EdWorkingPaper No. 21-436

The COVID-19 Pandemic Disrupted Both School Bullying and Cyberbullying

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VERSION: July 2021

Suggested citation: Bacher-Hicks, Andrew, Joshua Goodman, Jennifer Greif Green, and Melissa K. Holt. (2021). The COVID-19 Pandemic Disrupted Both School Bullying and Cyberbullying. (EdWorkingPaper: 21-436). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/7jy7-x816

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July 7, 2021

Abstract

School bullying is widespread and has substantial social costs. One in five U.S. high school students report being bullied each school year and these students face greater risks of serious mental health challenges that extend into adulthood. As the COVID-19 pandemic forced most students into online education, many have worried that cyberbullying prevalence would grow dramatically. We use data from Google internet searches to examine changing bullying patterns as COVID-19 disrupted in-person schooling. Pre-pandemic historical patterns show that internet searches provide useful information about actual bullying behavior. Real-time data then shows that searches for school bullying and cyberbullying both dropped about 30-40 percent as schools shifted to remote learning in spring 2020. This drop is sustained through the fall and winter of the 2020-21 school year, though the gradual return to in-person instruction partially returns bullying searches to pre-pandemic levels. These results highlight how in-person interaction is an important mechanism underlying not only in-person school bullying, but also cyberbullying. We discuss how this otherwise damaging shock to students and schools provides insight into the mixed impact of the pandemic on student well-being.

1 Introduction

For several decades, school-based bullying and cyberbullying have been the focus of policy and legislative initiatives due to their substantial impact on the physical and mental health of youth (Holt et al., 2015; Wolke et al., 2013). 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). The 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 the policy and legislative efforts to end bullying and its harmful effects, 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] This disruption to the traditional functioning of schools provides an opportunity to examine the association of bullying and cyberbullying with in-person schooling.

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. In a survey of U.S. adults, Barlett et al. (2021) found that those with personal pandemic-related experiences, such as having had COVID-19, were more likely to report conducting cyber-attacks, perhaps because of increased pandemic-related stress. 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. Using Twitter data from a six month window be-

[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).

tween 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).

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 document new facts about the prevalence and mechanisms behind school bullying and cyberbullying. We start by showing two pieces of evidence suggesting that pre-pandemic online search data is related to actual bullying prevalence. First, pre-pandemic online search intensity for both types of bullying closely follows the school calendar, with searches lowest during summers and highest during the school year. Second, pre-pandemic state-level variation in searches for bullying is strongly correlated with state-level variation in self-reported bullying rates, suggesting search contains information about actual bullying behavior.

Our main contribution is then to show the evolution of 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 K-12 students increased their online presence considerably due to remote schooling, past research suggests that cyberbullying prevalence might have increased (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 30-40 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 norms.

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 potential 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

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. Google Trends normalizes measures of search intensity in a way that masks the actual fraction of searches devoted to a topic but allows for comparison of relative intensity over time and across states. We can thus measure whether search intensity for a given term is, for example, twice as high in one time period relative to another or in one state relative to another state. Given the arbitrary nature of that normalization, we generally use the logarithm of search intensity so that differences over time and across states can be interpreted in percent terms.

We focus on three measures of online search intensity for bullying: the intensity of search for "school bullying", for "cyberbullying", and for the sum of those two, which we refer to as overall "bullying." We use Google Trends data on those search terms as "topics", which includes in the measure not only searches that contain that specific term but also searches that contain closely related keywords in English and other languages. Search intensity for the topic of "school bullying" will thus include searches containing the exact phrase "school bullying", closely related English variants such as "school bully", and versions of that phrase in Spanish, for example.

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 allows 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 have some potential limitations. First, publicly available data from Google Trends is limited to aggregate trends in the popularity of specific keywords. 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, or witness. 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 and the representativeness of data may 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.

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.[2] 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). Administered by the Centers for Disease Control and Prevention, YRBS surveys a large and both nationally and state-level representative sample of 9th through 12th grade students every two years. Across recent waves, the survey has asked 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 use answers to these questions to construct state-level fractions of students who report being bullied, either in school or virtually.

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 in-person schooling data comes from Burbio, a private company that began systematically collecting information about school districts' learning modes during the pandemic. Every three days, Burbio collects for over 1,200 school districts publicly available data on the district's learning mode from sources such as district websites and Facebook posts. Burbio then generates weekly measures by county of the fraction of grades in a given school district following an in-person, hybrid, or virtual learning mode. We then aggregate these measures to the state level to connect with our measures of search intensity for bullying.

3 Empirical Strategy

We estimate pandemic-induced changes in searches 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

[2]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), 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.

prior work using Google Trends to analyze the effects of COVID-19 on access to learning resources(Bacher-Hicks et al., 2021).[3]

An important first step for both approaches is to remove seasonal patterns in searches for bullying. As we highlight in the next section, searches for bullying typically peak in the beginning of the school year and fall substantially during the summer months. Any analysis that fails to account for seasonality may underestimate or overestimate the effects of COVID-19 on search intensity. To address this, we generate an adjusted measure of search intensity by removing calendar month effects and annual time trends based on pre-pandemic patterns in bullying-related internet searches. We use data only from the pre-pandemic sample period to estimate month effects and linear time trends but then apply these corrections to all months, including post-pandemic ones. This approach avoids potentially over-correcting for seasonality due to pandemic-induced changes. We use this adjusted measure as our main outcome variable in a series of ordinary least squares (OLS) regression models.

In the event study specification, we regress the logarithm of adjusted monthly search intensity in each state on a vector of month indicators and a vector of state indicators. We use the logarithm so that differences over time and across states can be interpreted in percent terms. By excluding the February 2020 indicator and including state indicators, the coefficients of interest represent the deviation in each month from calendar-predicted search intensity relative to the same deviation in February 2020.

The nationwide before-after specification uses the same underlying adjusted measure as the event study specification but replaces the vector of month indicators with a single post-pandemic indicator. Again, by adjusting for calendar effects and including state fixed effects, the coefficient of interest from this specification can be interpreted as the overall post-pandemic change in search intensity compared to those same weeks in prior years.

While our primary before-after specification uses a single indicator for the entire post-pandemic time period, we conduct several specifications with additional post-pandemic indicators 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 the single post-pandemic indicator in the main before-after specification with three separate indicators corresponding to each time period. Finally, to study how search intensity changed differentially by states' school instructional modes, we modify these before-after specifications by interacting the post-pandemic indicator(s) with a measure of the percentage of schools

[3] For a detailed discussion of our empirical strategy, see Appendix Section B.

offering in-person instruction in each state during the first half of the 2020-21 school year. These specifications identify whether school transitions back to in-person instruction changes the effect of COVID-19 on bullying-related searches. 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 begin by presenting 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. Figure 2 makes that even clearer by plotting the month "effects" from our regression model. Search for all forms of bullying is 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. This pattern over the calendar year is consistent with households searching for bullying-related resources much more when school is in session and bullying rates are presumably higher.

Second, pre-pandemic state-level self-reported rates of bullying are strongly correlated with state-level online search intensity for bullying-related terms. Figure 3 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.[4] We interpret this as further evidence that, pre-pandemic, online search intensity for bullying is closely related to actual bullying behaviors.

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

[4]See Figure C.1 for the graphical version of this evidence and Table C.3 for the corresponding correlation coefficients.

bullying-related terms appears to drop dramatically starting in March 2020 relative to historical trends. Figure 4 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 4 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 and cyberbullying search were historically low in spring 2020 and then again in the next school year. 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 5 plots state-level average bullying search intensity from September 2020 through February 2021 as a function of the proportion of schools offering only virtual instruction or in-person instruction, averaged over the same time period. Panel A shows that states with a higher fraction of schools offering only virtual instruction also see substantially lower search intensity for bullying. Panel B shows that states with a higher proportion of in-person instruction see substantially higher search intensity for bullying. These strong correlations hold both for school bullying and for cyberbullying considered separately.[5]

To further quantify the relationship between in-person instruction and bullying search, we run regres-

[5] See Figures C.2 and C.3.

sion 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 is strongly associated with in-person bullying 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 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.

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 also be updated in real time to study the 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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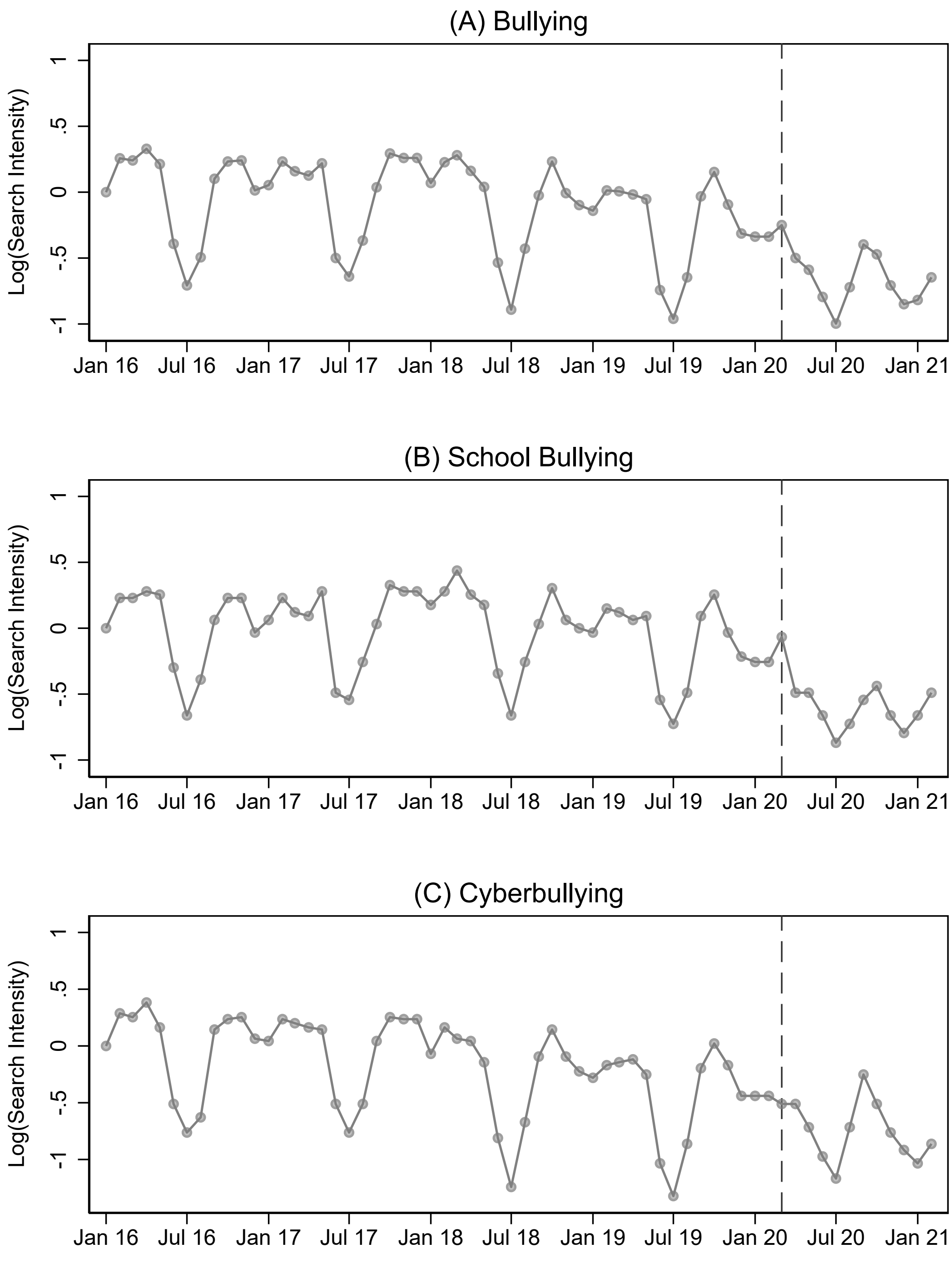
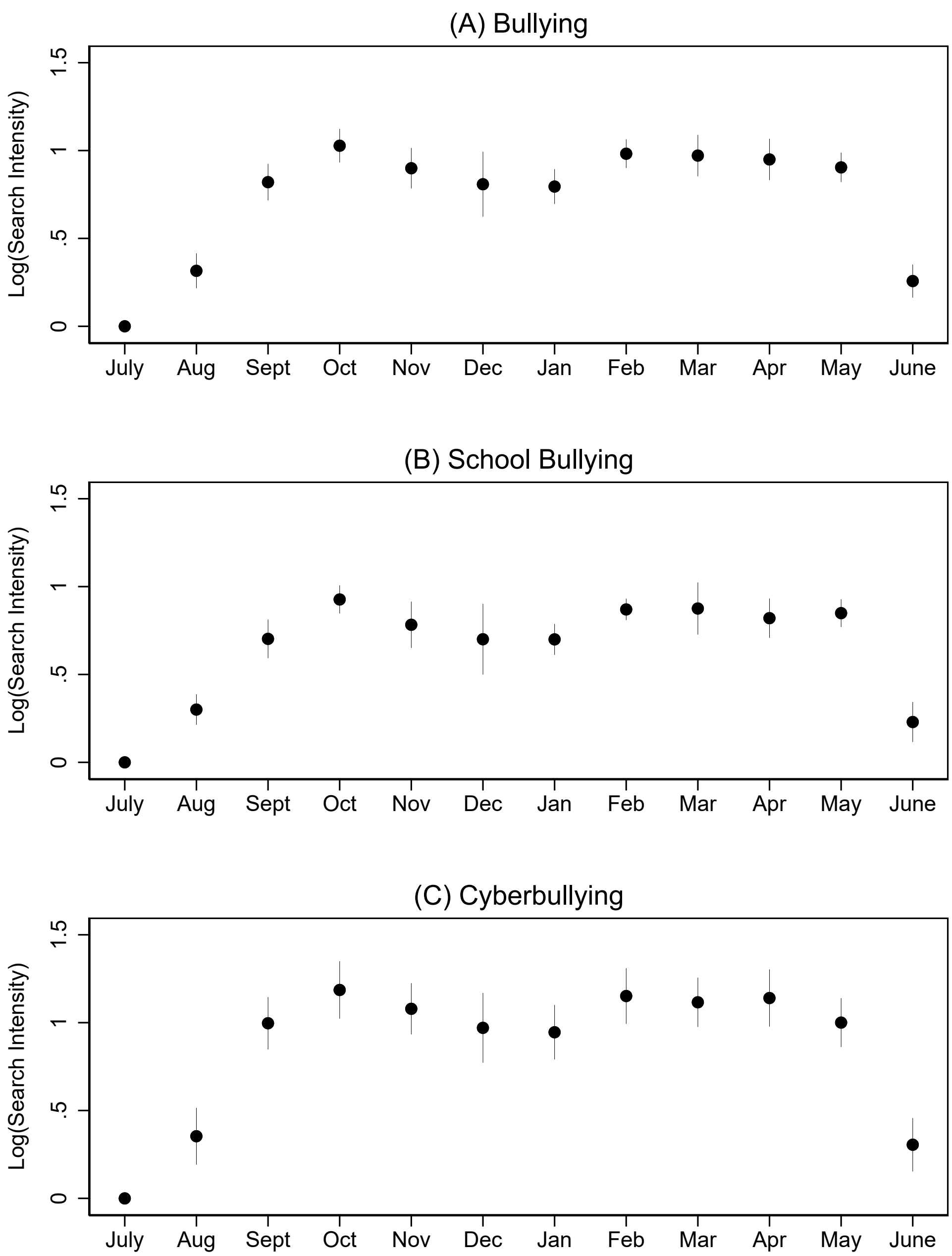
Figure 1: Nationwide Monthly Search Intensity for Bullying (Pre- and Post-COVID)



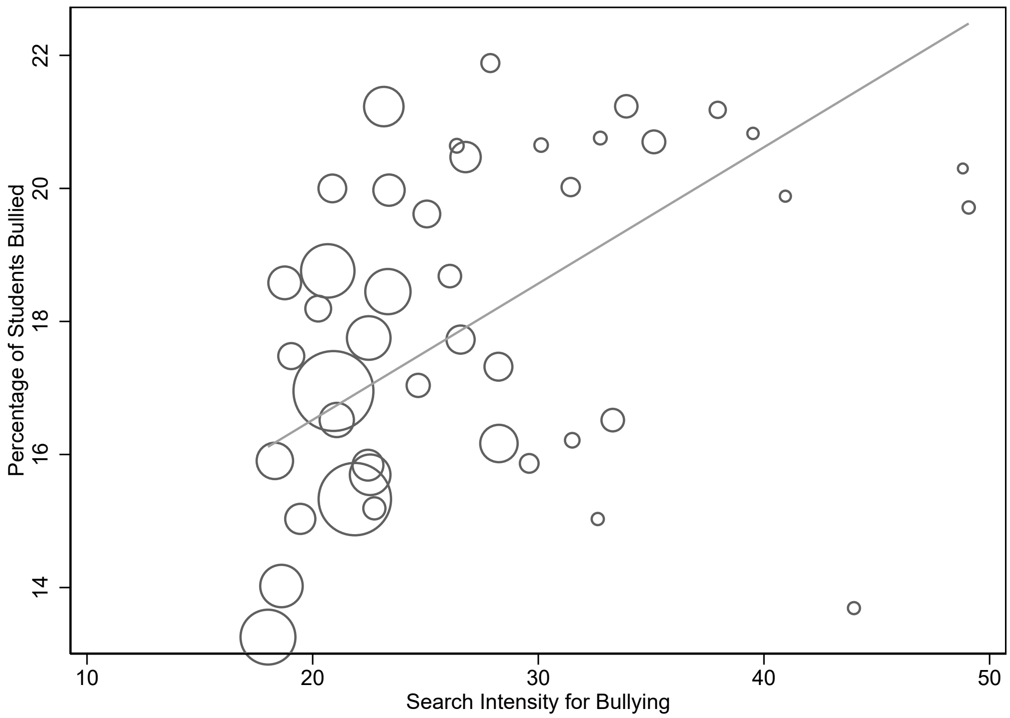
Notes: The figure above shows the logarithm of nationwide search intensity relative to intensity in January of 2016. Panel A shows search intensity for a composite search term that includes "School Bullying" and "Cyberbullying." Panel B shows search intensity for "School Bullying" and panel C shows search intensity for "Cyberbullying." The vertical dashed line is drawn between February and March 2020, during which time nearly all public schools shifted to remote learning.

Figure 2: Seasonality in Monthly Trends in Nationwide Search Intensity for School Bullying (Pre-COVID)



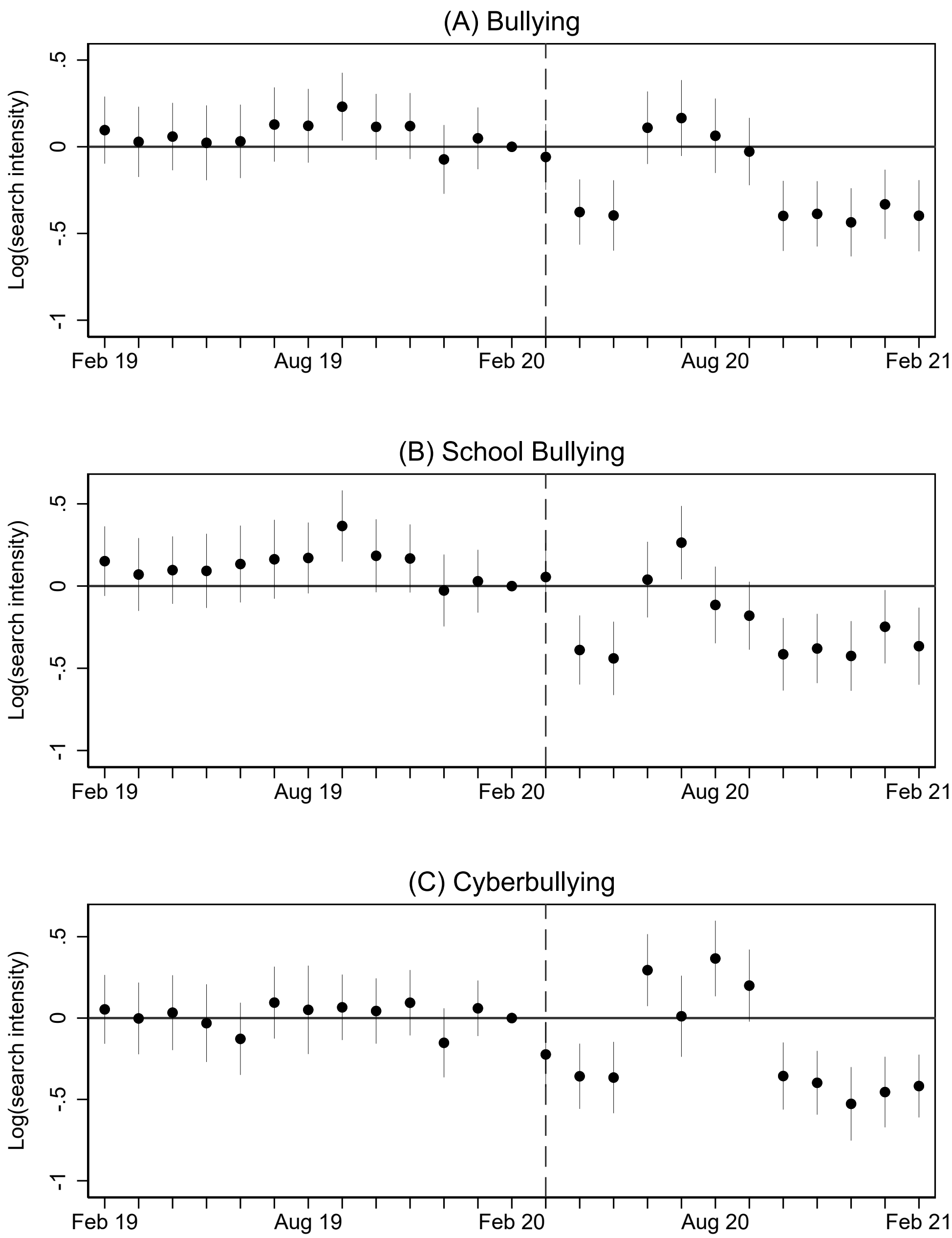
Notes: The figure above shows regression coefficients estimating the difference in the logarithm of monthly search intensity between July and the other 11 calendar months. Panel A shows search intensity for a composite search term that includes "School Bullying" and "Cyberbullying." Panel B shows search intensity for "School Bullying" and panel C shows search intensity for "Cyberbullying." The regressions include fixed effects for month (2-12) and 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 3: Relationship Between Overall Bullying in YRBS and Searches for Bullying (Pre-COVID)



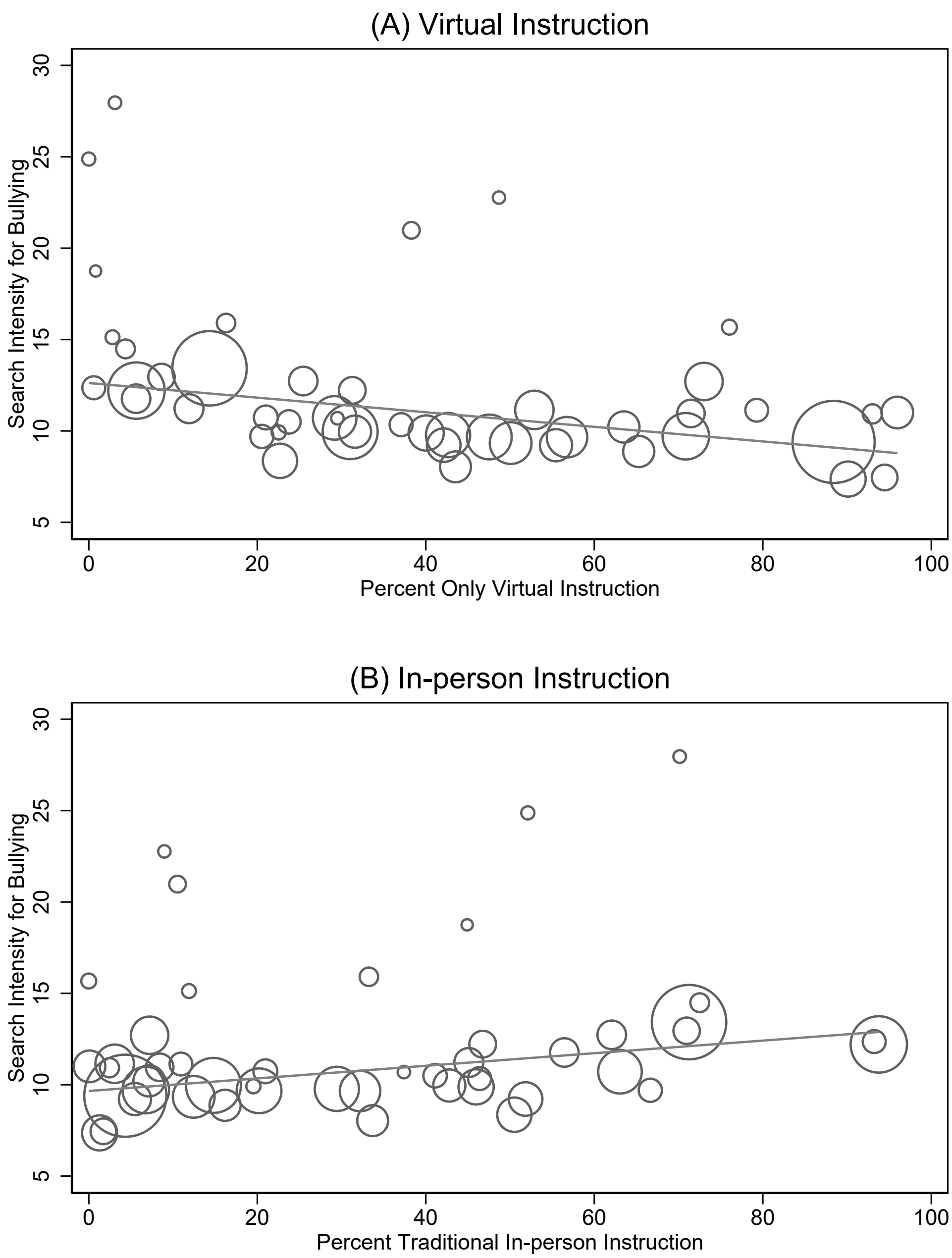
Notes: The figure above presents the relationship between the proportion of students who were bullied and search intensity in Google Trends for a composite search term that includes "School Bullying" and "Cyberbullying." Each circle represents a state, which is weighted by its 2019 population. Data include the 2013 through 2019 YRBS survey results and Google searches from the same time period. The population-weighted correlation coefficient is 0.45.

Figure 4: Nationwide Event Study of Search Intensity for Bullying



Notes: The figure above shows event study coefficients estimating the difference in the logarithm of monthly search intensity across all 50 U.S., states relative to the same months in prior years. We control for state fixed effects, adjusting for seasonality using fixed effects for month of year (1-12), and include a linear time trend to control for secular trends over time. 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." The vertical dashed line is drawn between February and March 2020, during which time nearly all public schools shifted to remote learning.

Figure 5: 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 search term 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 1: Changes in Search Intensity for Bullying Following Pandemic-Induced Shifts to Remote Learning

	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 In-Person			
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 search intensity for the specific topic. Panel A includes a single indicator for periods on or after March 2020. Panel B includes a set of three indicator for three distinct post-pandemic time periods: The end of the spring 2020 semester (March 2020 through May 2020), the summer period in 2020 (June 2020 through August 2020), and finally the beginning of the 2020–2021 school year (September 2020 through February 2021). Panel C estimates the relationship between bullying and school instruction mode in the 2020-21 school year using the percentage of schools that are offering full-time in-person instruction. This measure is collected at the state by month level from September 2020 through February 2021. We control for state fixed effects in addition to adjusting for seasonality using month fixed effects and a linear time trend. The sample contains search data from January 2016 through February 2021.

A Data details

A.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 in a state is divided by the total searches in that same state and month. The resulting raw measure of search intensity is therefore scaled on a range of 0 to 100 based on a term's proportion to all searches on all terms.

We then compare the relative intensity across keywords to re-normalize them so that each monthly measure can be compared 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 evidence that overall Google search volumes did not change substantially during the pandemic.[6]

We focus on three primary measures related to online searches for 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 the two terms, which we refer to simply as "Bullying." In addition to these three measures based on topics, we also derive three analogous measures based on search terms instead of topics. Topics represent a group of terms that share the same concept in any language whereas terms include only the specific term. Searching for the topic of "School Bullying" will include results that not only include the phrase "School Bullying" but also similar keywords in English and other languages.[7]

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

[7] Though it is impossible to determine the precise list of keywords included in each topic, Google Trends provides the following illustrative example: If you search the topic "London," your search includes results for topics such as: "Capital of the UK" and "Londres," which is "London" in Spanish.

A.2 Youth Risk Behavior Survey

To evaluate the predictive validity of Google searches for bullying, school bullying, and cyberbullying in the pre-pandemic period, we rely on survey data from the YRBS between 2013 and 2019. The YRBS is conducted by the Centers for Disease Control and Prevention (CDC) in partnership with state health agencies every two years to measure health behaviors and experiences among high school students in each state. 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 one class period (approximately 45 minutes) to complete.

We use responses from the four most recent biennial surveys prior the pandemic (i.e., 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.[8] 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.

A.3 Burbio

Over the course of the pandemic, the private firm Burbio has regularly tracked the learning modes of over 1,200 school districts representing over 35,000 schools in 50 states.[9] Burbio checks school district websites, Facebook pages, local news stories and other publicly available information to determine which learning mode 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 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

[8] For more information, see Underwood et al. (2020).

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

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 traditional, hybrid and virtual up 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 weekly state-level data set with the fraction of schools (or school grades) offering various learning modes.

B Regression analysis details

We estimate changes in search intensity for bullying following COVID-19 using both a month-by-month event study specification and a before-after specification. Before conducting these analyses, we first remove seasonality and secular time trends from our search intensity measures. Searches for bullying typically peak in the beginning of the school year and fall substantially during the summer months. Because COVID-19substantially disrupted these natural rhythms in search intensity, we adjust for seasonality and secular time trends using only the data from the pre-pandemic sample period, which avoids potentially over-correcting for seasonality due to pandemic-induced changes. We therefore generate residuals for the natural logarithm of search intensity in each state s in time period t as follows:

$$Log(SearchIntensity_{st}) = \beta_1 Year + \mu_{m(t)} + \varepsilon_t, \tag{1}$$

where $\mu_{m(t)}$ indicates a set of 12 fixed effects for the month of year (i.e., 1 through 12), and β_1 captures any secular time trends in the years before COVID-19 (i.e., 2016 through 2019). We then remove these monthly effects and the linear time trend from searches over the full sample period by extrapolating these effects to the post-pandemic period. Let $Log(SearchIntensity^*_{st})$ denote this adjusted measure, which accounts for seasonal fluctuations and secular trends. Using this adjusted, we then fit our event study as follows:

$$Log(SearchIntensity^*_{st}) = \sum_{t=-12}^{-1} \beta_t \, Before_t + \sum_{t=1}^{11} \beta_t \, After_t + \alpha PriorYears_t + \Gamma_s + \varepsilon_t. \tag{2}$$

We regress the adjusted logarithm of search intensity for state s in time t on a vector of month indicators t. Here, t indicates the event month, which identifies months relative to February 2020, which was the last month before states began closing schools. $Before$ and $After$ are indicators for month t falling before or after February 2020. Note that by adjusting $SearchIntensity^*_{st}$ for month of year $m(t)$ (i.e., 1 through 12) and time trends, coefficients β_t can be interpreted as differences in search intensity compared to the same months in prior years. Exclusion of the February 2020 indicator, and inclusion of state fixed effects (Γ_s) and a $PriorYears$ 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 replaces the vector of weekly pre- and post-pandemic indicators with a single post-pandemic indicator as follows:

$$Log(SearchIntensity^*_{st}) = \beta PostCOVID_t + \Gamma_s + \varepsilon_t. \tag{3}$$

Again, by adjusting for calendar effects and including state fixed effects, β can be interpreted as the overall post-pandemic change in search intensity compared to those same weeks in state s in prior years. In the first before-after specifications, we simply include one indicator for the entire sample period following COVID-19 (i.e, March 2020 through February 2021).[10] This difference-in-difference estimator β from Equation 3 is the average of the March 2020 through January 2021 event study coefficients β_1 through β_{11} from Equation 2.

We then modify the specification described in Equation 2 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 2 with three separate indicators corresponding to each time period:

$$Log(SearchIntensity^*_{st}) = \beta_1 PostSpring_t + \beta_2 PostSummer_t + \beta_3 PostFall_t + \Gamma_s + \varepsilon_t. \tag{4}$$

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 ($InPerson_s$):

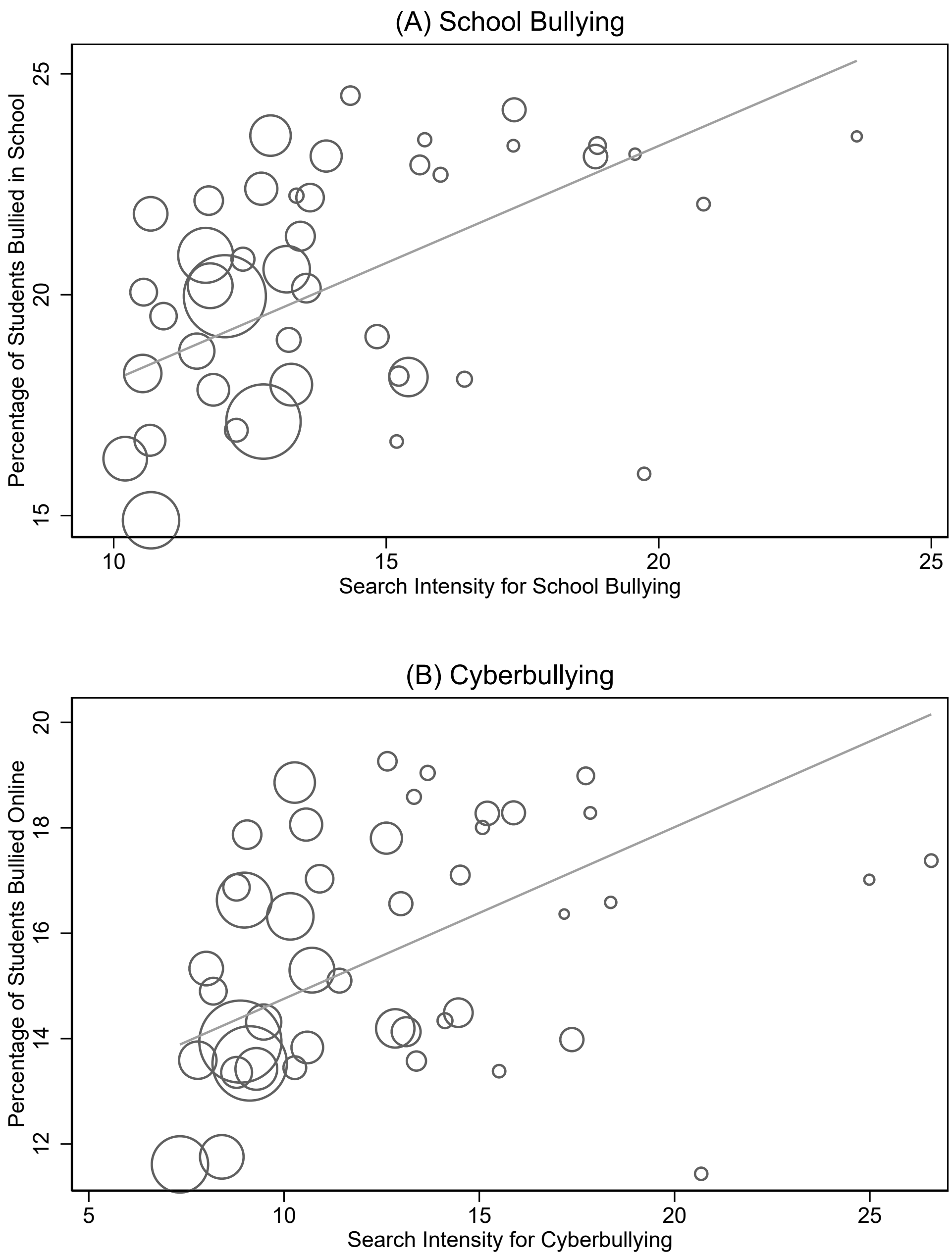
$$Log(SearchIntensity^*_{st}) = \beta_1 PostSpring_t + \beta_2 PostSummer_t + \beta_3 PostFall_t + \beta_4 (PostFall_t) * (InPerson_s) + \Gamma_s + \varepsilon_t. \tag{5}$$

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

[10]See Table C.2 for a list of state-by-state school closure dates, which all begin in March 2020.

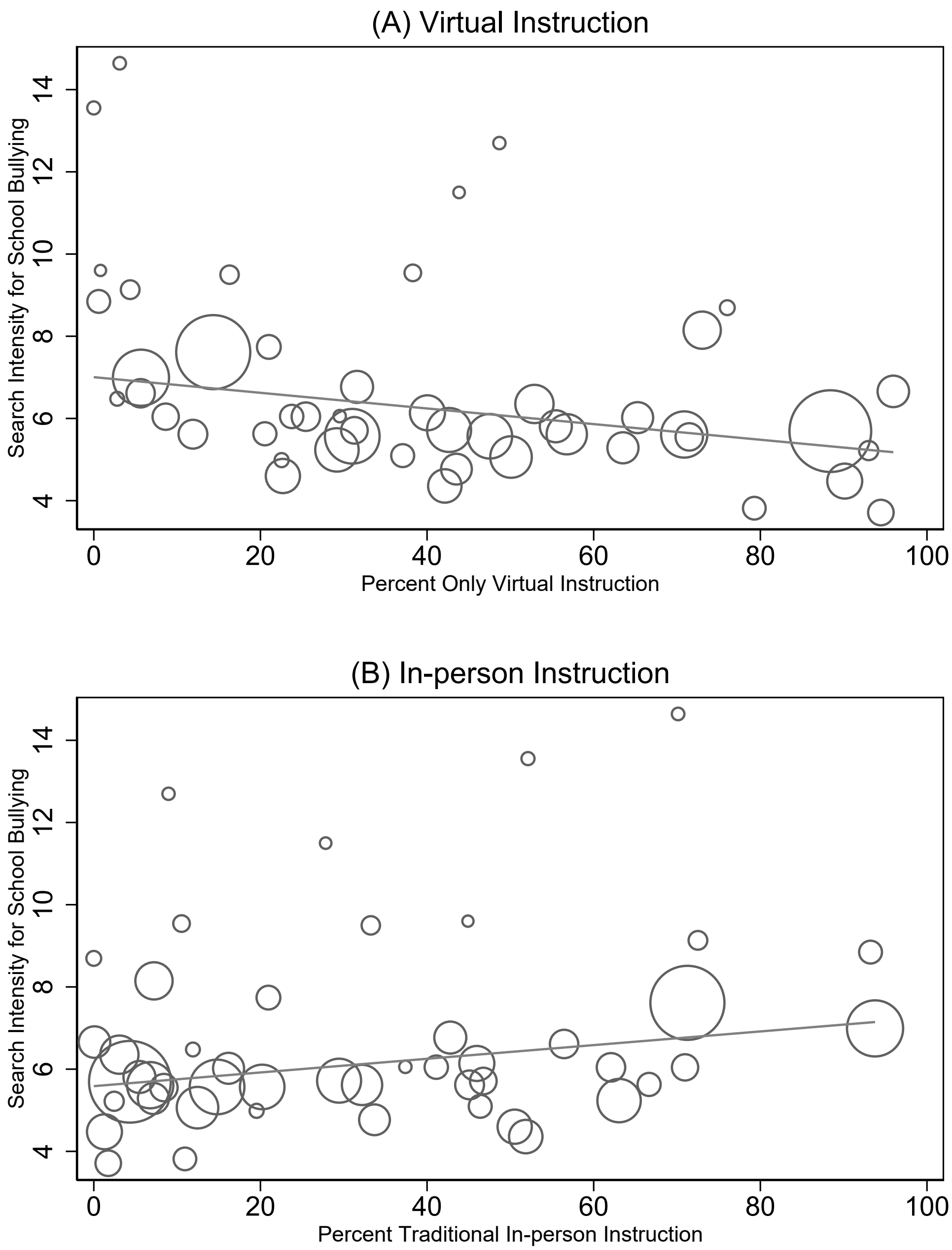
C Supplemental tables and figures

Figure C.1: Relationship Between Bullying in YRBS and Search Intensity for Bullying



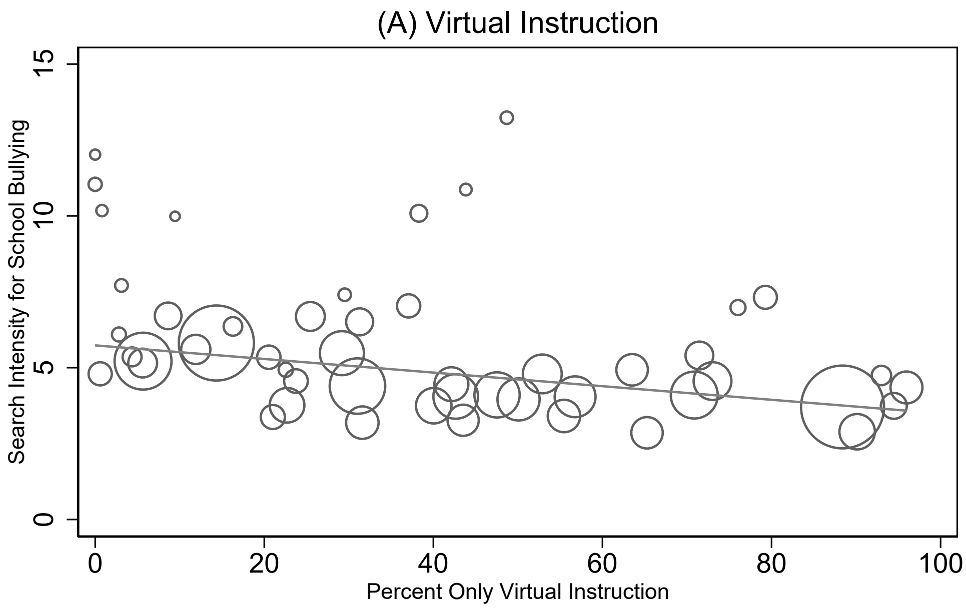
Notes: The figure above presents the relationship between the percentage of students who were bullied in school (Panel A) or online (Panel B) and search intensity for "School Bullying" and "Cyberbullying" repsectively. Each circle represents a state, which is weighted by its 2019 population. Data include the 2013 through 2019 YRBS survey results and Google searches 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).

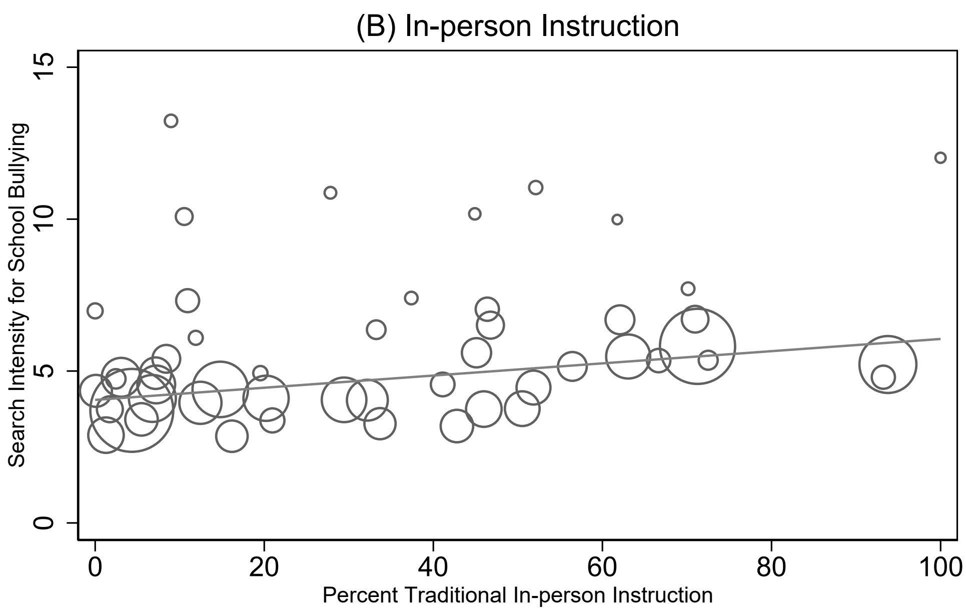
Figure C.2: Relationship Between Searches for School Bullying and School Instructional Modes (2020-21)



Notes: The figure above presents the relationship between school instructional modes and search intensity in Google Trends for "school bullying." 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.

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





Notes: The figure above presents the relationship between school instructional modes and search intensity in Google Trends for "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 C.1: Relationship Between Bullying and Student Reports of Hopelessness and Suicidal Ideation

	Sad or Hopeless (1)	Considered Suicide (2)	Attempted Suicide (3)
Bullied	0.287***	0.223***	0.123***
	(0.001)	(0.001)	(0.001)
BMI Index	0.003***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
Overweight	0.014***	0.012***	0.003*
	(0.002)	(0.002)	(0.002)
Obese	0.014***	0.015***	-0.002
	(0.003)	(0.003)	(0.002)
Female	0.151***	0.075***	0.024***
	(0.001)	(0.001)	(0.001)
Ameircan Indian / Alaska Native	0.003	-0.009**	0.036***
	(0.005)	(0.004)	(0.004)
Asian	-0.065***	-0.055***	-0.024***
	(0.003)	(0.003)	(0.003)
Black	-0.049***	-0.049***	0.010***
	(0.003)	(0.002)	(0.003)
Hispanic / Latino	0.016***	-0.030***	0.006***
	(0.003)	(0.002)	(0.002)
Native Hawaiian / other PI	-0.013***	-0.027***	0.032***
	(0.005)	(0.004)	(0.004)
White	-0.066***	-0.053***	-0.035***
	(0.002)	(0.002)	(0.002)
Year Fixed Effects	Yes	Yes	Yes
Grade Fixed Effects	Yes	Yes	Yes
N	655,384	596,497	432,681

Notes: Heteroskedasticity robust standard errors are in parentheses (* p<.10 ** p<.05 *** p<.01). Each column in each panel regresses an indicator of whether a student indicated feeling sad or hopeless (Column 1), considered suicide (Column 2), or attempted suicide (Column 3). In addition to the controls presented, we include fixed effects for year and grade. The sample contains data from students who completed the YRBS survey from 2013 thorough 2019.

Table C.2: 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 C.3: Correlations Coefficients of State-level YRBS and Google Trends Measures of Bullying

	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.