The COVID-19 Pandemic Disrupted Both School Bullying and Cyberbullying

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November 29, 2021

Abstract

One-fifth of U.S. high school students report being bullied each year. We use internet search data for real-time tracking of bullying patterns as COVID-19 disrupted in-person schooling. We first show that, pre-pandemic, internet searches contain useful information about actual bullying behavior. We then show that searches for school bullying and cyberbullying dropped 30-35 percent as schools shifted to remote learning in spring 2020. The gradual return to in-person instruction starting in fall 2020 partially returns bullying searches to pre-pandemic levels. This rare positive effect may partly explain recent mixed evidence on the pandemic's impact on students' mental health and well-being.

1 Introduction

The COVID-19 pandemic drastically disrupted students' educational experiences. As nearly every primary and secondary school in the United States shifted from in-person to remote instruction in spring 2020, students spent substantially more time online (Koeze and Popper, 2020; De et al., 2020). Even as some schools began re-opening for in-person instruction in fall 2020, most students remained at home, interacting with their teachers and peers only virtually (Diliberti and Kaufman, 2020). To date, research on the educational impacts of this shift have largely focused on the harmful effects on student achievement (Bailey et al., 2021; Chetty et al., 2020; Engzell et al., 2021; Kuhfeld et al., 2020) and the economic implications of pandemic-induced learning disruptions (Azevedo et al., 2020; Hanushek and Woessmann, 2020). In this paper, we focus on a new aspect of students' educational experiences that the pandemic disrupted, arguably in a positive way: school bullying.

School bullying is widespread and has substantial social costs. Youth involved in bullying, as both victims and aggressors, are more likely to experience depression (Wang et al., 2011), anxiety (Kowalski and Limber, 2013), and suicidal thoughts and behaviors (Holt et al., 2015) than their uninvolved peers. Cyberbullying has an even stronger association with suicidal ideation than in-person peer victimization (Van Geel et al., 2014). These negative effects of bullying persist even after the abuse has stopped and are linked to a wide range of physical, mental, and economic challenges in adulthood (Takizawa et al., 2014; Wolke et al., 2013; Wolke and Lereya, 2015). Despite recent policy and legislative efforts to end bullying and its harmful effects (Rees et al., 2020; Nikolaou, 2017), it remains a common occurrence in schools and online. Among U.S. high school students in 2019, 20 percent reported being bullied in person at school and 16 percent reported being cyberbullied at some point in the prior year (Basile et al., 2020).

The COVID-19 pandemic radically changed the context for bullying dynamics. As schools were forced to close and shift to remote learning across the U.S. in March 2020, there was a sudden decrease in in-person interaction and dramatic surge in the use of digital technology (Koeze and Popper, 2020; De et al., 2020). With this shift came public concern about the consequences of children's increased reliance on technology, including the potential for more exposure to cyberbullying (Sparks, 2020). Indeed, research prior to COVID-19 indicated that higher frequency of internet use was associated with increased youth reports of cyberbullying and cybervictimization (Kowalski et al., 2014, 2019). As such, media outlets expressed expectations that while in-person bullying might decline, cyberbullying would likely increase.[1]

[1] Examples of this include not only the general concern that additional time spent online would lead to increases in cyberbullying (Darmanjian, 2020; Farge, 2020; Sparks, 2020), but also a specific concern that online bullying regarding the pandemic would disproportionately target Asian-American youth (Wang, 2020).

Few studies have, however, examined how the reduction of in-person interaction and increased use of technology during the pandemic have impacted bullying and cyberbullying. Using Twitter data from a six month window between January and June 2020, Das et al. (2020) found increases in some bullying-related keywords (Twitter bullying) that are consistent with the onset of the pandemic, but not with others (online bullying). Using data from two separate samples of Indian 15-25 year-olds, one collected before and the other after pandemic-related lockdown, Jain et al. (2020) found that online behaviors associated with increased risk for cyberbullying increased during the pandemic. A similar survey approach among Grade 4-12 Canadian students found substantially lower rates of self-reported bullying victimization among students during the pandemic compared to before the pandemic, with cyberbullying showing clear but smaller declines than in-person bullying (Vaillancourt et al., 2021). Nearly half of German parents surveyed early in the pandemic reported that their children were less likely to experience bullying once schools had closed (Werner and Woessmann, 2021).

Given the small number and limitations of existing research, this study seeks to fill this gap by assessing in real time and with a measure of behavior generated by a wide cross-section of Americans whether bullying involvement has varied over the course of the pandemic. Using a long panel of publicly available Google Trends online search data, we start by showing two pieces of evidence that, in the pre-pandemic period, online search data is predictive of actual bullying behavior. First, pre-pandemic online search intensity for both types of bullying closely follows the school calendar, with searches peaking during the school year and dropping during summers and other school breaks. Second, pre-pandemic state-level variation in searches for bullying is strongly correlated with state-level variation in self-reported bullying rates. These results add to a growing literature using online search data to make real-time predictions of social and economic outcomes, such as disease outbreaks (Carneiro and Mylonakis, 2009), voting (Stephens-Davidowitz, 2014), fertility decisions (Kearney and Levine, 2015) and unemployment claims (Goldsmith-Pinkham and Sojourner, 2020).

Our main contribution uses an event study analysis to estimate changes in school bullying and cyberbullying during the pandemic. Given that schools in the United States shut down for substantial periods starting in March 2020 and that youth were around peers less frequently, it would be reasonable to expect in-person rates of bullying to have declined. In contrast, as many students increased their online presence considerably due to remote schooling, past research suggests that cyberbullying would likely increase (Kowalski et al., 2014, 2019). We show the former prediction is correct but the latter is not. In spring 2020, when schools shifted to remote learning due to the pandemic, search for school bullying and cyberbullying both dropped about 30-35 percent. That drop is sustained through the subsequent 2020-21 school year, particularly in areas where more schools remained fully remote. We show that the return to in-person instruction partially returns bullying search behavior to pre-pandemic levels.

These findings have two important implications. First, they suggest that this otherwise damaging shock to students and schools may provide insight into how schools can reduce bullying in a post-pandemic world. For example, in-person interactions at school appear to be important drivers not only of in-person school bullying but also of cyberbullying. Second, these results highlight one likely mechanism underlying COVID-19's mixed impacts on mental health more broadly. Brodeur et al. (2021), for example, find that COVID-19 has increased loneliness but decreased stress and suicidal ideation. Despite the substantial challenges of the pandemic, our results highlight one unlikely benefit of reduced in-person interaction and provide evidence of one mechanism to help explain the emerging evidence of COVID-19's mixed effects on children's mental health.

2 Data

2.1 Google Trends

Our measures of bullying search intensity come from Google Trends, which makes publicly available monthly internet search behavior both nationally and by state. The publicly available measure of search behavior for a given term or topic is "search intensity", which calculates the fraction of a given area's Google searches devoted to that term or topic. Raw search volume and raw search intensity are not available. Instead, Google Trends normalizes measures of search intensity to allow for comparison of relative intensity over time and across states. Each monthly measure of search intensity for a given term or topic is scaled relative to the highest search intensity observed over that time and geography. The result is a measure of search intensity reported on a 0 to 100 scale, where 100 represents the highest search intensity observed.

We then calculate relative search intensities to allow for comparison across terms, geography, and time. Given the challenge of interpreting such magnitudes, we often use the logarithm of search intensity so that estimates can be interpreted as percent changes. We implicitly assume increased search intensity for a term or topic corresponds to increased raw search volume, given some evidence that overall Google search volumes did not change substantially during the pandemic.[2]

[2]One private firm, Statista, estimates that monthly US-based Google search volumes were 12.7 billion in April 2020, compared to 11.9 in January 2020, and that such search volumes have held fairly steady between 10 and 13 billion since 2015. See "Number of explicit core search queries powered by search engines in the United States as of April 2020", accessed at `https://www.statista.`

Using this process, we estimated the monthly search intensity from January 2016 through February 2021 for three measures related to bullying. Our first measure is for the topic of "School Bullying" and the second measure is for the topic of "Cyberbullying." The third measure is the combination of these two, which we refer to simply as "Bullying." Topics represent a group of search terms that share the same concept in any language whereas terms include only the specific term. Searching for the topic of "School Bullying" will not only include searches for "School Bullying" but also similar keywords in English and other languages. Though it is impossible to determine the precise list of keywords included in each topic, Google Trends provides the following illustrative example: If one searches the topic "London", the reported search intensity includes results for topics such as "Capital of the UK" and "Londres", the Spanish word for London.

Using internet search data offers several advantages over survey data. First, unlike survey-based efforts to collect information on well-being following COVID-19 (Jaeger et al., 2021), Google Trends data is available over a long panel and at much higher frequency than typical surveys, allowing for the analysis of trends before, during, and after the onset of COVID-19. Second, Google Trends data are not self-reported and are less susceptible to interviewer or social desirability biases (Conti and Sobiesk, 2007). Third, Google Trends data do not have the potential issue of differential response from only a self-selected sub-sample of respondents. Instead, it is representative of the full population of Google search users in the United States.

The data also have limitations. First, publicly available data from Google Trends is limited to aggregate trends in the search intensity. There is no information on the person who performed the search or the specific reason for the search, such as whether they were a victim, perpetrator, witness, or anyone else interested in the topic. Second, Google Trends search data are available only for individuals with internet access and who use Google for internet searches. This method may exclude individuals living in under-resourced communities. The representativeness of the data may also have changed somewhat over time as schools increased technology access to families and students became more adept at searching the internet. Finally, we rely on search terms specifically related to bullying and cyberbullying, which aligns with this paper's focus but may exclude bullying-related searches that reference other terms, such as harassment or victimization.

`com/statistics/265796/us-search-engines-ranked-by-number-of-core-searches` through the Wayback Machine's July 17, 2020 archive.

2.2 Youth Risk Behavior Survey

Another potential concern is whether internet searches serve as useful proxies for actual bullying. While online search has been used to predict a wide variety of economic and social outcomes, it has yet to be used to assess bullying.[3] Therefore, to evaluate the predictive validity of online search intensity for actual bullying behavior in the pre-pandemic period, we collect data from the Youth Risk Behavior Survey (YRBS) between 2013 and 2019. Administered by the Centers for Disease Control and Prevention, the YRBS surveys a large and both nationally and state-level representative sample of 9th through 12th grade students every two years. Questions focus on four main areas: Health behaviors and experiences related to sexual behavior, high-risk substance use, violence victimization, and mental health and suicide. The survey is self-administered anonymously by using a computer-scannable questionnaire booklet and takes approximately 45 minutes to complete.

We use responses from the four most recent biennial surveys prior the pandemic (2013, 2015, 2017, 2019) and focus on two bullying-related questions: "During the past 12 months, have you ever been bullied on school property?" and "During the past 12 months, have you ever been electronically bullied?" We aggregate individual responses to these questions using state sampling weights to generate measures that are representative of high school population in each state in each year. Therefore, the first question measures the fraction of each state's high school population who indicated that they were bullied in school and the second question measures the fraction of each state's high school population that was bullied online. We use answers to these questions to construct state-level fractions of students who report being bullied, either in school or virtually.

2.3 Burbio

Finally, we combine the Google Trends data with national data on school instructional modes in the 2020-2021 school year to examine the link between in-person schooling and bullying. The instructional mode data comes from Burbio, a private company that began systematically collecting information about school districts' learning modes during the pandemic. Every three days, Burbio (re)collects learning modes of over 1,200 school districts representing over 35,000 schools in 50 states.[4] Burbio checks school district websites,

[3]Prior work shows the utility of search data in predicting economic and social outcomes such as parents' preferences for schools (Schneider and Buckley, 2002), disease spread (Polgreen et al., 2008; Carneiro and Mylonakis, 2009), consumer behavior (Choi and Varian, 2012), voting (Stephens-Davidowitz, 2014), and fertility decisions (Kearney and Levine, 2015). Most recently, Goldsmith-Pinkham and Sojourner (2020) use the volume of online search for unemployment benefits to predict unemployment claims during the pandemic.

[4]For details about how the sample of districts is constructed, see `https://about.burbio.com/methodology/`.

Facebook pages, local news stories and other publicly available information to determine which learning mode is currently in place. School districts are checked every 72 hours for updates and Burbio generates an updated database of school instructional modes once a week.

School district learning modes are categorized as either traditional, hybrid or virtual. "Traditional" refers to students attending in-person every day. "Hybrid" refers to students being divided into cohorts and attending 2-3 days in-person and 2-3 days virtually. "Virtual" refers to students learning entirely remotely. Burbio assigns to each district a learning mode based on the most in-person option available to the general student population. A district offering both traditional and virtual options would be categorized as "traditional". If learning modes vary by grade, districts are assigned a value proportional to the fraction of grades using that learning mode. For example, if grades K-5 are traditional and grades 6-12 are virtual, the district would be labeled as 46 percent traditional and 54 percent virtual.

Burbio then aggregates those district fractions of traditional, hybrid, and virtual modalities to the county level by weighting each district by its student enrollment. We then further aggregate those county numbers up to the state level, again weighting by county-level student enrollment. The final result is a monthly state-level dataset with the fraction of schools offering each of these three learning modes. We compared Burbio's data to school learning mode data provided by 17 state Departments of Education to the COVID-19 School Data Hub spearheaded by Emily Oster. The correlation between the two data sets' state-level fractions of students with an in-person learning option was 0.95, suggesting Burbio is collecting information matching what school districts themselves report to state agencies and across a more complete set of states than available elsewhere.

3 Empirical Strategy

We estimate pandemic-induced changes in search intensity for bullying using two complementary analytic strategies. The first, a month-by-month event study specification, estimates the effect of COVID-19 on search intensity in each month beginning in March 2020. The second approach, a before-after specification, is a simplified version of the month-by-month event study and provides an estimate of the average effect of COVID-19 on bullying-related internet searches. These approaches follow the methodology established in prior work using Google Trends to analyze the effects of COVID-19 on access to learning resources (Bacher-Hicks et al., 2021).

An important first step for both approaches is to remove seasonal patterns and time trends in searches for bullying. As we highlight in the next section, searches for bullying typically peak in the beginning of the school year and drop substantially during the summer months. Pre-pandemic, we also observe a slight downward trend in these search intensities. To address these, we generate a measure of search intensity that removes calendar month fixed effects and linear year trends based on pre-pandemic patterns in bullying-related internet searches. We fit a regression of the natural logarithm of search intensity in each state s in time period t using data from January 2016 through December 2019 as follows:

$$LogSearch_{st} = \beta Year_t + \mu_{m(t)} + \varepsilon_{st}, \tag{1}$$

where $\mu_{m(t)}$ indicates a set of 12 fixed effects for the month of year and β captures a linear time trend in the years before COVID-19. Using the estimated coefficients from Equation 1, we then predict the logarithm of search intensity for every state-month in the full panel of data. We compute a measure of excess search intensity, called $LogSearch^*_{st}$, as the difference between the actual and predicted logarithm of search intensity in a given state-month. This excess measure is our main outcome of interest and captures the extent to which search intensity deviates from predicted search intensity based on pre-pandemic time trends and month effects.

Our event study model regresses excess search intensity for state s in time t on a vector of month indicators, using data from January 2016 through February 2021:

$$LogSearch^*_{st} = \sum_{t=-12}^{-1} \beta_t\, Before_t + \sum_{t=1}^{12} \beta_t\, After_t + \alpha PriorYears_t + \Gamma_s + \varepsilon_{st}. \tag{2}$$

Here, t indicates the event month, which identifies months relative to February 2020, the last month before states began closing schools. $Before$ and $After$ are indicators for month t falling up to or after February 2020, and we include indicators for each of the 12 months prior to February 2020 (February 2019 through January 2020) and each of the 12 months after February 2020 (March 2020 through February 2021). Exclusion of the February 2020 indicator, and inclusion of state fixed effects Γ_s and a $PriorYears_t$ indicator for months between January 2016 and January 2019, means the coefficients β_t can be interpreted as month t's deviation from calendar-predicted search intensity relative to February 2020 in state s.

The nationwide before-after specification relies on the same data described in Equation 2, but replaces the vector of monthly pre- and post-pandemic indicators with a single post-pandemic indicator as follows:

$$LogSearch^*_{st} = \beta PostCOVID_t + \Gamma_s + \varepsilon_{st}. \tag{3}$$

By including state fixed effects, β can be interpreted as the post-pandemic change in excess search intensity in state s. In the first set of before-after specifications, we simply include one indicator for the entire sample period following COVID-19 (March 2020 through February 2021).[5] Therefore, β from Equation 3 is the average of the March 2020 through February 2021 event study coefficients β_1 through β_{12} from Equation 2.

We then modify the specification described in Equation 3 to separately examine three distinct time periods: the end of the spring 2020 school year (March 2020 through May 2020), the summer of 2020 (June 2020 through August 2020), and the first half of the 2020-2021 school year (Sept 2020 through February 2021). We do so by replacing $PostCOVID_t$ in Equation 3 with three separate indicators corresponding to each time period:

$$LogSearch^*_{st} = \beta_1 PostSpring_t + \beta_2 PostSummer_t + \beta_3 PostFall_t + \Gamma_s + \varepsilon_{st}. \tag{4}$$

Finally, to study how search intensity changed differentially by states' school instructional modes, we modify Equation 4 by interacting the $PostFall_t$ indicator with a measure of the percentage of schools that offered in-person instruction in state s during the first half of the 2020-2021 school year ($InPerson_s$):

$$LogSearch^*_{st} = \beta_1 PostSpring_t + \beta_2 PostSummer_t + \beta_3 PostFall_t + \beta_4 (PostFall_t) * (InPerson_s) + \Gamma_s + \varepsilon_{st}. \tag{5}$$

All regressions use standard errors clustered by state and month and are weighted by state population to be nationally representative at the individual level.

4 Results

We first present two forms of evidence consistent with online search for bullying proxying for actual bullying behavior in the pre-pandemic period. First, online search intensity for bullying closely tracks the school year calendar. As shown in the raw data in Figure 1, pre-pandemic search intensity for both school bullying and cyberbullying decreases dramatically during the summer and ramps up again in months when school is in session. Search for all forms of bullying tends to be lowest in July, increases as schools reopen in August and September, and remains relatively steady until June, when the school year ends. Slight dips in November, December, and January correspond to months with more school vacations. Figure A.1 makes these seasonal patterns even clearer by plotting the 12 month-of-year fixed effects ($\mu_{m(t)}$) from Equation 1. This pattern over the calendar year is consistent with households searching for bullying-related resources

[5] See Table A.1 for a list of state-by-state school closure dates, which all begin in March 2020.

much more when school is in session and bullying rates are presumably higher.

Second, pre-pandemic self-reported rates of bullying track online search intensity for bullying-related terms, both nationally and at the state level. Nationally, 14.8 percent of students report being cyberbullied and 19.2 percent report being bullied in school, as measured in the YRBS over the three years prior to the pandemic's onset. This suggests that school bullying is roughly 30 percent more common than cyberbullying. Remarkably, over that same pre-pandemic period, the search intensity for school bullying is also roughly 30 percent higher than the search intensity for cyberbullying. This consistency across search intensity and survey responses is reassuring and suggests that the relative magnitude of search for these two topics reflects the relative frequency of victimization.

Moreover, state-level self-reported rates of bullying are strongly correlated with state-level online search intensity for bullying-related terms. Figure 2 plots the state-level relationship between the fraction of students reporting being bullied or cyberbullied in the YRBS against the average search intensity for bullying, both measured from 2013 through 2019. The state population-weighted correlation coefficient between these two variables is 0.45, which is statistically significant at the 1 percent level. States where students are more likely to report being bullied are states where a higher fraction of Google searches are devoted to bullying. This strong correlation between state-level reported bullying rates and search intensity holds not only for overall bullying but also for school bullying and cyberbullying separately.[6] We interpret this as further evidence that, pre-pandemic, online search intensity for bullying is closely related to actual bullying behaviors.

The claim that subsequent changes in bullying search correspond to actual changes in bullying behavior assumes that the pre-pandemic connection between search and actual behavior persists in the post-pandemic period. While we have no evidence to the contrary, one can envision scenarios in which the relationship changed during the pandemic. For example, remote schooling could have made it easier for students to report bullying directly to teachers, reducing the need to search for online resources. Conversely, the pandemic may have made it harder for students to report bullying to teachers with whom they had less contact or felt less comfortable with given online interactions. The stresses of the pandemic could also have changed children's or parents' perceptions of what behaviors were sufficiently important to warrant attention or be labeled as bullying. We have no evidence of such a shift in the relationship between bullying search and behavior, and the calendar and in-person schooling patterns we document below are arguably inconsistent with dramatic changes in this relationship.

[6]See Figure A.2 for the graphical version of this evidence and Table A.2 for the corresponding correlation coefficients.

If the pre-pandemic relationship between online search for bullying and actual bullying continued to hold after the pandemic started, then the pandemic dramatically reduced both school bullying and cyberbullying. We see this first in the raw data in Figure 1, where online search intensity for both sets of bullying-related terms appears to drop dramatically in the months after March 2020 relative to historical trends. Figure 3 makes this even clearer by plotting, in an event study framework, monthly deviations from pre-pandemic trends in bullying search intensity, with February 2020 as the benchmark. In the year leading up to the pandemic, school bullying and cyberbullying search intensity were indistinguishable from their usual monthly levels. Search intensity for both forms of bullying then dropped substantially in spring 2020, rebounded to at or slightly above their usual low levels during the summer, then dropped again in fall 2020.

The magnitude of these drops in bullying search intensity are substantial. Table 1 shows regression estimates of these post-pandemic drops, essentially averaging the monthly coefficients from Figure 3 across various time periods. Panel A shows that, across the entire post-pandemic period of March 2020 through February 2021, search intensity for bullying dropped by an average of 27 percent (-32 log points). This drop combines a 33 percent (-40 log points) drop in school bullying search and a smaller but still substantial 20 percent (-22 log points) drop in cyberbullying search.

Consistent with the event study graphs, panel B of Table 1 shows search for bullying dropped most relative to historical norms during the school year and much less so during the summer. Both school bullying and cyberbullying search were historically low in spring 2020 and then again in the next school year. From March 2020 through May 2020, bullying search decreased by 32 percent (-39 log points), a combination of a school bullying decrease of 35 percent (-44 log points) and a cyberbullying decrease of 30 percent (-35 log points). From September 2020 through February 2021, bullying search decreased by 36 percent (-44 log points), driven by a school bullying decrease of 40 percent (-52 log points) and a cyberbullying decrease of 30 percent (-36 log points). Overall bullying search intensity during the summer is statistically indistinguishable from historical norms, though there is some evidence for an increase in cyberbullying relative to its usually low summer levels.

Given the evidence that bullying drops relative to historical norms only during the school year and not in the summer, we turn to more direct evidence that bullying decreased during the pandemic because of school closures. Figure 4 plots the average, from September 2020 through February 2021, of state-level average bullying search intensity against the proportion of schools offering only virtual instruction or in-person instruction. We present the search intensity for each state as a fraction of the national average search intensity for the same search topics. Panel A shows that states with a higher fraction of schools offering only virtual instruction had substantially lower search intensity for school bullying. Panel B shows that states with a higher proportion of in-person instruction had higher search intensity for school bullying. Panels C and D show that the same patterns also hold for cyberbullying, with in-person instruction positively associated not only with school bullying but also with cyberbullying. Virtual instruction, on the other hand, is associated with lower search intensity for both school bullying and cyberbullying.[7]

To further quantify the relationship between in-person instruction and bullying search, we run regression models estimating how much the 2020-21 school year drop in bullying varies by the extent to which a given state has re-started in-person schooling. Panel C of Table 1 shows the results of those models, which estimate that in areas where schooling remained fully remote bullying dropped by 42 percent (-55 log points). Offering in-person schooling offsets that effect, with the coefficient suggesting that bullying only dropped by 19 percent (34 - 55 log points) in areas where all students were given an in-person option. Interestingly, the coefficients suggest that fully re-starting in-person instruction is associated with cyberbullying nearly completely returning to pre-pandemic levels but with school bullying returning only halfway.

5 Discussion

Using online search data in the U.S., we provide the first nationwide measures of in-person bullying and cyberbullying during the COVID-19 pandemic. Our results suggest that both in-person bullying and cyberbullying decreased dramatically during the school years affected by the pandemic. The decrease in cyberbullying is particularly noteworthy as it stands in contrast to fears that it would increase during the pandemic as youth spend more time online. That both forms of bullying decreased is, however, consistent with prior evidence that cyberbullying rarely occurs independently of in-person bullying (Waasdorp and Bradshaw, 2015) and primarily reflects in-person bullying enacted through a different medium (Modecki et al., 2014; Gini et al., 2018).

We show that school transitions to remote learning are likely a major explanation for this drop in both forms of bullying. Areas where more schools re-started in-person instruction saw a greater return to pre-pandemic levels of bullying search. Our estimates do not, however, suggest that a full return to in-person instruction led to a complete return to pre-pandemic bullying levels during the school year. This may be driven by the fact that, even in school districts providing an in-person option, not all students chose to

[7] Appendix Figure A.3 shows that this relationship, unsurprisingly, holds for the overall measure of bullying.

exercise that option. Those remaining fully or partially remote may have continued to benefit from the apparent protective effects of remote learning on exposure to bullying in its various forms. The finding that cyberbullying rates increased in the summer, relative to their usual low summer rates, further suggests that the overall decline in cyberbullying during the pandemic is linked to decreased in-person schooling. We can not, however, rule out broader curtailment of social contact between children during the pandemic as another potential source of this bullying reduction. Children saw their peers less both in school and out of school for much of this time period.

This reduction in bullying, even in districts offering in-person schooling, may partly explain the mixed results among early studies of the impact of COVID-19 on adolescent mental health. In particular, the pandemic-induced decrease in bullying may have offset otherwise substantial negative impacts on adolescent mental health. Early concerns that the pandemic would substantially harm students' mental health (Golberstein et al., 2020) have been partially but not fully supported by subsequent data suggesting arguably small increases in such measures (Kemper et al., 2021; Leeb et al., 2020). Some surveys even suggest that a non-trivial portion of adolescents describe their mental health as having improved during school closures (Ford et al., 2021). Forced isolation from peers may have been beneficial for those who would be victims, or even perpetrators, of bullying.

The reductions in bullying documented here may also relate to the changed nature of in-person schooling during the pandemic. For example, those who returned to school experienced substantially more structured educational environments than in prior years. Public health measures such as social distancing, mask wearing, and attempts to reduce mixing of students across different classrooms substantially restricted the number of interactions students might otherwise have experienced and increased the amount of adult supervision. Such measures likely reduced the amount of unstructured and unsupervised time students spent with each other in large groups, including during lunch, recess, and movement between classrooms. Such unstructured times and spaces are often where students feel least safe and are most likely to experience bullying (Vaillancourt et al., 2010). The collective experience of the pandemic may have also increased school staff awareness and responsiveness to student social-emotional wellbeing. For example, school staff might have more readily attended to and addressed particular forms of bullying highlighted by public media during the pandemic, such as anti-Asian harassment. Taken together, our results suggest that schools might find constructive lessons to be drawn to keep bullying from returning to the high levels of pre-pandemic times.

Because surveillance of bullying typically occurs in school settings via self-reported surveys such as the

YRBS, there are very few studies on bullying during the pandemic and even fewer using publicly-available nationwide data. In this context, Google Trends data provide a unique opportunity for real time surveillance of bullying, while posing no risk to children and families. Our analyses can be updated in real time to study future changes, can be modified to study additional search terms, and can be replicated in other countries. Further work along these lines will help identify the mechanisms underlying decreases in bullying during the pandemic and inform which aspects of pandemic-era schooling are worth considering as bullying reduction strategies while otherwise returning students and schools to their pre-pandemic routines.

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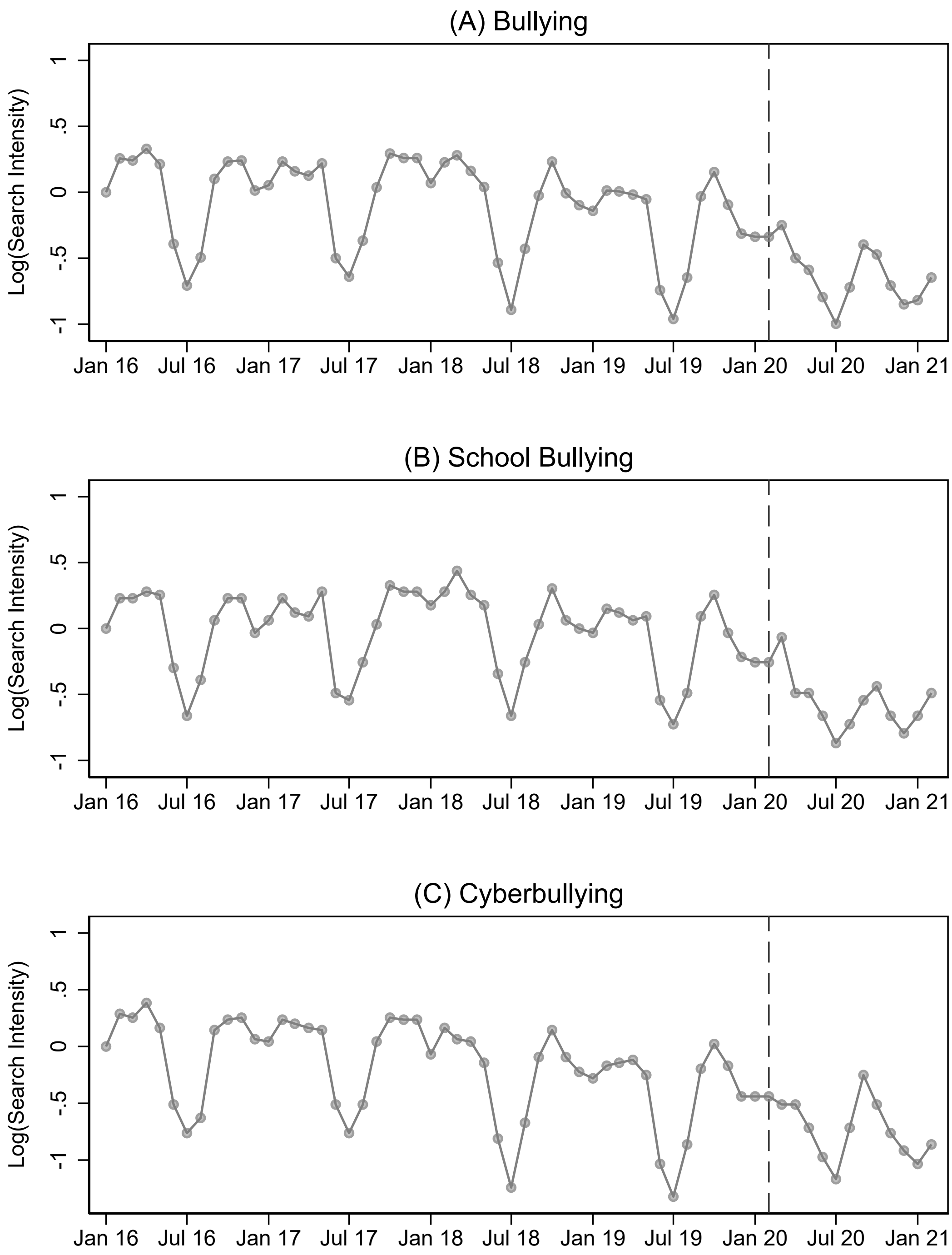
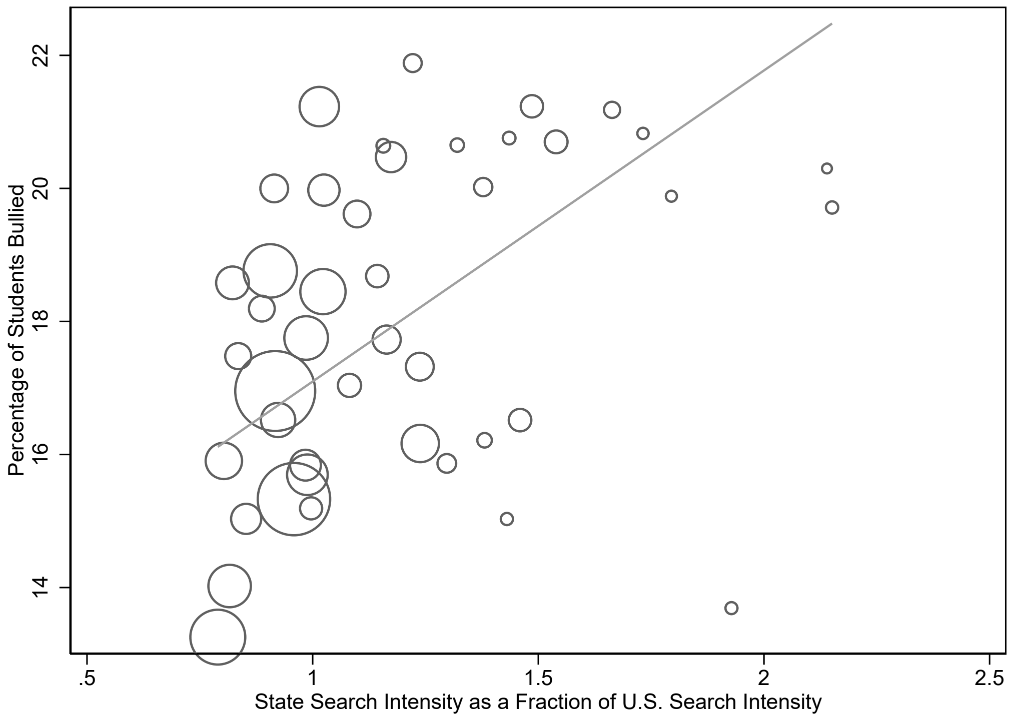
Figure 1: Nationwide Monthly Search Intensity for Bullying (Pre- and Post-COVID)



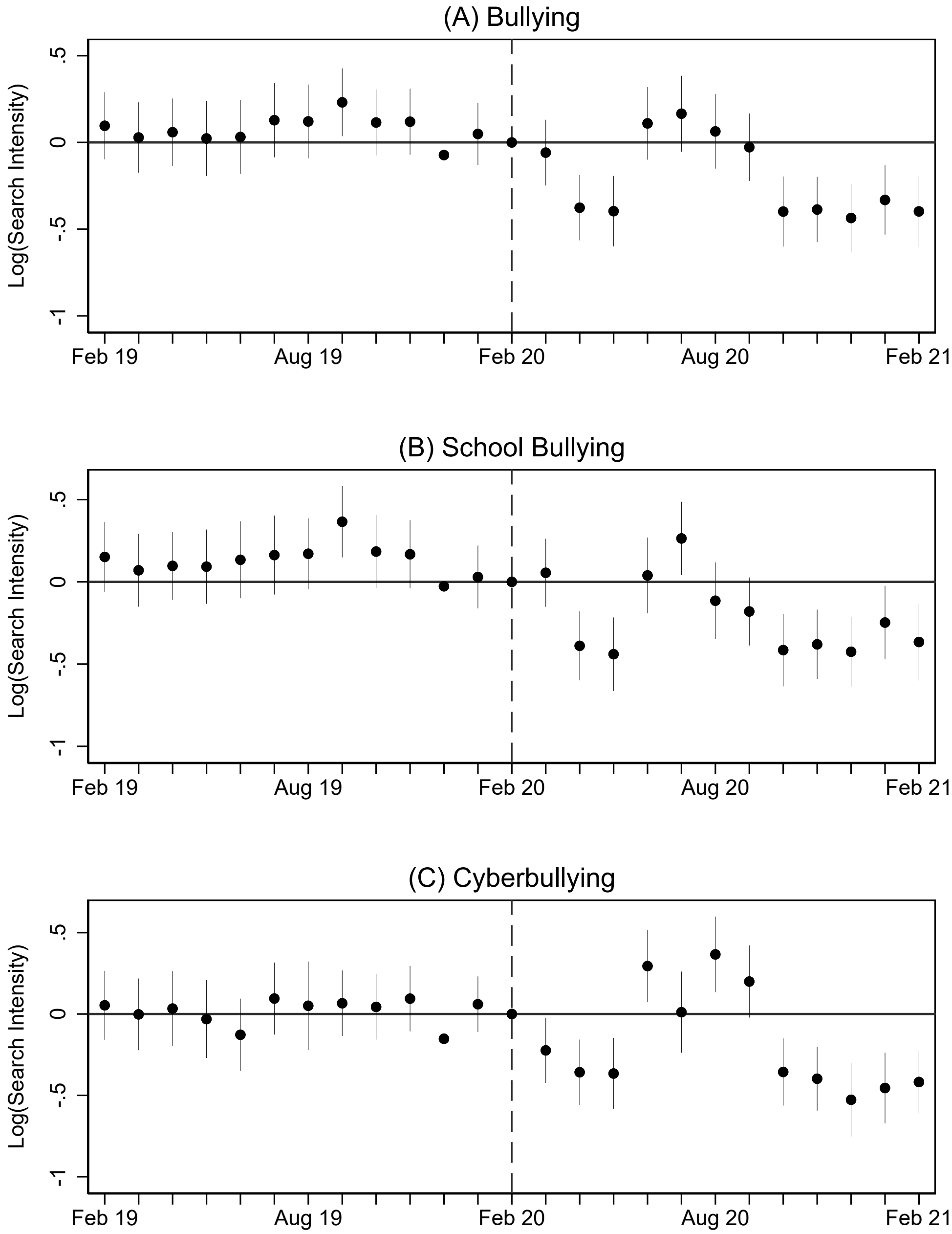
Notes: The figure above shows the logarithm of nationwide search intensity relative to intensity in January of 2016. Panel A shows search intensity for a composite search measure that includes "School Bullying" and "Cyberbullying." Panel B shows search intensity for "School Bullying" and panel C shows search intensity for "Cyberbullying". The vertical dashed line is drawn at February 2020, which marks the last full month before public schools in the U.S. began shifting to remote learning in mid-March.

Figure 2: Relationship Between Survey Results and Internet Searches for Bullying (Pre-COVID)



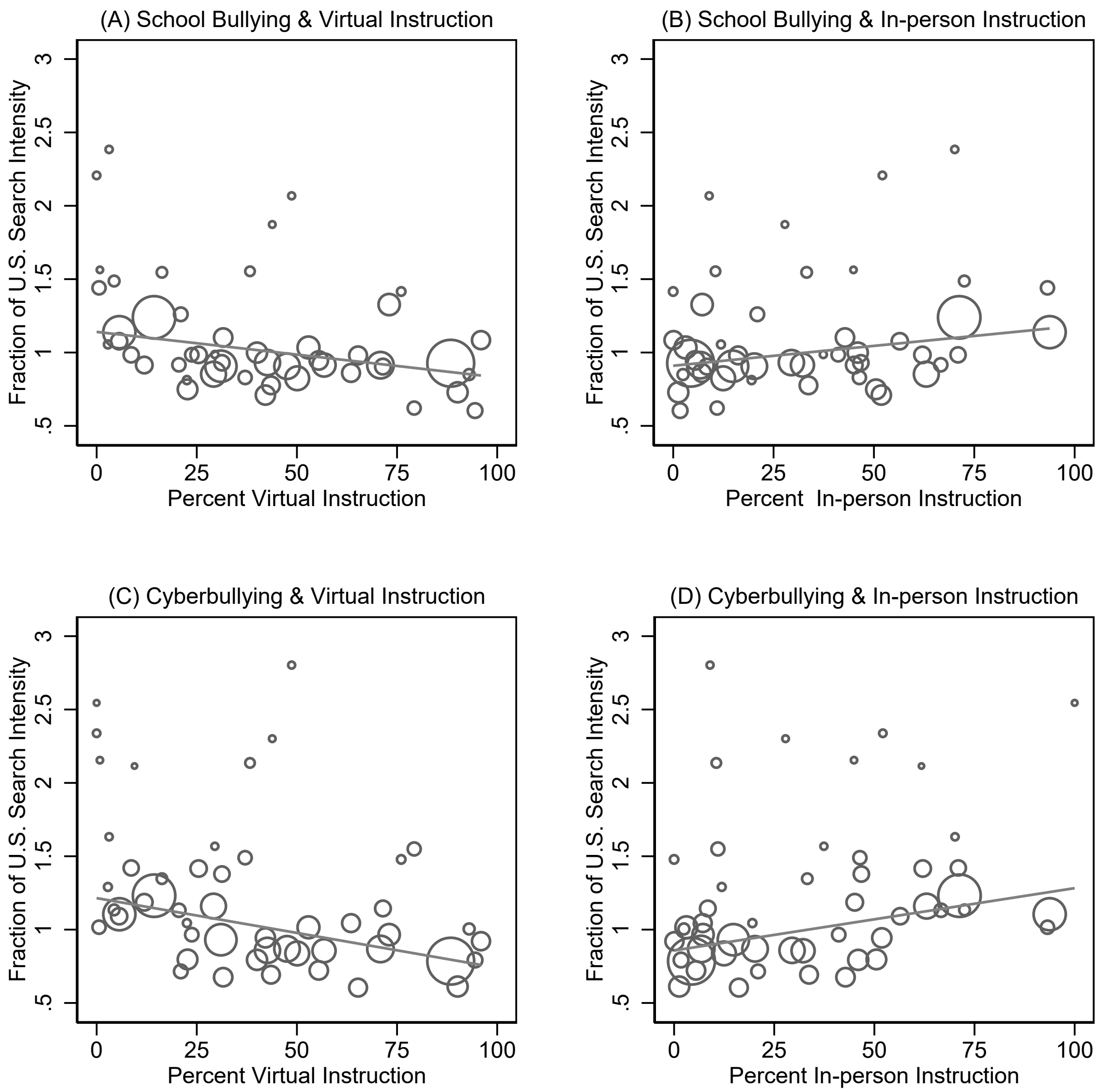
Notes: The figure above presents the relationship between the percentage of students who were bullied and search intensity in Google Trends for a composite search measure that includes "School Bullying" and "Cyberbullying". Each circle represents a state, which is weighted by its 2019 population. The search intensity for each state is presented as a fraction of the national average search intensity for the same composite search measure. Data include the 2013 through 2019 responses from the Youth Risk Behavior Survey and Google search intensity from the same time period. The population-weighted correlation coefficient is 0.45.

Figure 3: Nationwide Event Study of Search Intensity for Bullying



Notes: The figure above shows event study coefficients based on Equation 2, which estimates each month's deviation in log search intensity from predicted log search intensity. As described in Equations 1 and 2, the predictions are based on pre-Covid month effects and an extrapolated pre-Covid linear time trend. The sample includes data from January 2016 through February 2021 and we present event study coefficients for each of the 12 months prior to February 2020 and each of the 12 months after February 2020, which marks the last full month before public schools in the U.S. began shifting to remote learning in mid-March. The plotted coefficients can be interpreted as the deviation from calendar-predicted search intensity relative to February 2020. Also shown are 95 percent confidence intervals corresponding to heteroskedasticity robust standard errors clustered by state and month. Panel A shows search intensity for a composite search term that includes "School Bullying" and "Cyberbullying". Panel B shows search intensity for "School Bullying" and panel C shows search intensity for "Cyberbullying".

Figure 4: Relationship Between Searches for Bullying and School Instructional Modes (2020-21)



Notes: The figure above presents the relationship between state-level school instructional modes and search intensity. Each circle represents a state, which is weighted by its 2019 population. Google search intensity and data from Burbio on school instructional modes span September 2020 to February 2021, during which time schools across the U.S. began re-opening for in-person instruction. The search intensity for each state is presented as a fraction of the national average search intensity for the same search topic. Panel A presents the relationship between search intensity for school bullying and the percentage of schools within each state offering virtual instruction. Panel B presents the relationship between search intensity for school bullying and the percentage of schools within each state offering in-person instruction. Panels C and D present the analogous relationships using cyberbullying instead of school bullying.

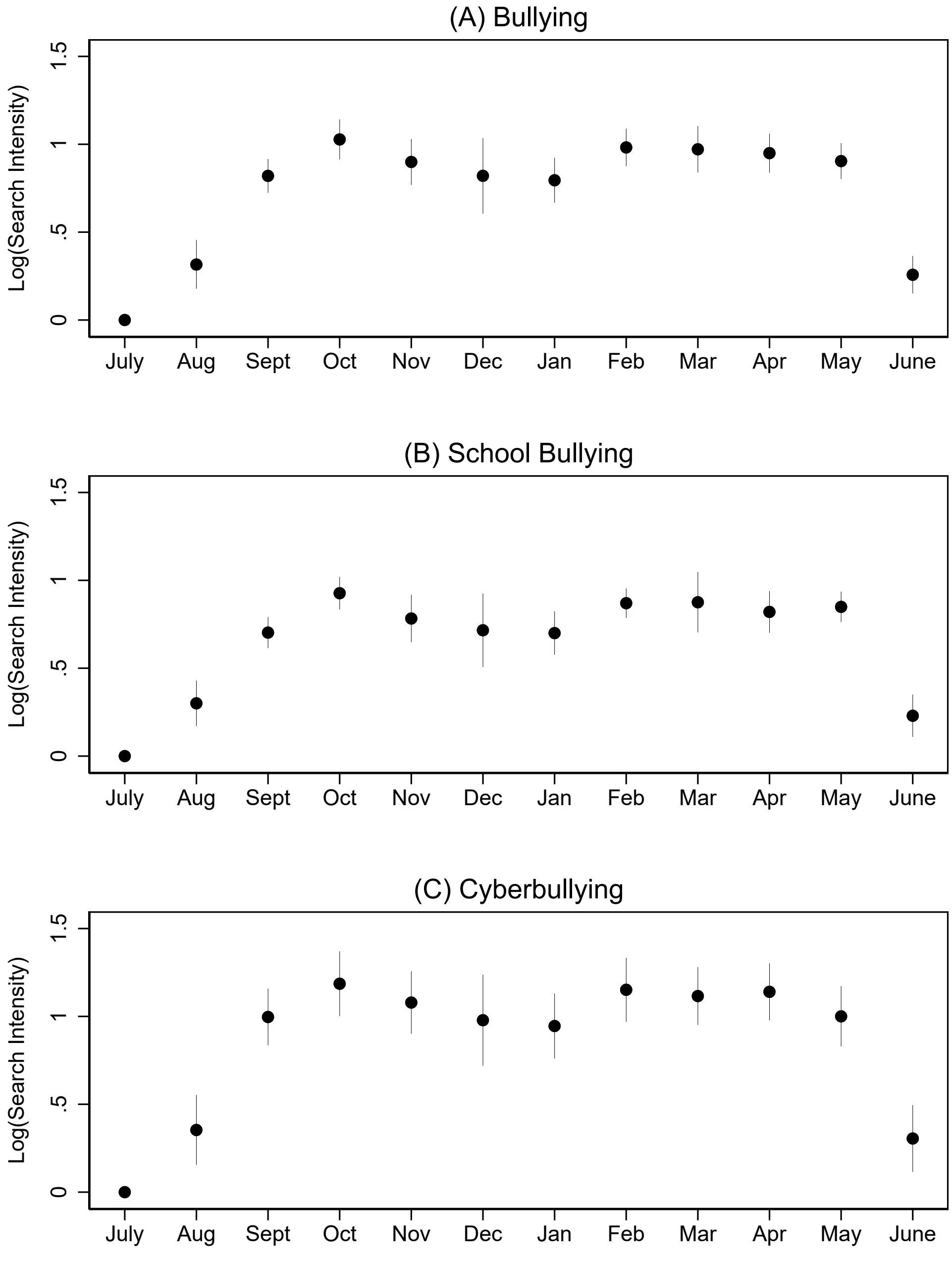
Table 1: Changes in Search Intensity for Bullying Following Covid-Induced School Closures

	Bullying (1)	School Bullying (2)	Cyberbullying (3)
(A) Overall Pre-Post Changes			
Post Covid	-0.318***	-0.397***	-0.223**
	(0.071)	(0.068)	(0.092)
(B) Changes by Specific Time Periods			
Post Covid 19–20 SY (3/20–5/20)	-0.388***	-0.438***	-0.353***
	(0.091)	(0.131)	(0.038)
Post Covid Summer 2020 (6/20–8/20)	0.003	-0.117	0.189**
	(0.032)	(0.090)	(0.089)
Post Covid 20–21 SY (9/20–2/21)	-0.440***	-0.516***	-0.361***
	(0.067)	(0.047)	(0.108)
(C) Changes by Proportion of Schools Reopened			
Proportion of Schools in Person (9/20–2/21)	0.342***	0.309***	0.411***
	(0.102)	(0.097)	(0.123)
Post Covid 20–21 SY (9/20–2/21)	-0.553***	-0.618***	-0.498***
	(0.055)	(0.042)	(0.082)
N	3,100	3,100	3,100

Notes: Heteroskedasticity robust standard errors clustered by state and month are in parentheses (* $p<.10$ ** $p<.05$ *** $p<.01$). Each column in each panel regresses the logarithm of excess search intensity for a specific topic on a set of indicators for various post-Covid time periods. Panel A includes a single indicator for months on or after March 2020, based on Equation 3. Panel B includes a set of three indicators for three distinct post-Covid time periods, based on Equation 4: (1) the end of the spring 2020 semester (March 2020 through May 2020), (2) the summer period in 2020 (June 2020 through August 2020), and (3) the beginning of the 2020–2021 school year (September 2020 through February 2021). Panel C is based on Equation 5 and interacts the 2020–2021 school year indicator with the percentage of schools that are offering full-time in-person (i.e., traditional) instruction. This measure is based on data from Burbio and is collected at the state by month level from September 2020 through February 2021. All models include state fixed effects and the outcome variable in all models is the excess logarithm of search intensity (as defined in Equation 1). The sample used in all regression models contains search data from January 2016 through February 2021.

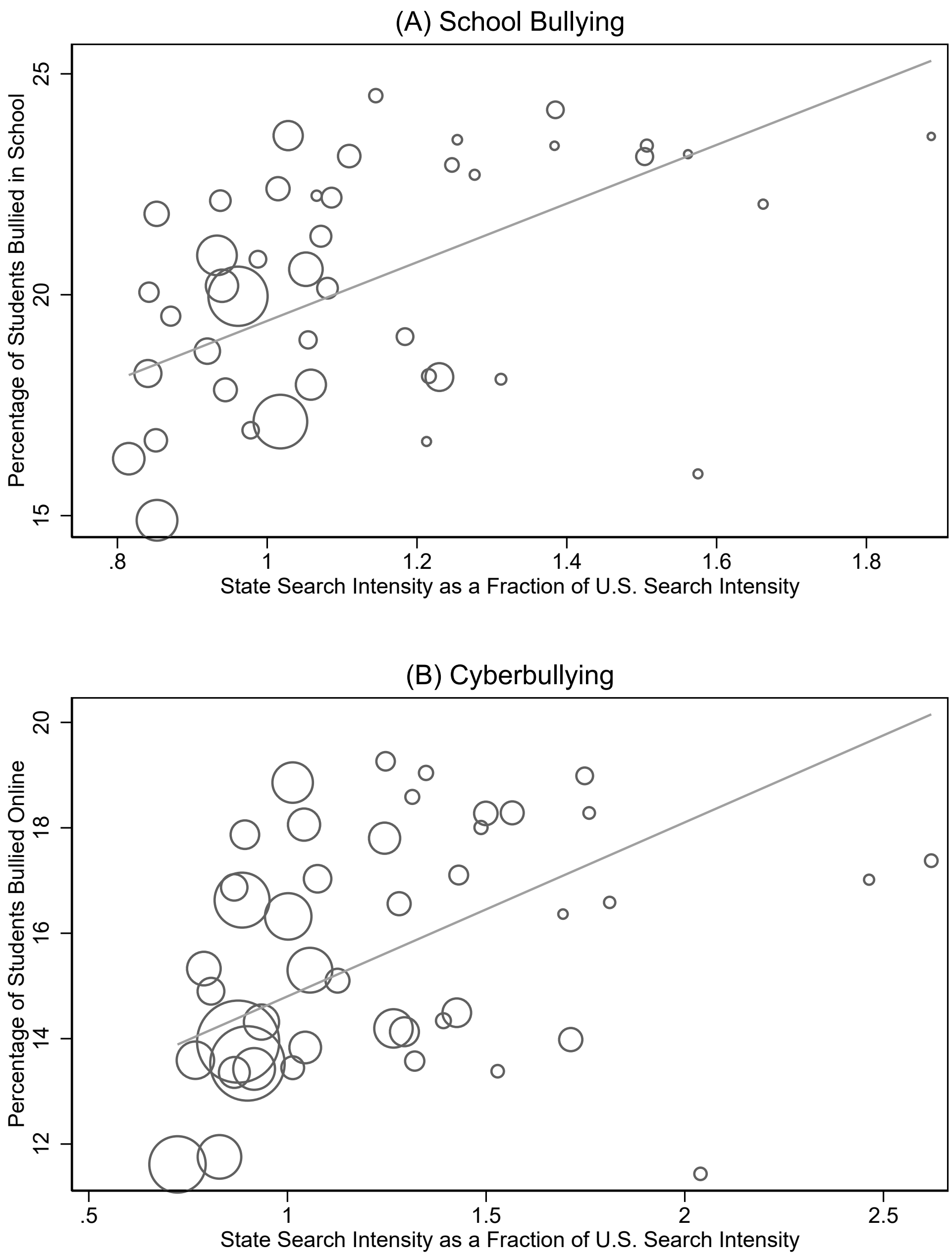
A Supplemental tables and figures

Figure A.1: Seasonality in Monthly Trends in Nationwide Search Intensity for School Bullying (Pre-COVID)



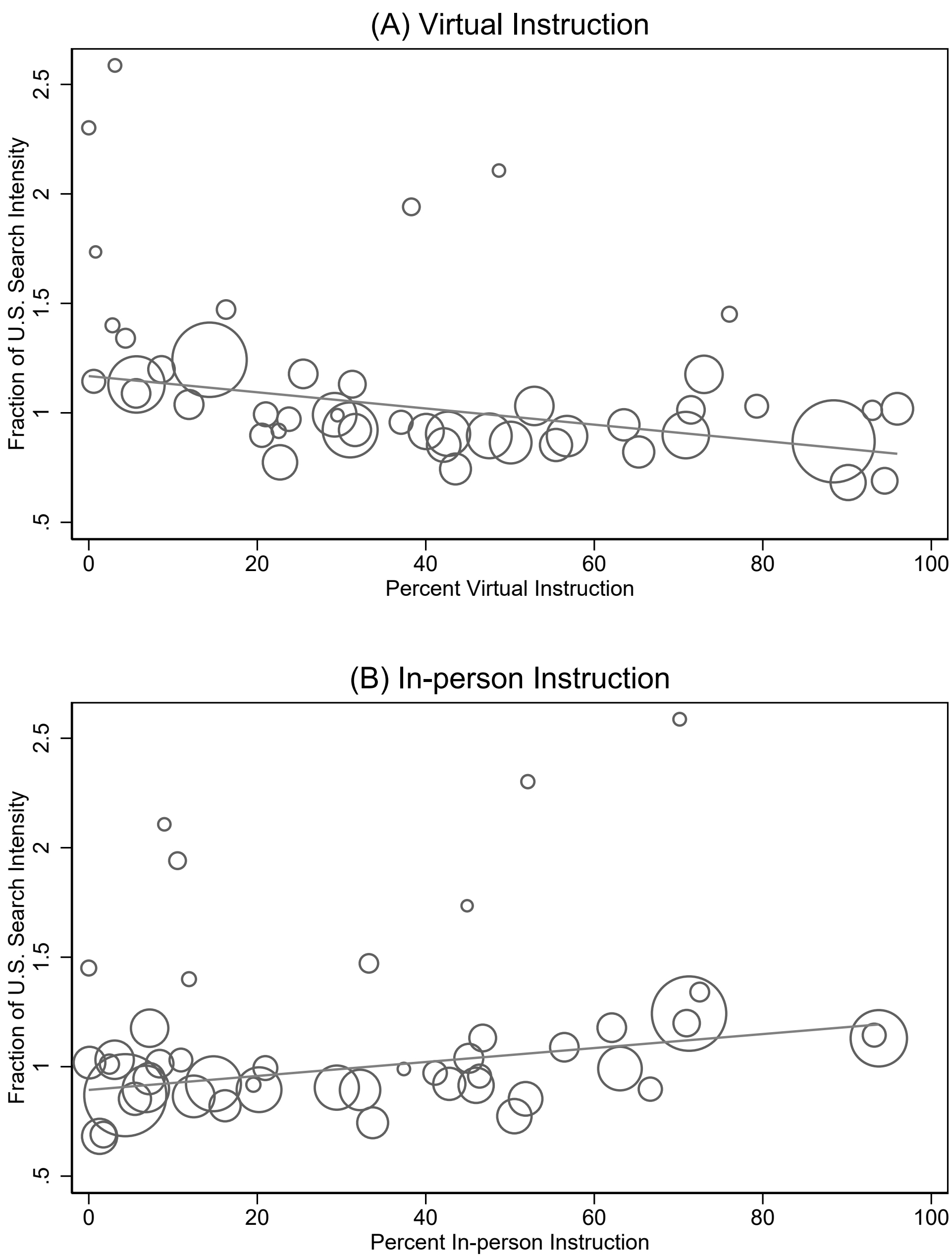
Notes: The figure above shows regression coefficients based on Equation 1 that estimate the difference in the logarithm of monthly search intensity between July and the other 11 calendar months. Panel A shows search intensity for a composite measure that includes "School Bullying" and "Cyberbullying". Panel B shows search intensity for "School Bullying" and panel C shows search intensity for "Cyberbullying." The regressions include fixed effects for month (2-12) and a linear trend for year (2016-2019). Also shown are 95 percent confidence intervals calculated with heteroskedasticity robust standard errors. The sample contains search data from January 2016 through December 2019.

Figure A.2: Relationship Between Survey Results and Internet Searches for Bullying (Pre-COVID)



Notes: The figure above presents the relationship between the percentage of students who were bullied and search intensity in Google Trends for a composite measure that includes "School Bullying" and "Cyberbullying". Each circle represents a state, which is weighted by its 2019 population. The search intensity for each state is presented as a fraction of the national average search intensity for the same composite search term. Data include the 2013 through 2019 responses from the Youth Risk Behavior Survey and Google search intensity from the same time period. The population-weighted correlation coefficients are 0.42 for school bullying (Panel A) and 0.42 for cyberbullying (Panel B).

Figure A.3: Relationship Between Searches for Bullying and School Instructional Modes (2020-21)



Notes: The figure above presents the relationship between school instructional modes and search intensity in Google Trends for a composite measure that includes "School Bullying" and "Cyberbullying". Panel A presents this relationship based on the percentage of schools offering only virtual instruction. Panel B presents this relationship based on the percentage of schools offering only in-person instruction. Each circle represents a state, which is weighted by its 2019 population. Google searches and data from Burbio on school instructional modes spans September 2020 to February 2021.

Table A.1: School Closure Dates by State

State	Legal status	State closure start date	Date closed for the year	Public school enrollment
Alabama	Ordered	March 19	April 6	744,930
Alaska	Ordered	March 16	April 9	132,737
Arizona	Ordered	March 16	March 30	1,123,137
Arkansas	Ordered	March 17	April 6	493,447
California	Recommended	March 19	April 1	6,309,138
Colorado	Ordered	March 23	April 20	905,019
Connecticut	Ordered	March 17	May 5	535,118
Delaware	Ordered	March 16	April 24	136,264
District of Columbia	Ordered	March 16	April 17	85,850
Florida	Recommended	March 16	April 18	2,816,791
Georgia	Ordered	March 18	April 1	1,764,346
Hawaii	Ordered	March 23	April 17	181,550
Idaho	Recommended	March 24	April 6	297,200
Illinois	Ordered	March 17	April 17	2,026,718
Indiana	Ordered	March 20	April 2	1,049,547
Iowa	Ordered	March 16	April 17	509,831
Kansas	Ordered	March 18	March 17	494,347
Kentucky	Recommended	March 16	April 20	684,017
Louisiana	Ordered	March 16	April 15	716,293
Maine	Recommended	March 16	March 31	180,512
Maryland	Ordered	March 16	May 6	886,221
Massachusetts	Ordered	March 17	April 21	964,514
Michigan	Ordered	March 16	April 2	1,528,666
Minnesota	Ordered	March 18	April 23	875,021
Mississippi	Ordered	March 20	April 14	483,150
Missouri	Ordered	March 23	April 9	915,040
Montana	Closure expired	March 16	n/a	146,375
Nebraska	Ordered	March 23	April 3	319,194
Nevada	Ordered	March 16	April 21	473,744
New Hampshire	Ordered	March 16	April 16	180,888
New Jersey	Ordered	March 18	May 4	1,410,421
New Mexico	Ordered	March 16	March 26	336,263
New York	Ordered	March 18	May 1	2,729,776
North Carolina	Ordered	March 16	April 24	1,550,062
North Dakota	Ordered	March 16	May 1	109,706
Ohio	Ordered	March 17	April 20	1,710,143
Oklahoma	Ordered	March 17	March 25	693,903
Oregon	Ordered	March 16	April 8	606,277
Pennsylvania	Ordered	March 16	April 9	1,727,497
Puerto Rico	Ordered	March 16	April 24	365,181
Rhode Island	Ordered	March 23	April 23	142,150
South Carolina	Ordered	March 16	April 22	771,250
South Dakota	Recommended	March 16	April 6	136,302
Tennessee	Recommended	March 20	April 15	1,001,562
Texas	Ordered	March 23	April 17	5,360,849
Utah	Ordered	March 16	April 14	659,801
Vermont	Ordered	March 18	March 26	88,428
Virginia	Ordered	March 16	March 23	1,287,026
Washington	Ordered	March 17	April 6	1,101,711
West Virginia	Ordered	March 16	April 21	273,855
Wisconsin	Ordered	March 18	April 16	864,432
Wyoming	Closure expired	March 16	n/a	94,170

Notes: Data come from Education Week's "Coronavirus and School Closures" website, last updated on May 15, 2020. All closure dates refer to 2020.

Table A.2: Correlations Coefficients of State-level Bullying Survey Results and Bullying Search Intensity

	YRBS Overall Bullying (1)	YRBS School Bullying (2)	YRBS Cyber Bullying (3)	Google Overall Bullying (4)	Google School Bullying (5)	Google Cyber Bullying (6)
YRBS Overall Bullying	1.000					
YRBS School Bullying	0.982	1.000				
	(0.000)					
YRBS Cyberbullying	0.973	0.913	1.000			
	(0.000)	(0.000)				
Google Overall Bullying	0.445	0.437	0.432	1.000		
	(0.003)	(0.003)	(0.003)			
Google School Bullying	0.430	0.415	0.423	0.957	1.000	
	(0.004)	(0.006)	(0.004)	(0.000)		
Google Cyber Bullying	0.442	0.439	0.422	0.979	0.889	1.000
	(0.003)	(0.003)	(0.004)	(0.000)	(0.000)	

Notes: P-values in parentheses. Data are at the state level and weighted by each state's 2019 population. Data include the 2013 through 2019 YRBS survey results and Google searches from the same time period.