leq p\text{-value} < 0.001$.

Appendix Table 1- School Reopening Mode Transition Matrix

	Hybrid (Oct.10)	On Premises (Oct.10)	Online Only (Oct.10)	Other (Oct.10)
Hybrid (Start school year)	37.47%	8.61%	5.41%	1.68%
On Premises (Start school year)	7.27%	11.48%	1.47%	0.40%
Online Only (Start school year)	6.98%	1.65%	15.33%	0.29%
Other (Start school year)	1.15%	0.25%	0.29%	0.26%

Notes: This table shows the percent of districts that started school in the mode show in the left column (time t) and how this compared to their mode as of October 10 (t+1).

Appendix Table 2 - Propensity Score Matching Difference in Differences Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020) Log vs Inverse Hyperbolic Sine Function

	Inverse Hyperbolic Sine Function		Log (Y+1)	
Panel A. All Counties	MCH	Burbio	MCH	Burbio
Share In-Person/Hybrid x T-10 to T-5	-0.072 (0.037)	0.016 (0.024)	-0.063 (0.035)	0.012 (0.024)
Share In-Person/Hybrid x T+2 to T+6	0.001 (0.027)	-0.006 (0.019)	-0.019 (0.028)	-0.005 (0.016)
Number of Observations	51,274	59,452	51,274	59,452

Notes – See notes to Table 6. This model is the same except we transform the dependent variable using Log (Y+ 1) and using the inverse hyperbolic sine function to compare. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.01 \leq p\text{-value} < 0.001$.

Appendix Table 3 – IV Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations
(January to October 2020) by Baseline Hospitalizations (March to July 2020)

	Inverse Hyperbolic Sine Function	Log Total Hospitalizations Log (Y+1)
Panel A: MCH	All Counties	All Counties
Share In-Person/Hybrid x T-10 to T-5	-0.165** (0.075)	-0.184*** (0.072)
Share In-Person/Hybrid x T+2 to T+6	-0.161** (0.082)	-0.207** (0.084)
Number of Observations	30,815	30,815
Panel B: Burbio	All Counties	All Counties
Share In-Person/Hybrid x T-10 to T-5	-0.018 (0.102)	-0.016 (0.095)
Share In-Person/Hybrid x T+2 to T+6	-0.106 (0.092)	-0.091 (0.084)
Number of Observations	27,604	27,604

Notes – See notes to Table 4. This model is the same except we transform the dependent variable using Log (Y+ 1) and using the inverse hyperbolic sine function to compare. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.01 \leq p\text{-value} < 0.001$.

Appendix Table 4- Propensity Score Matching Difference in Differences Estimates of the
Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020) with Controls
for College Opening Modality and Time

Panel A: MCH	Per 100K Hospitalizations	Per 100K Hospitalizations	Log Total Hospitalizations	Log Total Hospitalizations
Share In-Person/Hybrid x T-10 to T-5	-0.078 (0.252)	0.053 (0.253)	-0.063 (0.035)	-0.083* (0.033)
Share In-Person/Hybrid x T+2 to T+6	0.295 (0.187)	0.258 (0.149)	-0.019 (0.028)	-0.020 (0.027)
Mean Dependent Var	7.24	7.24		
Controls for Hybrid/In- person College Reopening	NO	YES	NO	YES
Number of Observations	51,274	51,274	51,274	51,274
Pane B: Burbio				
Share In-Person/Hybrid x T-10 to T-5	-0.250 (0.229)	-0.083 (0.178)	0.012 (0.024)	0.005 (0.020)
Share In-Person/Hybrid x T+2 to T+6	0.133 (0.114)	0.073 (0.097)	-0.005 (0.016)	-0.006 (0.018)
Mean Dependent Var	9.79	7.24		
Controls for Hybrid/In- person College Reopening	NO	YES	NO	YES
Number of Observations	59,452	59,452	59,452	59,452

Notes – See notes to Table 6. Here we compare the model in table 6 to another model where we add time varying controls for hybrid/In-Person college reopening in the county . ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.01 \leq p\text{-value} < 0.001$.

Appendix Table 5- Effect of K-12 Teacher Union Power on College Reopening Modality

	College Hybrid /In Person
Share of Collective Bargaining Union	-0.037 (0.071)
Share of Meet and Confer Union	-0.041 (0.103)
F-statistic for Joint Significance	0.850
Mean Dep Variable	0.180
Number of Obsv. (counties)	1809
adj. R-sq	0.07

Notes – The level of observation is the county. The table reports estimate from a regression of whether a county has a college that opened with in-person/hybrid instruction on two measures of K-12 teacher unionization (see notes to Table 2 for details). Hybrid/in-person is defined as zero if the county does not have a college or does not have a college that offered in-person/hybrid instruction. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.01 \leq p\text{-value} < 0.001$.

Appendix Table 6 – IV Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020) by Baseline Hospitalizations (March to July 2020) with Controls for College Opening Modality and Time

Panel A: MCH	Per 100K Hospitalizations	Per 100K Hospitalizations	Log Total Hospitalizations	Log Total Hospitalizations
Share In-Person/Hybrid x T-10 to T-5	-0.180 (0.687)	0.607 (0.680)	-0.184*** (0.072)	-0.165** (0.076)
Share In-Person/Hybrid x T+2 to T+6	0.329 (0.539)	0.268 (0.534)	-0.207** (0.084)	-0.187** (0.084)
Mean Dependent Var	9.46	9.46		
Controls for Hybrid/In- person College Reopening	NO	YES	NO	YES
Number of Observations	30,815	30,815	30,815	30,815
Pane B: Burbio	All		All	
Share In-Person/Hybrid x T-10 to T-5	0.564 (0.873)	0.372 (0.946)	-0.016 (0.095)	0.265* (0.104)
Share In-Person/Hybrid x T+2 to T+6	-0.886 (0.457)	-0.883 (0.589_	-0.091 (0.084)	-0.131 (0.081)
Mean Dependent Var	6.39	6.39		
Controls for Hybrid/In- person College Reopening	NO	YES	NO	YES
Number of Observations	27,604	27,604	27,604	27,604

Notes – See notes to Table 4. Here we compare the model in table 4 to another model where we add time varying controls for hybrid/In-Person college reopening in the county. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.01 \leq p\text{-value} < 0.001$.

Appendix Table 7- Propensity Score Matching Difference in Differences Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020)

	Per 100 K		Log Total Hospitalizations		Poisson Model	
Panel A. All Counties	MCH	Burbio	MCH	Burbio	MCH	Burbio
Share In-Person/Hybrid x T-10 to T-5	-0.078 (0.252)	-0.250 (0.229)	-0.063 (0.035)	0.012 (0.024)	0.058 (0.042)	-0.042 (0.045)
Share In-Person/Hybrid x T+2 to T+6	0.295 (0.187)	0.133 (0.114)	-0.019 (0.028)	-0.005 (0.016)	0.042 (0.065)	0.008 (0.040)
Mean Dependent Variable	7.24	9.79			3.61	3.44
Number of Observations	51,274	59,452	51,274	59,452	51,274	59,452

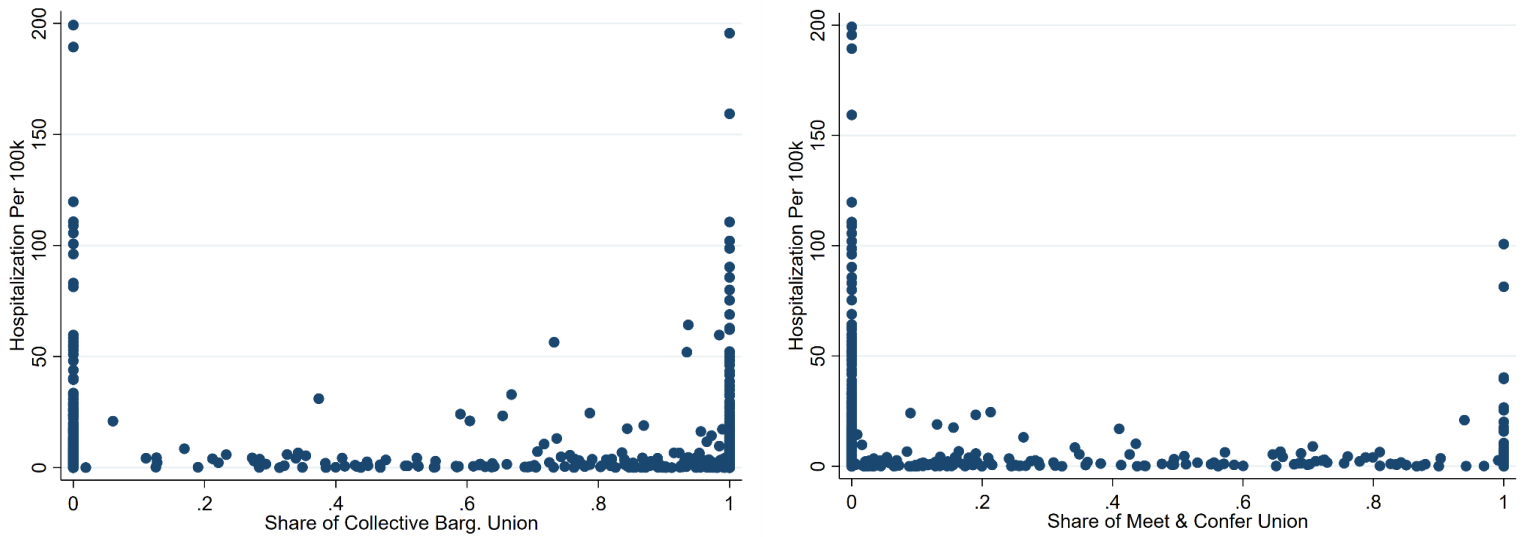
Notes – See notes to Table 6. This model is the same except we add estimates from a Poisson model. ** indicates $0.01 < \text{p-value} \leq 0.05$, *** indicates $0.01 \leq \text{p-value} < 0.001$.

Appendix Table 8 – IV Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020) by Baseline Hospitalizations (March to July 2020)

Panel A: MCH	Per 100K Hospitalizations	Log Total Hospitalizations	Poisson Model Total Hospitalizations
Share In-Person/Hybrid x T-10 to T-5	-0.180 (0.687)	-0.184*** (0.072)	0.152 (0.180)
Share In-Person/Hybrid x T+2 to T+6	0.329 (0.539)	-0.207** (0.084)	0.143 (0.230)
Mean Dependent Var	9.46		4.12
Number of Observations	30,815	30,815	30,815
Panel B: Burbio	All	All	
Share In-Person/Hybrid x T-10 to T-5	0.564 (0.873)	-0.016 (0.095)	0.589*** (0.176)
Share In-Person/Hybrid x T+2 to T+6	-0.886 (0.457)	-0.091 (0.084)	-0.010 (0.220)
Mean Dependent Var	6.39		4.14
Number of Observations	27,604	27,604	27,604

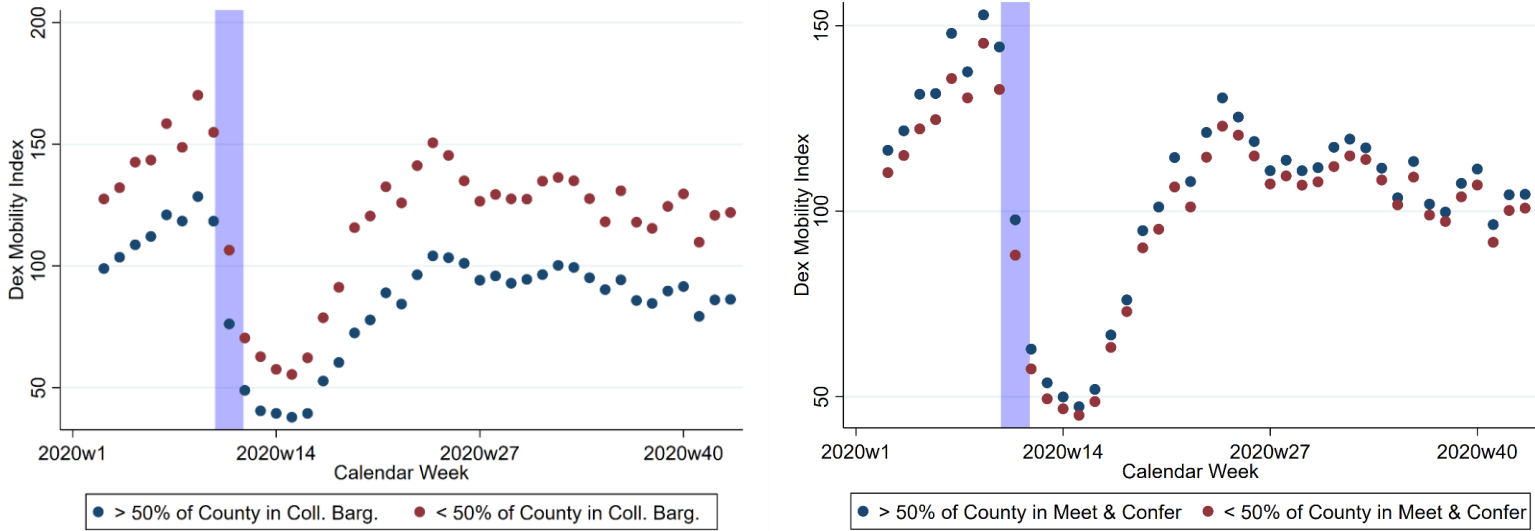
Notes – See notes to Table 7. Here we compare the model in table 4 to another model where we add time varying controls for hybrid/In-Person college reopening in the county. ** indicates $0.01 < p\text{-value} \leq 0.05$, *** indicates $0.01 \leq p\text{-value} < 0.001$.

Appendix Figure 1- Average Covid-19 Hospitalizations Per 100k Prior to Schools' Reopening (March to July 2020) and Teacher Union Presence



Notes: The unit of observation is the county. Appendix Figure 1(i) presents the baseline (Feb to July 2020) hospitalization per 100k rate in a county on the y-axis and the share of collective bargaining in the county at baseline on the x-axis. Similarly, Appendix Figure 1(ii) presents the baseline (Feb to July 2020) hospitalization per 100k rate in a county on the y-axis and the share of meet and confer in the county at baseline on the x-axis.

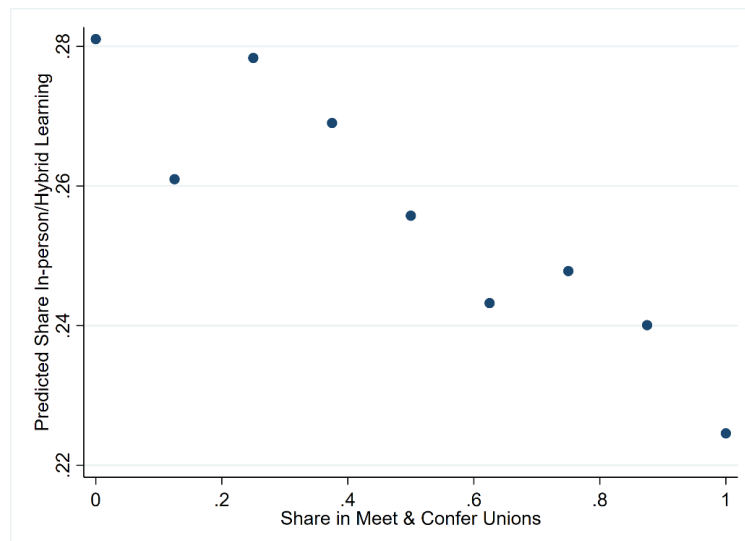
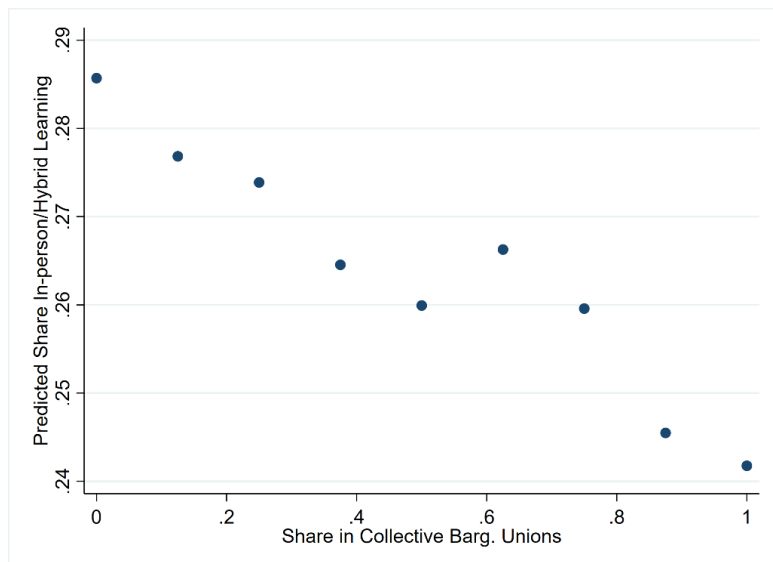
Appendix Figure 2 - Mobility and Teacher Union Presence Over Time



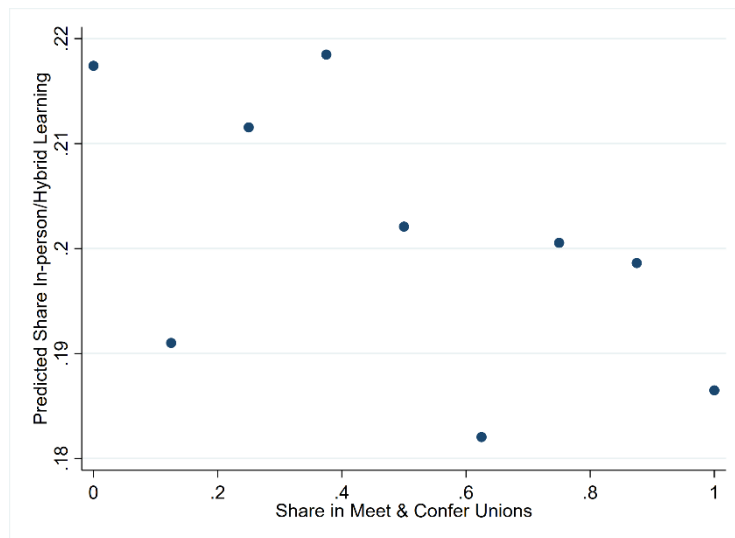
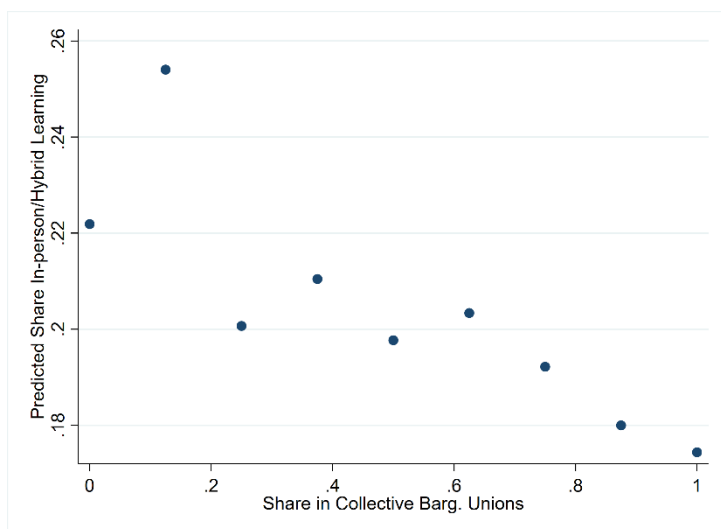
Notes: The unit of observation is the week. The vertical line indicates the week of March 13th when the Covid-19 federal emergency declaration was implemented. Appendix Figure 1(i) presents the average Dex mobility index (from PlaceIQ) on the y-axis and the calendar-week on the x-axis. We present one trend line for counties with more than 50 percent in collective bargaining unions and counties with less than 50 percent in collective bargaining unions. Appendix Figure 1(ii) is analogous, except focusing on meet and confer.

Appendix Figure 3 - Share in Hybrid/In-person learning and K-12 Teacher Union Presence

(i) MCH

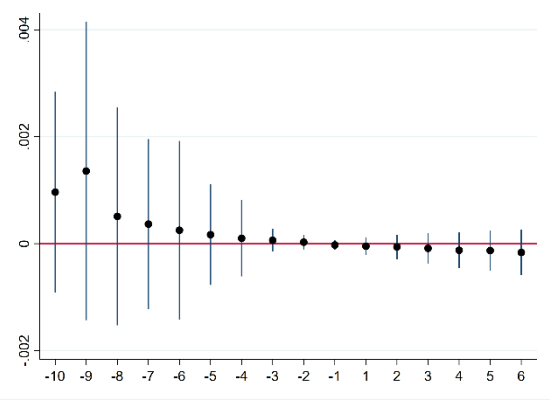


(ii) Burbio

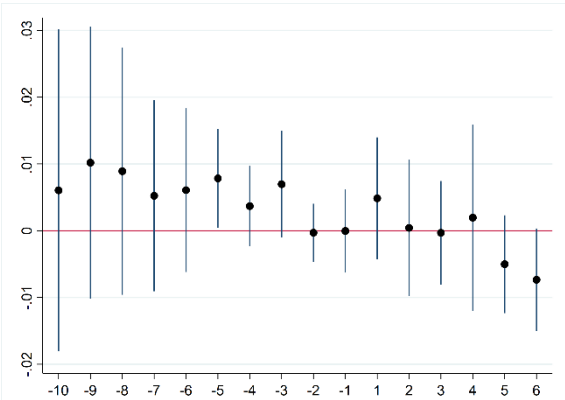


Notes – Appendix Figure 3 (i) presents the predicted share in in-person/hybrid from the MCH data against the share in collective bargaining and meet and confer unions. Appendix Figure 3 (ii) presents the predicted share in in-person/hybrid from the Burbio data against the share in collective bargaining and meet and confer unions. Table (3), the first stage, presents the coefficient estimates for these figures.

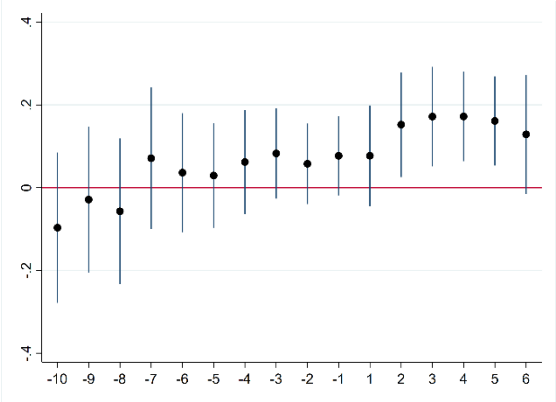
Appendix Figure 4A (i) DD Estimates of the Hybrid/In-Person Teaching on Log Total Covid19 Hospitalizations (January to October 2020) using MCH by Baseline Hospitalizations



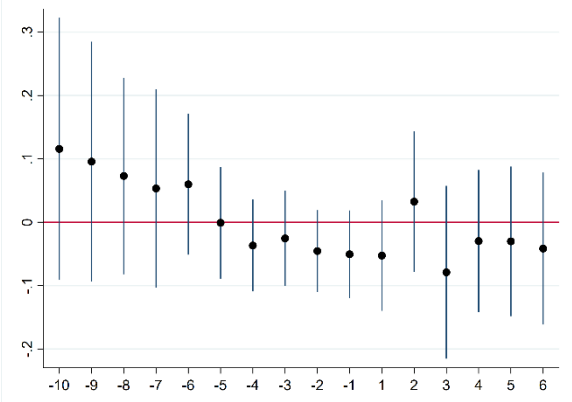
<57th Percentile



58th to 75th Percentile

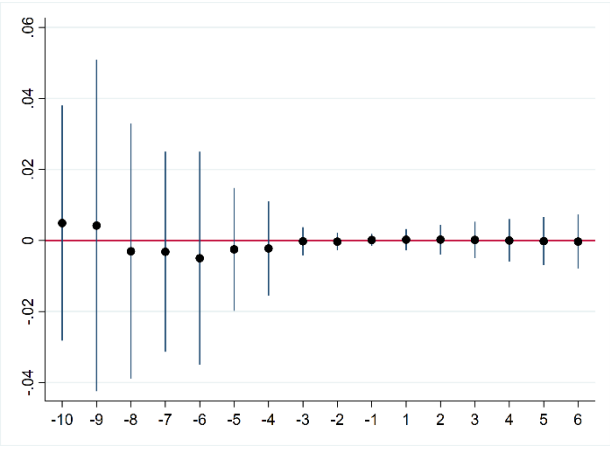


76th to 90th Percentile

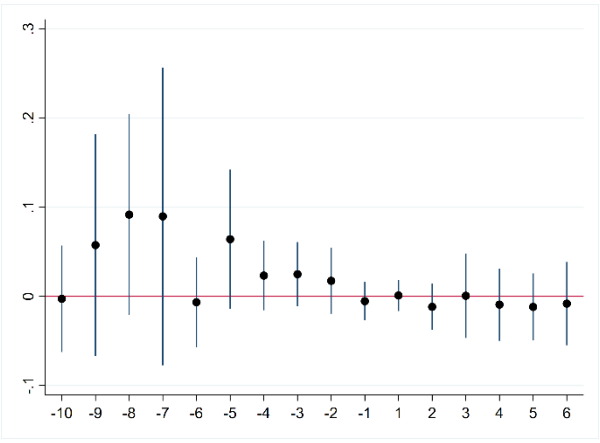


> 90th Percentile

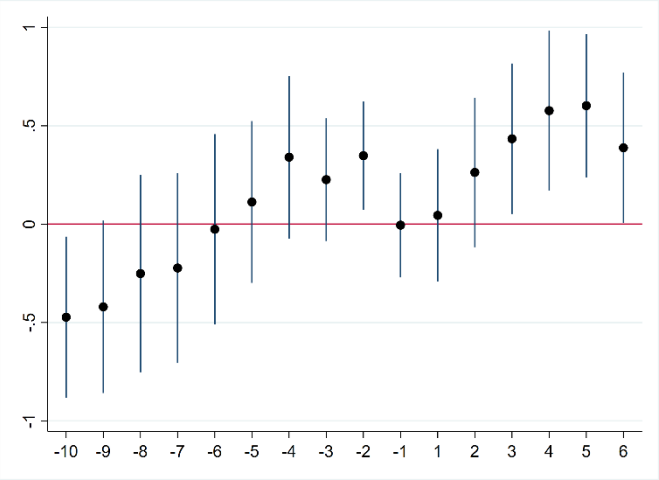
Appendix Figure 4B (ii) DD Estimates of the Hybrid/In-Person Teaching on Per 100 K Covid19 Hospitalizations (January to October 2020) using MCH by Baseline Hospitalizations



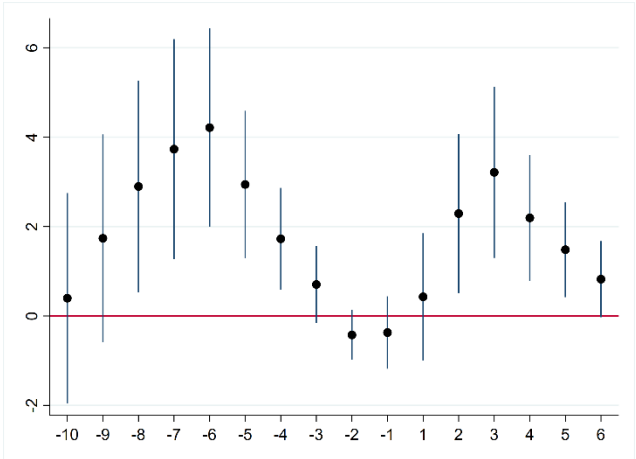
<57th Percentile



<58th to 75th Percentile

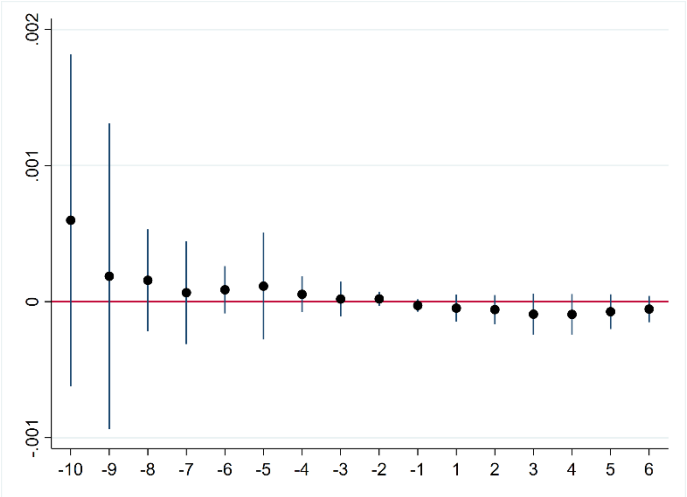


76th to 90th Percentile

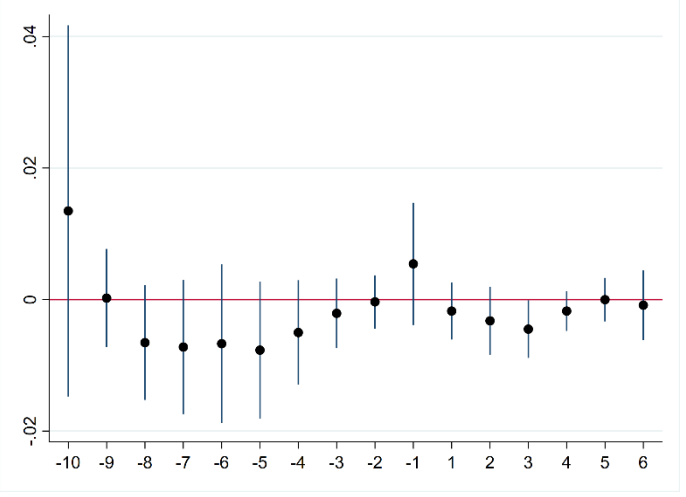


>90th Percentile

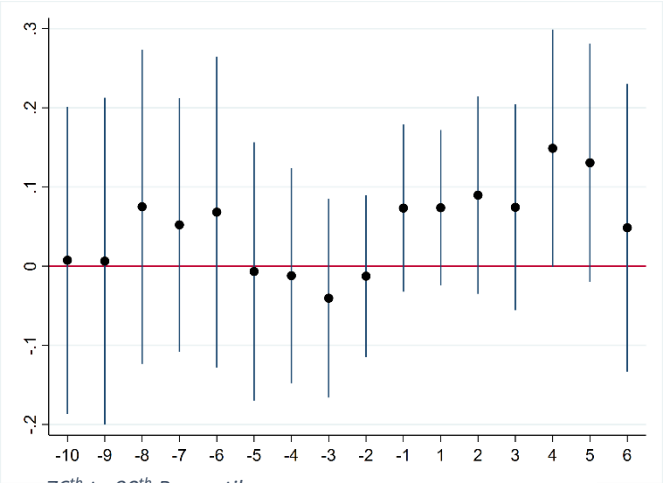
Appendix Figure 4C (i) –DD Estimates of the Hybrid/In-Person Teaching on Log Total Covid19 Hospitalizations (January to October 2020) using Burbio by Baseline Hospitalizations



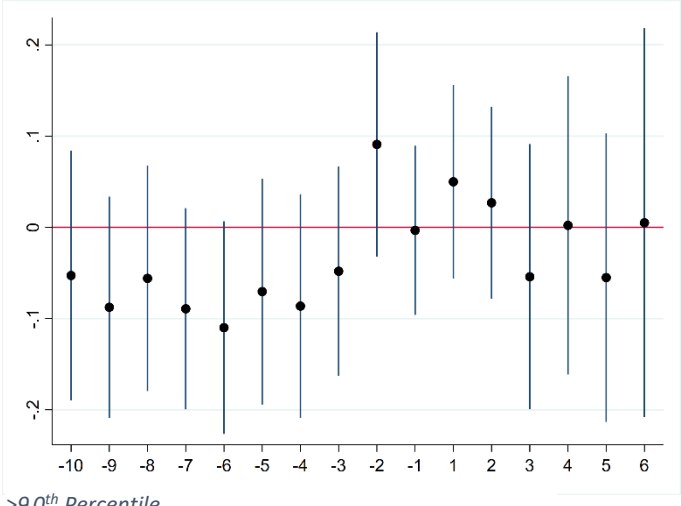
<57th Percentile



56th to 75th Percentile

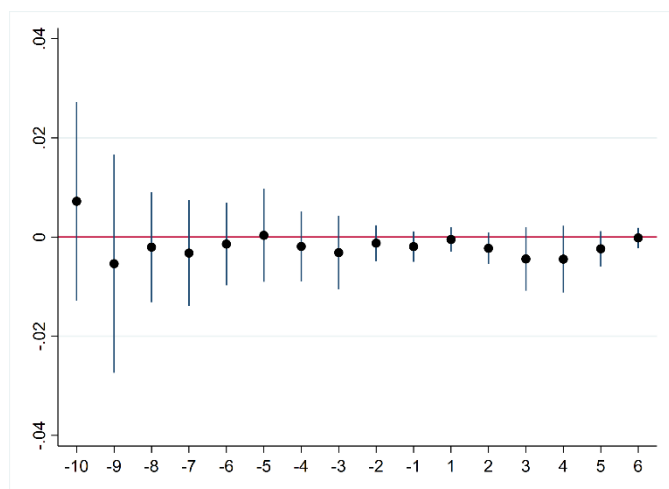


76th to 90th Percentile

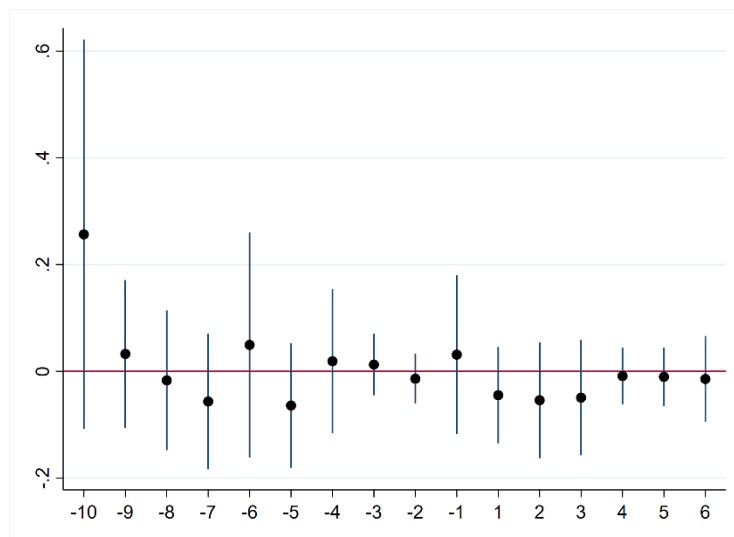


>90th Percentile

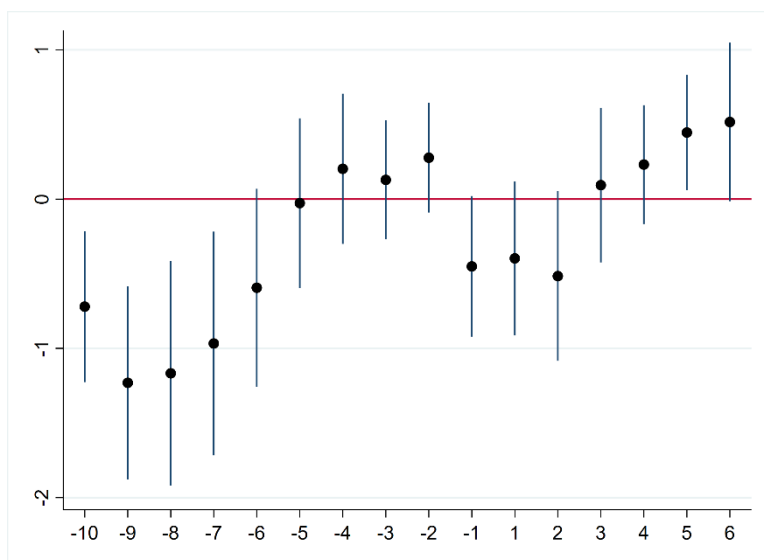
Appendix Figure 4D (i) DD Estimates of the Hybrid/In-Person Teaching on Per 100K Covid19 Hospitalizations (January to October 2020) using Burbio by Baseline Hospitalizations



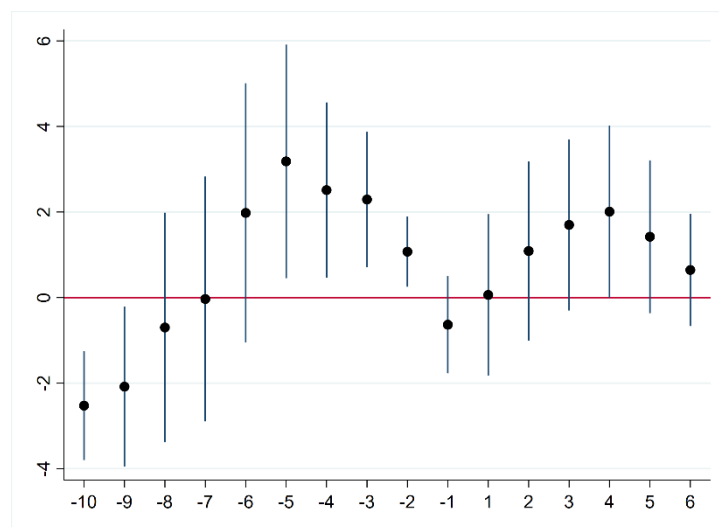
<57th Percentile



56th to 75th Percentile



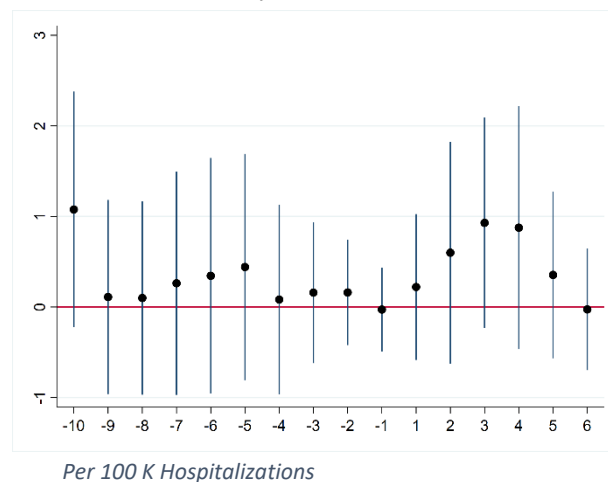
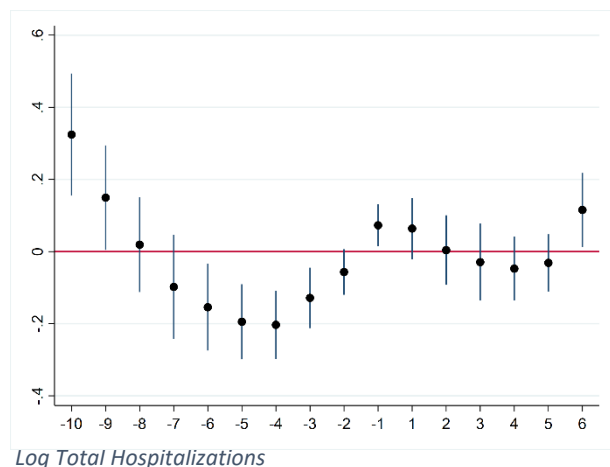
76th to 90th Percentile



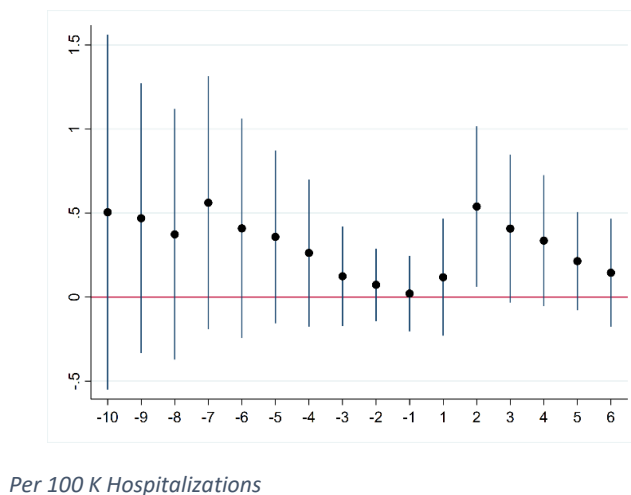
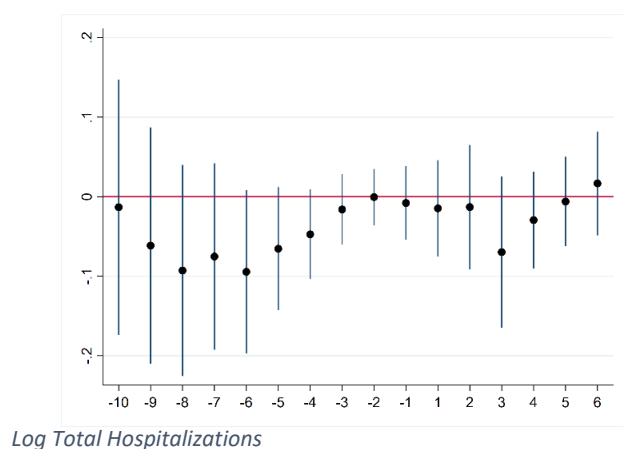
>90th Percentile

Appendix Figure 5A – Fixed Effects and DD Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020) using MCH and Including only the IV Sample of Counties

i. Fixed Effects (Continuous Share In-Person/Hybrid)



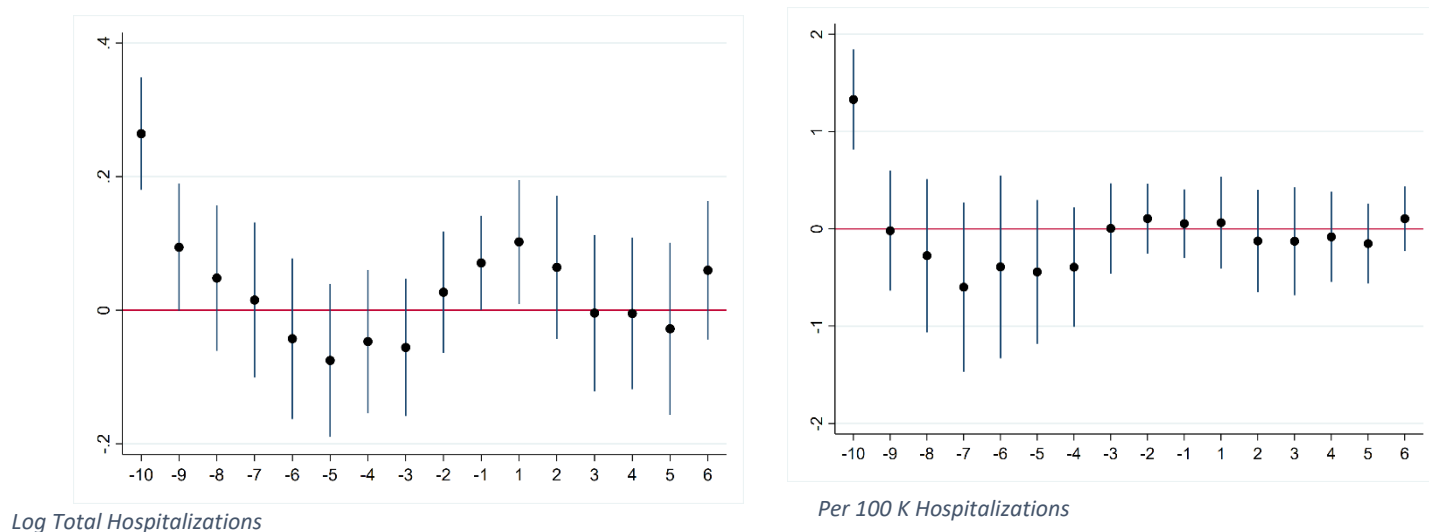
ii. DD (Yes/No Teaching In-Person/Hybrid)



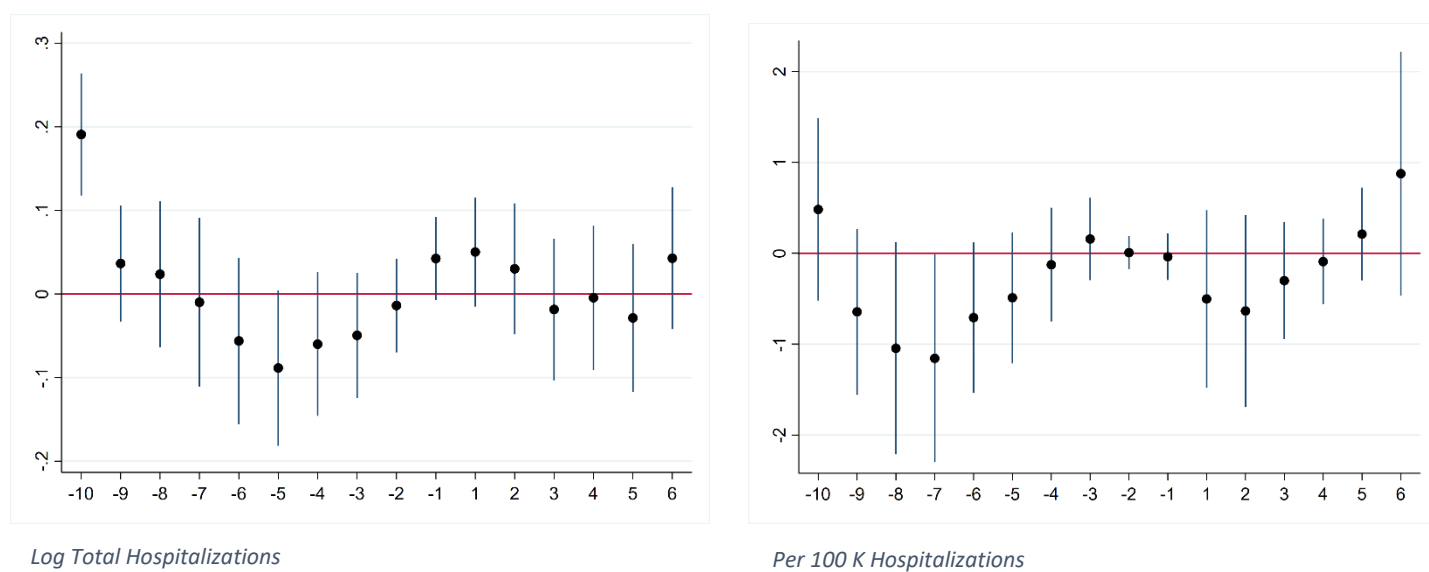
Notes: The level of observation is the county-week. We include all counties for which data on instruction modality was reported from MCH (2,404 counties). The first panel (i) presents estimates from a regression of hospitalizations on indicator variables for weeks pre- and post-school reopening interacted with the share of students in in-person/hybrid instruction(FE Model). The second panel (ii) presents estimates from a regression of hospitalizations on indicator variables for weeks pre and post school reopening interacted with and indicator fpr whether a county had any students attending fully in-person (DD Model). All regressions include county fixed effects, state time varying controls for covid19 policies. Estimates are weighted by the county population. N=76,725 and mean hospitalizations per 100k=6.87

Appendix Figure 5B – Fixed Effects and DD Estimates of the Hybrid/In-Person Teaching on Covid19 Hospitalizations (January to October 2020) using Burbio and Including only the IV sample of counties

(iii) Fixed Effects (Continuous Share In-Person/Hybrid)

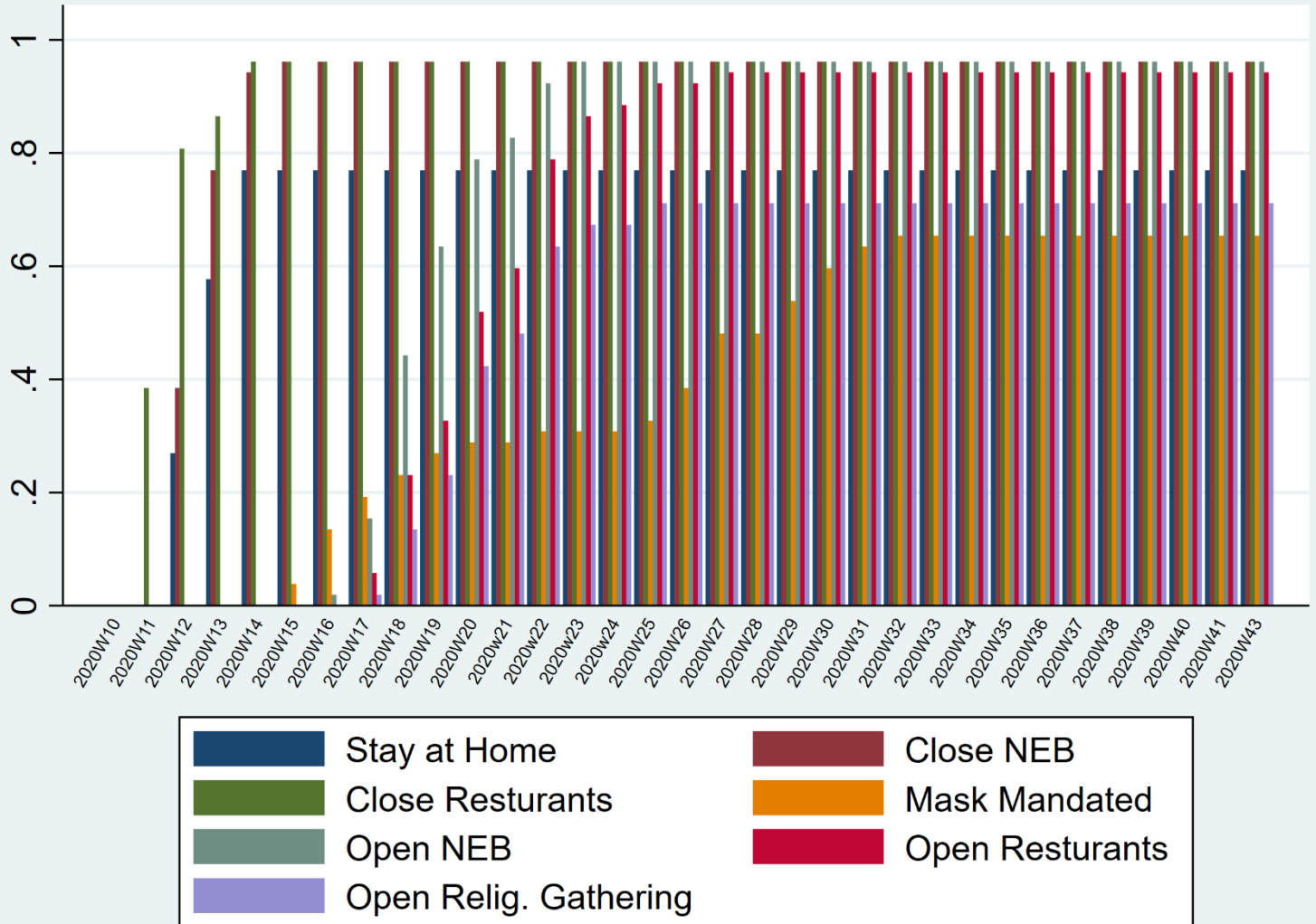


(iv) DD (Yes/No Teaching In-Person/Hybrid)



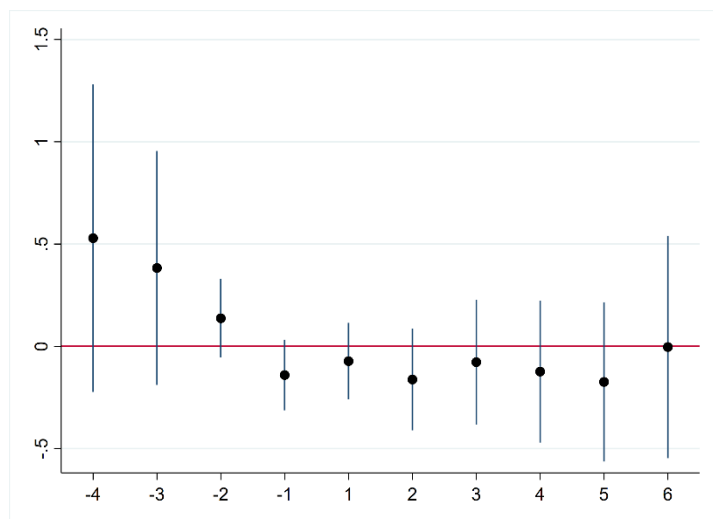
Notes – See notes to Appendix Figure 4A. Appendix Figure 4B is the same except for using Burbio data. N= 69,766 and mean hospitalizations per 100k=6.12

Appendix Figure 6 - State Policies over Time

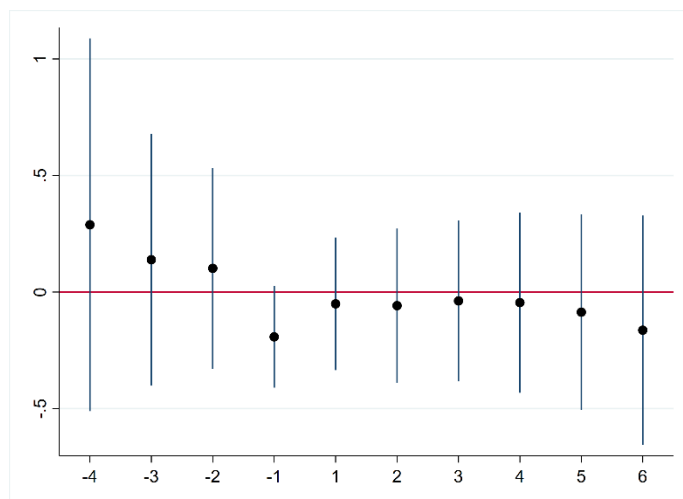


Notes – the level of observation is the calendar week level. The figure spans early March (week 10) to later October (week 43). We graph the share of states that enacted stay at home orders, closed and then re-opened restaurants, closed and then re-opened non-essential business, resumed religious gatherings after the March 13th federal emergency declaration, and mandated masks.

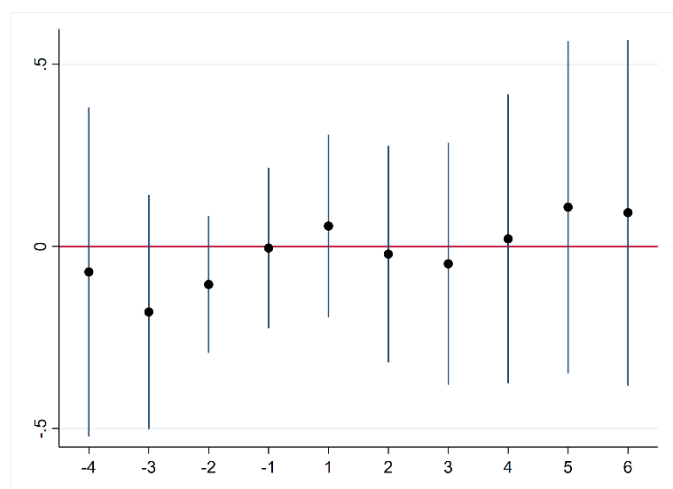
Appendix Figure 7 - DD Estimates of the Hybrid/In-Person Teaching on Log Total Covid19 Hospitalizations (January to October 2020) using MCH by Baseline Hospitalizations and HHS data



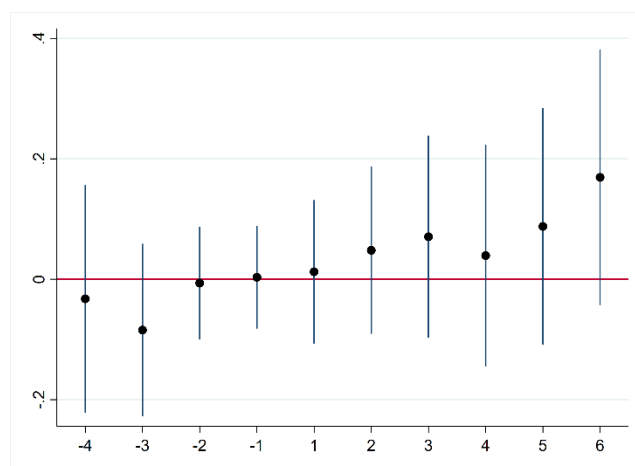
<50th percentile



51st - 75th percentile

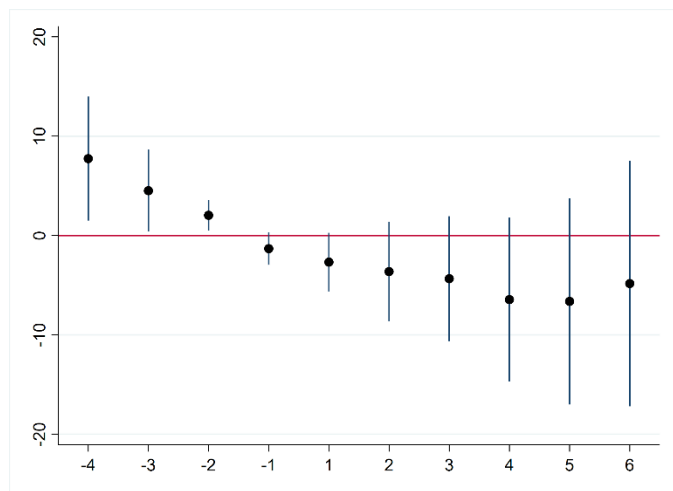


76th - 90th percentile

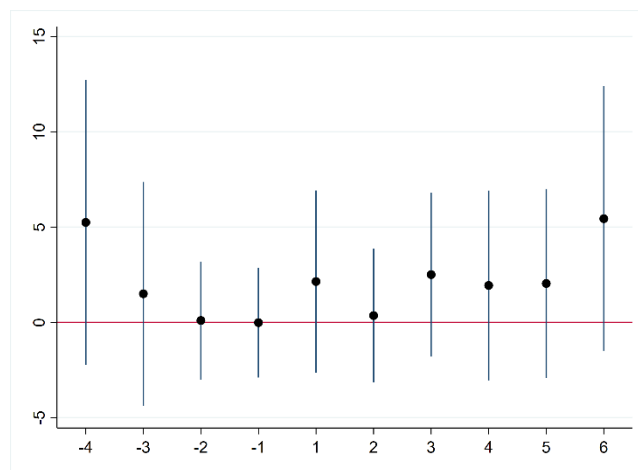


>90th percentile

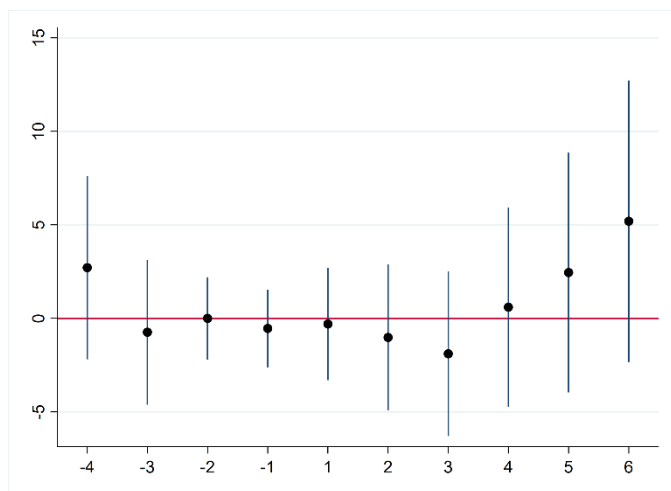
Appendix Figure 8 - DD Estimates of the Hybrid/In-Person Teaching on Per 100 K Covid19 Hospitalizations (January to October 2020) using MCH by Baseline Hospitalizations and HHS data



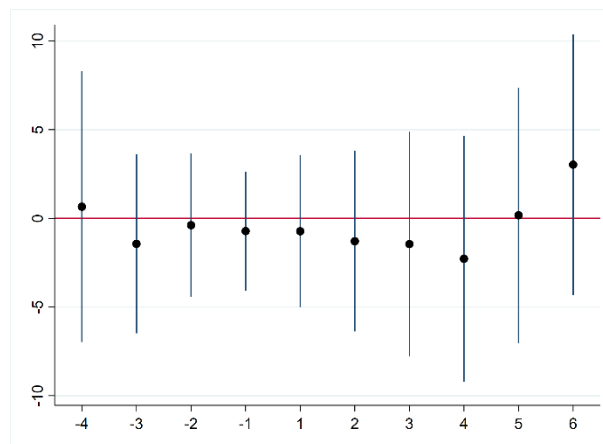
<50th percentile



51st - 75th percentile

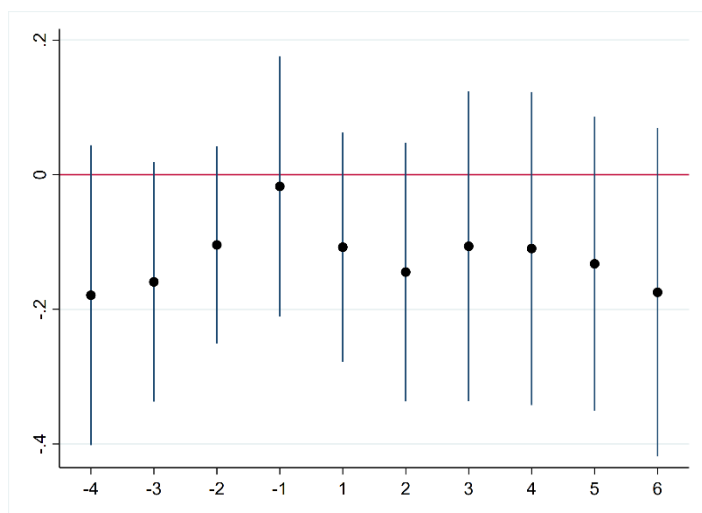


76th - 90th percentile

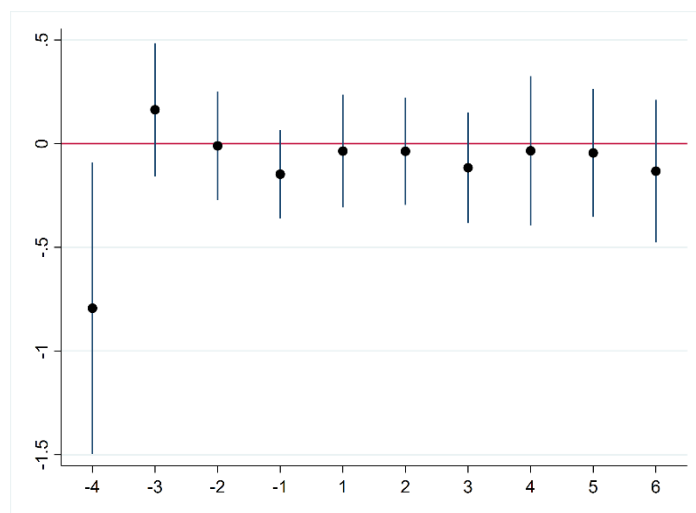


>90th percentile

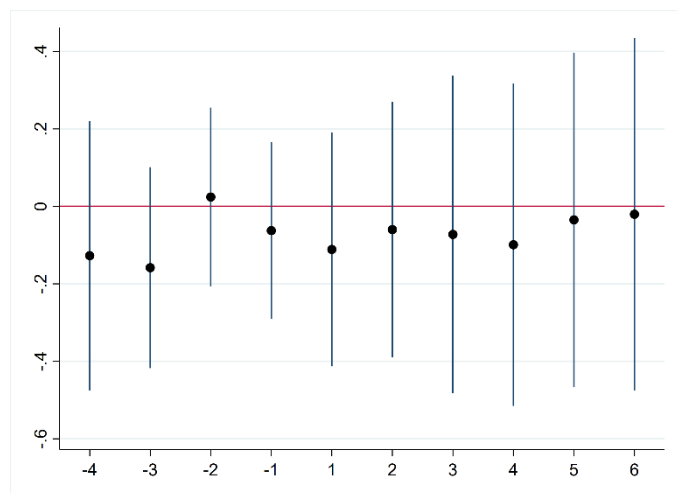
Appendix Figure 9- DD Estimates of the Hybrid/In-Person Teaching on Log Total Covid19 Hospitalizations (January to October 2020) using Burbio by Baseline Hospitalizations and HHS data



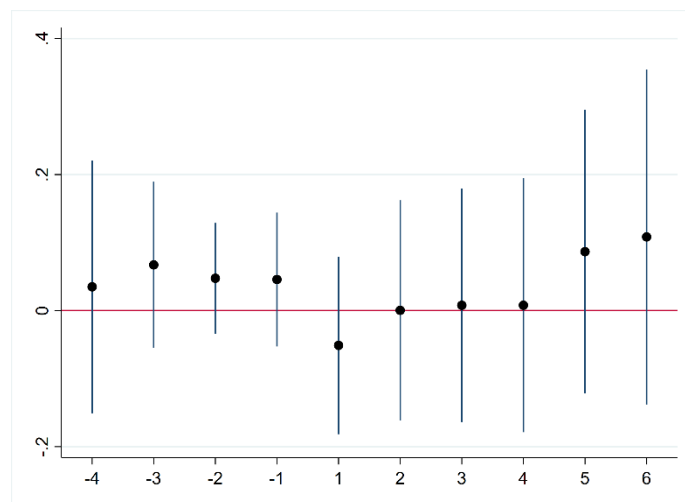
<50th percentile



51st – 75th percentile

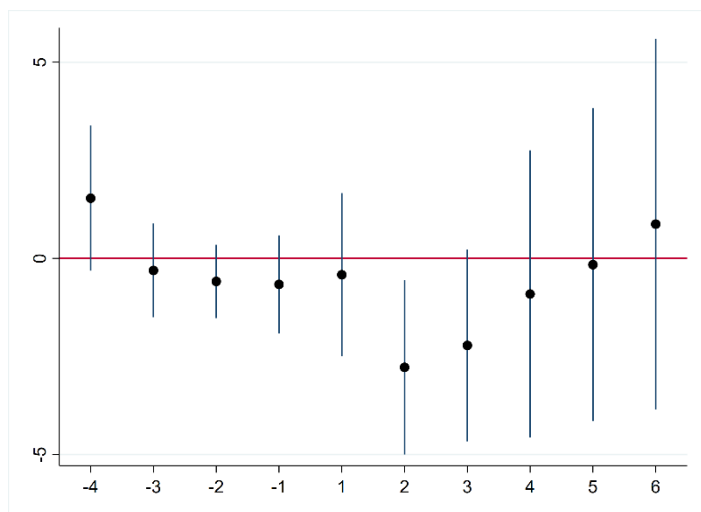


76th -90th percentile

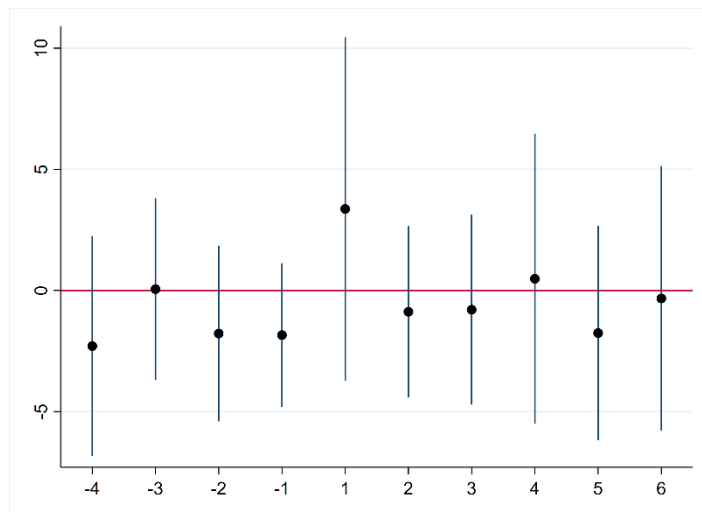


>90th percentile

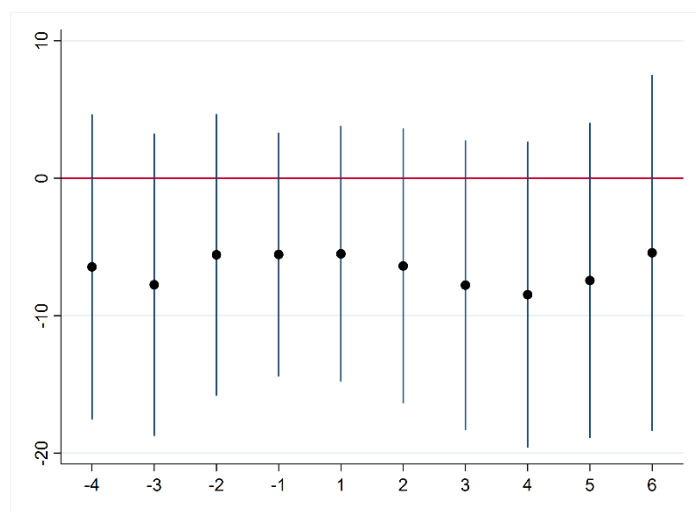
Appendix Figure 10- DD Estimates of the Hybrid/In-Person Teaching on Per 100 K Covid19 Hospitalizations (January to October 2020) using Burbio by Baseline Hospitalizations and HHS data



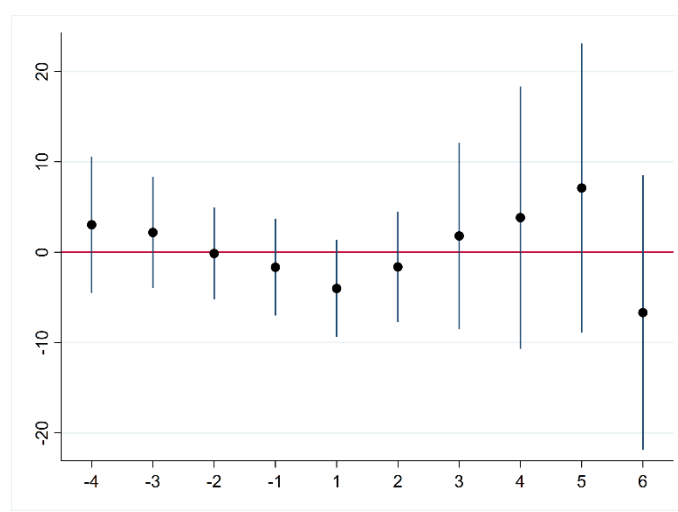
<50th percentile



51st – 75th percentile

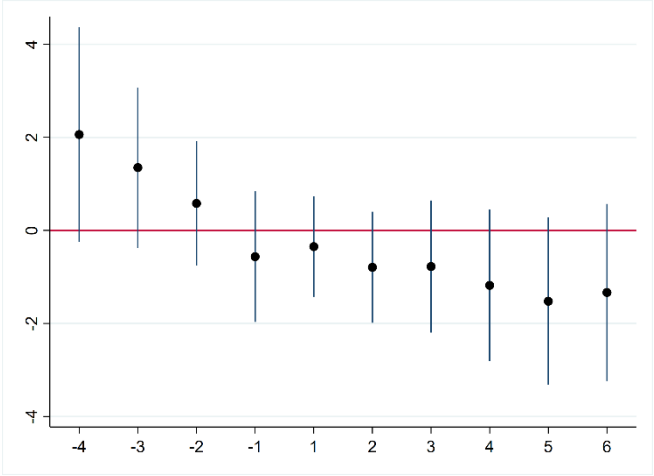


76th - 90th percentile

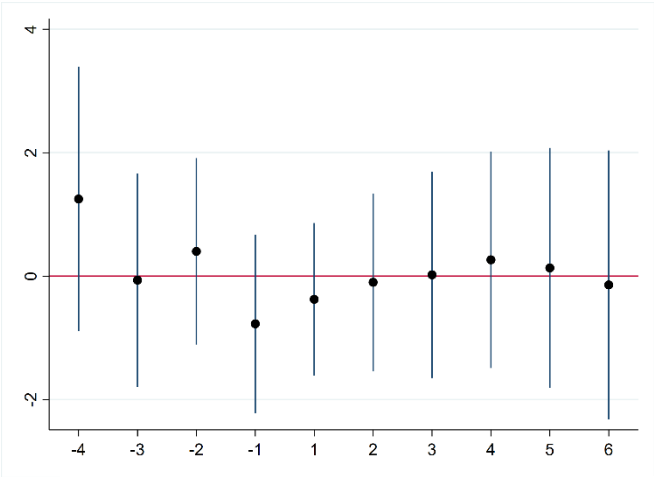


>90th percentile

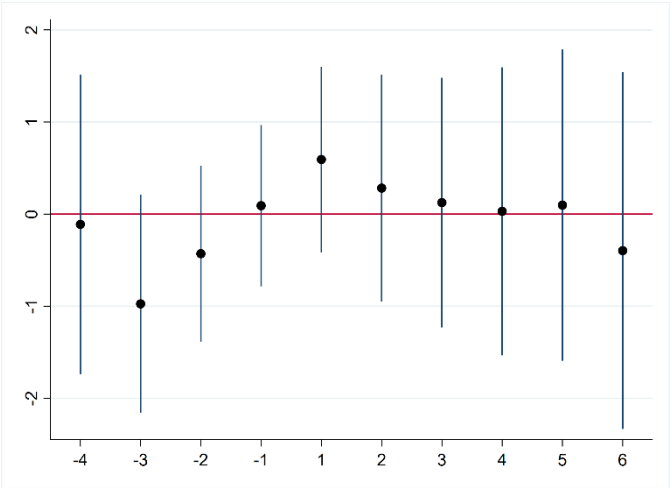
Appendix Figure 11- IV-Event Study Coefficients for the effect of Share hybrid/in-person on Log Total Covid19 Hospitalizations using MCH and HHS data



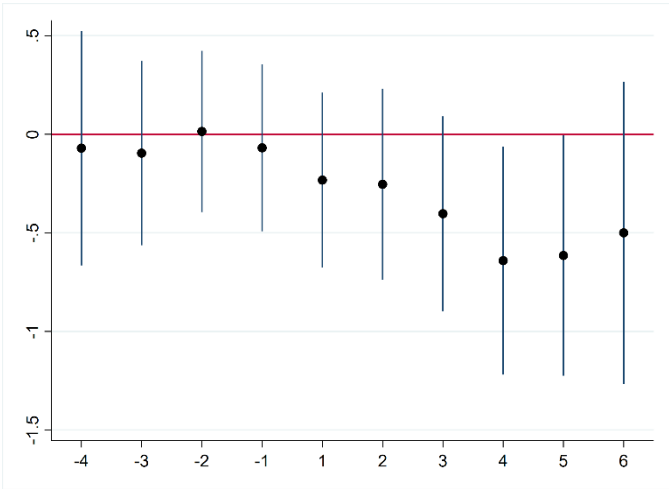
<50th percentile



51st – 75th percentile

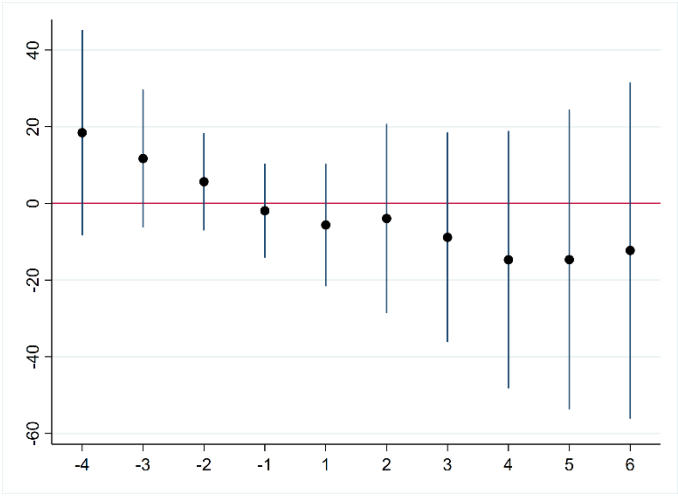


76th -90th

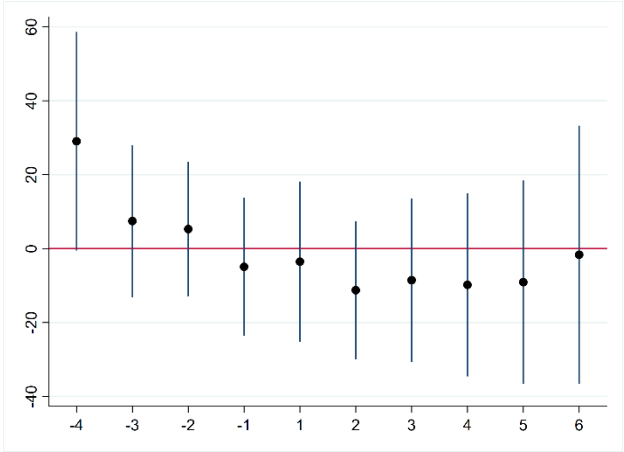


>90th percentile

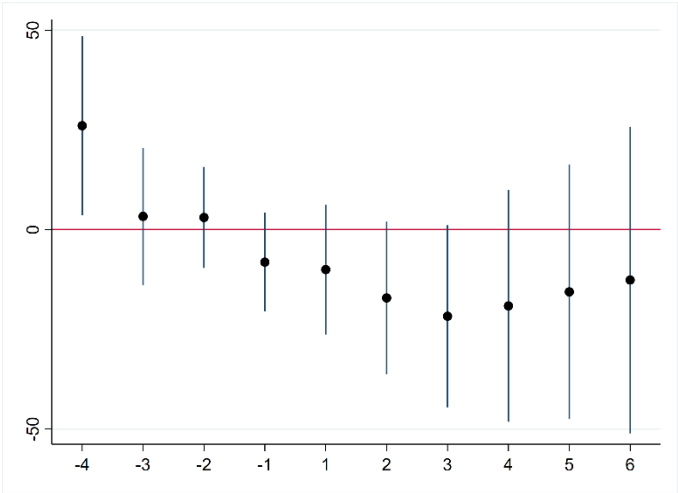
Appendix Figure 12- IV-Event Study Coefficients for the effect of Share hybrid/in-person on Per 100K Covid19 Hospitalizations using MCH and HHS data



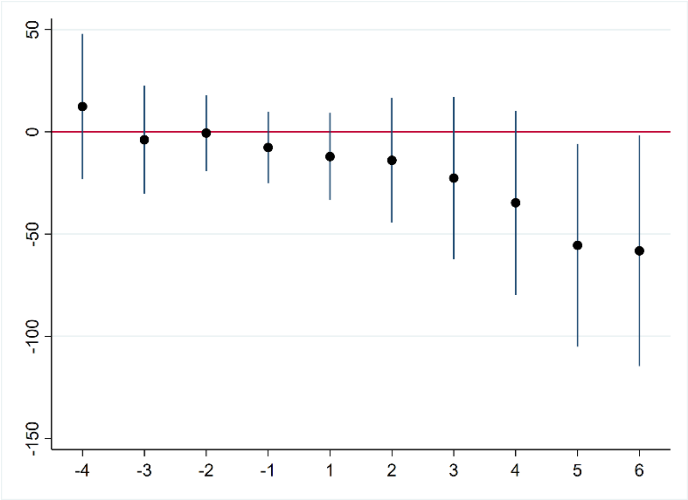
<50th percentile



51st – 75th percentile

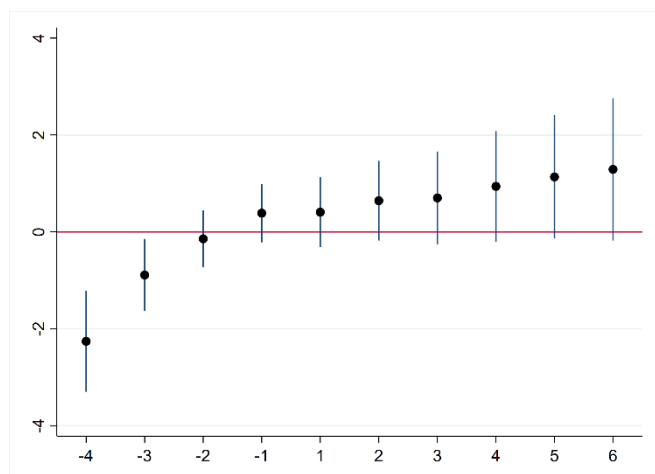


76th -90th percentile

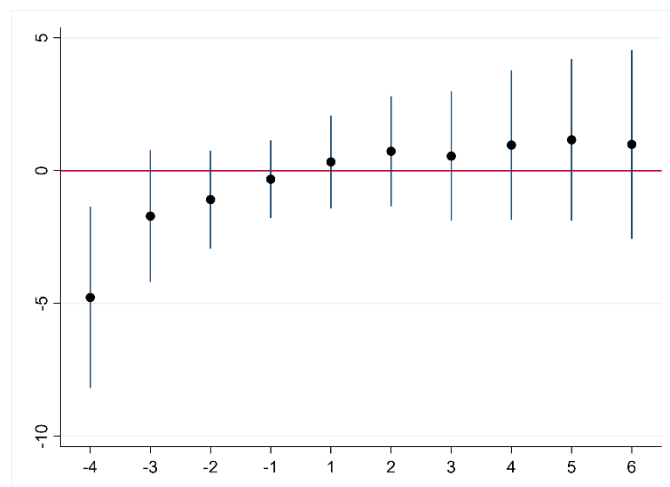


>90th percentile

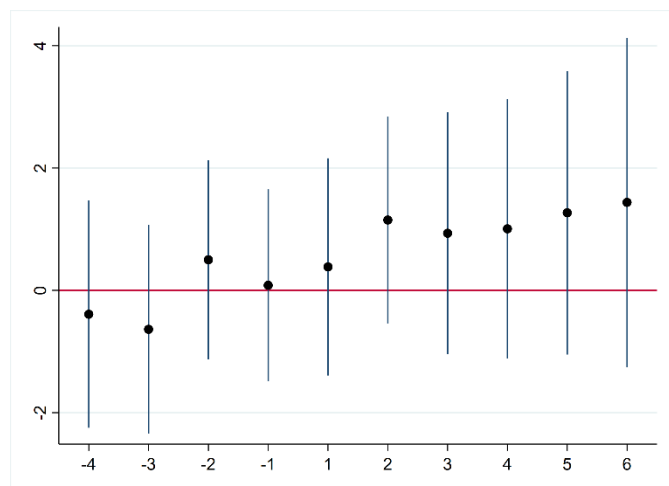
Appendix Figure 13- IV-Event Study Coefficients for the effect of Share hybrid/in-person on Log Total Covid19 Hospitalizations using Burbio and HHS data



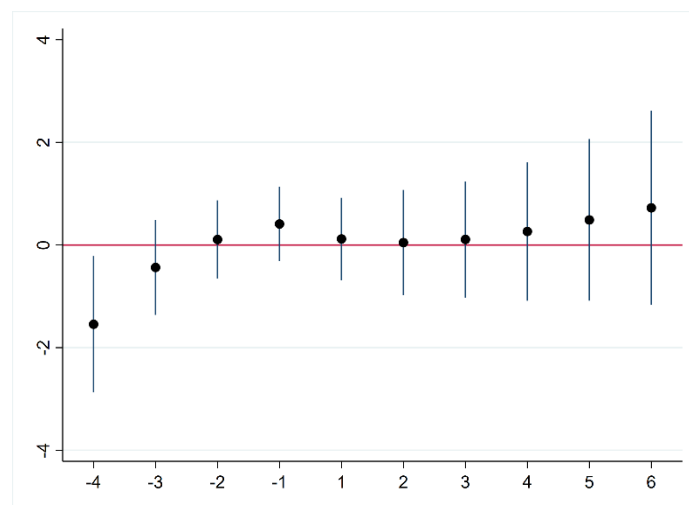
<50th percentile



51st – 75th percentile

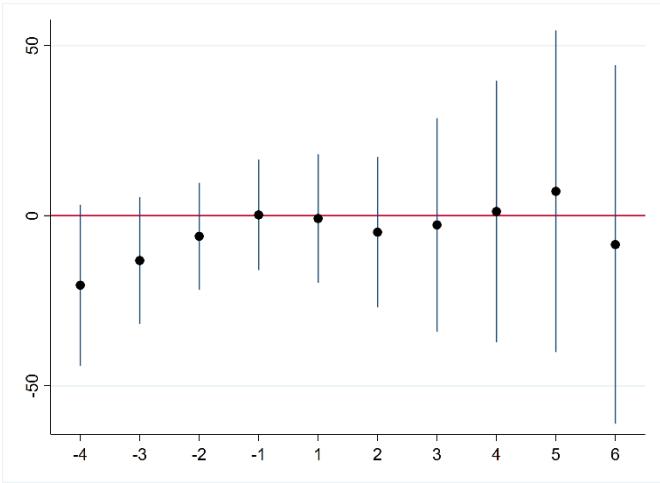


76th- 90th percentile

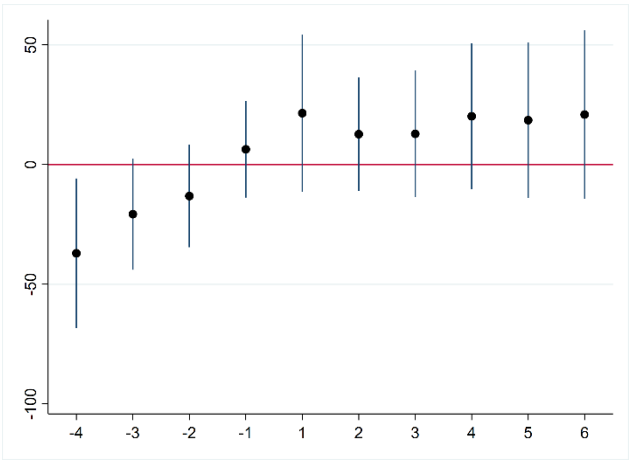


>90th percentile

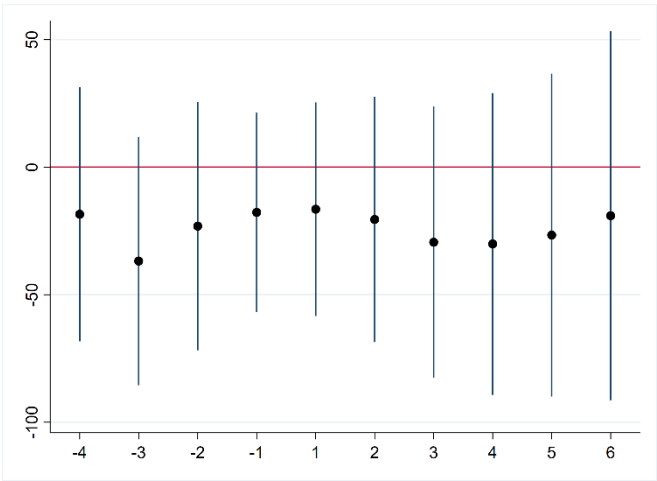
Appendix Figure 14- IV-Event Study Coefficients for the effect of Share hybrid/in-person on Per 100K Covid19 Hospitalizations using Burbio and HHS data



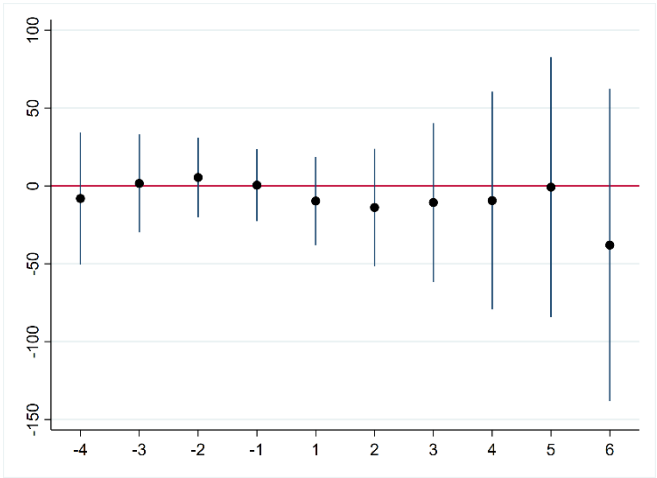
<50th percentile



51st - 75th percentile



76th - 90th percentile



>90th percentile