Going Viral in a Pandemic:
Social Media and Allyship in the Black Lives Matter Movement

Vladimir Avetian * Annalí Casanueva Artís †

Sulin Sardoschau ‡ Kritika Saxena §

September 2021

Abstract

How do modern social movements broaden coalitions? Triggered by the viral video footage of George Floyd's murder, the Black Lives Matter (BLM) movement has gained unprecedented scope during the pandemic. Using Super Spreader Events as a source of exogenous variation at the county level, we find that exposure to COVID-19 mobilized "new allies" to join the movement for the first time during the pandemic. We can attribute this mobilization effect to an increase in the use of social media (particularly twitter). Social media is most effective in mobilizing those who are not directly impacted by the movement's grievances, i.e. more affluent, whiter and more rural counties. We rule out competing mechanisms such as increased salience of racial inequality, lower opportunity costs of protesting, as well as heightened overall agitation and propensity to protest.

Keywords: BLM, COVID-19, protest, social media
JEL classification: P16, D7

*Sciences Po: vladimir.avetian@sciencespo.fr
†Paris School of Economics: annali.casanueva@gmail.com
‡Humboldt University : sulin.sardoschau@hu-berlin.de
§Graduate Institute of International & Development Studies: kritika.saxena@graduateinstitute.ch The authors would like to thank Ekaterina Zhuravskaya, Lore Vandewalle and Sergei Guriev, Davide Cantoni for their useful comments and suggestions. We would also like to thank Marlon Seror for his invaluable inputs. We are thankful to all the participants of the 25th Annual ISNIE / SIOE conference, HiCN 2020 conference, the AFSE conference, brown bag seminar at The Graduate Institute of International and Development Studies, and Science Po, the Empirical Economics Seminar at LMU, and the Applied Young Economists Webinar.

1 Introduction

There is a far more representative cross-section of America out on the streets [...]
That didn't exist back in the 1960s. That broad coalition.
- Barack Obama, June 3rd 2020

Social movements are integral to democratic politics and can bring about social, economic and institutional change (Ostrom, 1990; Della Porta and Diani, 2015; Acemoglu et al., 2018). Protesters take to the streets in order to put pressure on politicians and appeal to the broader public in the hopes of influencing policies that address their grievances. The effectiveness of social movements depends on their ability to mobilize allies and build coalitions, thereby inspiring reform through collective action (Olson, 1989; Della Porta and Diani, 2020).

Traditionally, such protest mobilization was organized at the local level. For instance, the Civil Rights Movement in the 1960s depended heavily on local chapters as decision making, mobilization, coordination and persuasion tools (Morris, 1986). Today, social movements depend less on face-to-face interactions and have shifted their activism into the virtual space[1]. The Black Lives Matter (BLM) movement - successor to the Civil Rights Movement - encapsulates the features of a modern social movement that draws heavily on social media (Mundt et al., 2018; McKersie, 2021).

BLM was born on twitter in 2013 and since then the #BlackLivesMatter hashtag has become one of the most frequently used hashtags on twitter, peaking at 8.8 million tweets per day in May 2020[2]. Videos on twitter about the murder of George Floyd at the hands of the police officer Derek Chauvin were watched over 1.4 billion times within two weeks[3]. The ensuing protest were labeled the "largest"[4] and the "broadest"[5] social movement in the history of the United States.

In this paper, we investigate the role of social media in mobilizing new protesters and broadening coalitions. We use the example of the BLM movement and focus on the pandemic period for various reasons. The BLM movement *i*) existed well before the pandemic, allowing us to distinguish between traditional protesters and new allies, *ii*) BLM draws heavily on social media as a persuasion tool and *iii*) was subject to an unexpected protest trigger during the pandemic, namely the murder of Floyd.

Using Super Spreader Events as a source of exogenous variation, we show that - indeed - exposure to COVID-19 at the county level is associated with an increase in protest behavior but only among those counties that have never protested for a BLM-related cause before. We also show that the uptake of online activities *before* the murder of Floyd was higher among these new allies. We connect these two observations by using the predicted number of new twitter accounts on subsequent protest behavior and find that new accounts only matter for counties

[1] As McKersie (2021) notes: "Even though an organization like BLM does not have a constituent base like the CCCO, through which affiliated congregations and neighborhood organizations issued calls for participants, current BLM organizations more than compensate by utilizing the power of social media to mobilize participants for protests."

[2] See PEW Research Center (2020)

[3] See Listing of Twitter Videos with GF and BLM hashtag

[4] See New York Times

[5] See Washington Post

for which the salience of racial inequality was low initially, e.g. counties with no BLM protest before, as well as more rural, affluent and whiter counties. Lastly, using survey data, we show that exposure to COVID-19 is associated with more favorable views towards BLM but not other progressive issues. We rule out alternative explanations, such as pandemic-induced rise in the salience of racial inequality before the protests, lower opportunity costs for protesting during the pandemic or COVID-19 increasing overall protest propensity.

Based on these results, we hypothesize that the binding constraint of modern social movements no longer lies in the presence of local chapters or social ties on the ground but rather depends on increased exposure to their existing social media content and messaging. Previous work has shown that social media can solve the collective action and coordination problem for individuals already sympathetic to a political cause in the early stages of social media expansion (Enikolopov et al., 2018; Manacorda and Tesei, 2020). In contrast, we focus on the role of social media as a protest mobilization tool targeting new allies in a setting where social media platforms are already widely available.

Our identification is based on a small "window of opportunity" between the end of March and mid April of 2020 during which COVID-19 was prevalent enough but lock-down stringency lax enough to allow for so called Super Spreader Events (SSE) to occur. These events are characterized by presence of one highly infectious individual (a super-spreader) and took place mainly at birthday parties, nursing homes or prisons. We exploit cross-sectional variation in the number of SSEs within a 50 kilometer radius from the county border but not within the county 6 weeks prior to the murder of George Floyd to construct our instrument for exposure to COVID-19 at the county level.

We include state fixed effects and a vast set of county level controls, most notably, the number of past BLM events between 2014 and 2019, as well as socio-demographic variables and proxies for political leaning and social capital. A causal interpretation is based on the assumption that - conditional on controls and state fixed effects - SSEs in the neighboring counties 6 weeks before GF's murder only impacted BLM protest in the county through it's spreading of COVID-19.

We complement this identification strategy with an additional instrument (touristic flows to Florida spring break destinations) and a difference in differences approach (combined with the SSE IV), for which we scrape information on all similar BLM protest triggers (deadly force used by police against a Black person that received national media coverage) since 2014 to estimate the differential response to a protest trigger before and after the pandemic.

We find robust evidence that exposure to COVID-19 increased BLM protest. This holds for various iterations of our SSE instrument (varying distance, time lag, and cases associated with SSEs) and replicates across the different identification strategies. Specifically, we show that a one standard deviation increase in the number of COVID-19 related deaths in the county at the time of GF's murder (approximately 25 deaths per 100K inhabitants), increases the likelihood of a BLM event occurring in the three weeks following the murder by 5%. This effect doubles in size and only holds for the sub-sample of counties that have never protested for a BLM related cause before the pandemic.

We repeat this analysis now taking as outcomes three different proxies for online activity *before* the murder of Floyd but after the outbreak of the pandemic in the United States (i.e. the first detected case on January 20, 2020). First, we look at the effect of instrumented cumulative COVID-19 related deaths on the number of new twitter accounts, which we obtain by scraping and geo-coding information on the creation date of new twitter accounts at the county level from approximately 45 million tweets. Second, the number of searches for twitter on Google at the county level, hypothesizing that new users will Google the term first to then create an account. Third, Google mobility data on residential stay at the county level, assuming that lower social, work and leisure mobility is associated with more time spent online. We find that the pandemic consistently increased proxies associated with higher online presence and that this effect is stronger for the sub-sample of counties that have never protested before.

In a next step, we regress the predicted number of new users on the presence of BLM events to show that twitter usage is associated with a higher likelihood of BLM events occurring. We also show that this effect is driven by counties that are whiter, more rural and more affluent, confirming the idea that there was a broadening of the coalition beyond "traditional" protesters.

In order to probe the social media mechanism further, we use individual-level survey data. Interpreting these results with caution[6], we find that individuals living in a county with higher COVID-19 deaths, are more likely to receive news about George Floyd through social media than through other channels. We also find, that COVID-19 exposure is associated with larger sympathy for the movement and higher salience of racial injustice among respondents (controlling for race, gender, education, income, education, and political leaning) without changing attitudes towards other progressive issues, such as "illegal" immigration.

Lastly, we consider three alternative explanation for why exposure to COVID-19 could be associated with higher levels of protest beyond the increase in the use of social media. First, the pandemic may have increased overall salience of racial inequality *before* the murder of Floyd. We test this by interacting COVID-19 with a proxy for disproportional death burden on Blacks and the number of BLM related search terms on Google. Second, we investigate whether the pandemic has decreased the opportunity cost of protesting during the pandemic. We interact COVID-19 with the unemployment rate at the county level and stringency at the state level. Third, we look at the effect of COVID-19 on other protests. If the pandemic increased overall agitation and propensity to protest, then we would expect this to also hold for other causes beyond BLM. We show that none of these channels explain the COVID-19 induced rise in protest behavior.

Our analysis contributes to a large literature that analyzes the determinants of social movements and protest, ranging from macro level drivers, such as local institutions or socio-economic conditions (Lipsky, 1968; Eisinger, 1973; McCarthy and Zald, 1977; Besley and Persson, 2011; Dube and Vargas, 2013; Berman et al., 2017) , to micro level drivers, including individual decision making processes (Ellis and Fender, 2011; Guriev and Treisman, 2015; Sangnier and Zylberberg, 2017) and different aspects of individual and social psychology as well as protest as a collective action problem (Guriev and Treisman, 2015; Sangnier and Zylberberg, 2017; Passarelli

[6]The data set does not contain information on the location of the respondent but only whether they live in a low, medium or high COVID-19 county

and Tabellini, 2017; Cantoni et al., 2019; Enikolopov et al., 2020; Manacorda and Tesei, 2020; González and Prem, 2020; Hager et al., 2020; Bursztyn et al., 2021).

This paper also participates in the nascent literature on the effect of the internet on political outcomes (Falck et al., 2014; Lelkes et al., 2017; Boxell et al., 2017; Campante et al., 2018; Guriev et al., 2019) and the effect of social media on xenophobia, polarization, political preferences, social capital and protests more specifically (Acemoglu et al., 2018; Enikolopov et al., 2018; Bursztyn et al., 2019; Enikolopov et al., 2020; Manacorda and Tesei, 2020; Müller and Schwarz, 2020; Zhuravskaya et al., 2020; Müller and Schwarz, 2021; Fujiwara et al., 2021; Campante et al., 2021). For instance, Cantoni et al. (2019) and Bursztyn et al. (2021) show in an experimental setting in Hong-Kong that information about other people's turnout encourages individual protest participation and that this has longer-run effects on the propensity to protest if a sufficiently large fraction of the network is mobilized. They conclude that one-time mobilization shocks can have persistent effects on the dynamics of social movements.

Enikolopov et al. (2020) show that social media helps to solve the collective action problem in a one-shot setting, where the expansion of a social media platform coincides with a contested election in Russia. Similarly, Manacorda and Tesei (2020) exploit the expansion of mobile phone reception in Africa to show that access to information and communication technologies will only increase protest if economic grievances are high and opportunity costs are low (e.g., during economic downturns). In contrast to these papers, we are able to identify for which groups exposure to social media is particularly effective and how it can persuade individuals that are not directly affected by the grievances of the movement.

We tangentially add to the literature on on the causes and consequences of the COVID-19 pandemic (Dave et al., 2020; Borgonovi and Andrieu, 2020; Abouk and Heydari, 2020; Allcott et al., 2020; Bertocchi and Dimico, 2020; Desmet and Wacziarg, 2020; Bazzi et al., 2020; Makridis and Rothwell, 2020; Bursztyn et al., 2020; Bloem and Salemi, 2020; Durante et al., 2020; Lasry et al., 2020; Friedson et al., 2020; Dave et al., 2021; Iacoella et al., 2021) as well as the determinants and characteristics of the BLM movement (Freelon et al., 2016; Anderson and Hitlin, 2016; Tillery, 2019; Mazumder, 2019).

The remainder of the paper is organized as follows. We describe the construction of our data set and data sources in section 2. Section 3 provides a background of the current COVID-19 pandemic and of the BLM movement in the USA as well as some motivating evidence. In section 4, we outline our empirical strategy before reporting our main results on the effect of COVID-19 on BLM in section 5. In section 6, we turn to mechanisms and conclude with section 7.

2 Data Sources

2.1 COVID-19 pandemic

COVID-19 Data on COVID-19 related deaths and cases in the USA at the county level comes from the New York Times. This data set provides the cumulative count of cases and deaths every day for each county in the USA, starting from January 21, 2020 when the first COVID-19 case was reported in the country. A key limitation of COVID-19 cases data is that it depends on the testing facility and availability of the test kits in the region. We therefore mainly rely on COVID-19 related deaths as a measure of exposure to the pandemic. We also obtain data on daily COVID-19 hospitalizations and deaths by race and ethnicity at the state-level from the Center for Disease Control and Prevention.

Super spreader events We collect data on COVID-19 super spreading events from a project started by independent investigators and researchers from London School of Hygiene and Tropical Medicine (Swinkels, 2020). Data are put together based on news reports of super spreader events and so one key limiting factor is that if the event was not identified as a super spreader event in the media, it is not included in the data set. We overcome this limitation by focusing on one popular super spreading event, which is the Florida spring break (described in appendix) for our IV. We assign each event to a county. For the whole period, we identify a total of 1074 super spreader events in the USA. Most commonly, events occur in nursing homes, prisons, factories, and retribution or medical centers. Figure 11 shows the distribution of these events by their type and Table C3 provides descriptive statistics about each type of event. This mainly shows that variation for our identification is not limited to one type of event.

Lockdown Stringency Measures We use data from the Oxford COVID-19 Government Response Tracker (Hale et al., 2020) to measure the restrictiveness of policy under the current pandemic. Use of this data is inspired by recent work which shows that stringent policies lead to lower mortality, mobility and consequently spread of infection during pandemic (Jinjarak et al., 2020; Askitas et al., 2020). This data provides four key indices (i) an overall government response index, (ii) a containment health index, (iii) an economic support index, and (iv) an original stringency index which captures the strictness of lockdown style policies. Each of this index reports values between 1 to 100 and varies across states and weeks.

2.2 BLM movement and other protests

Black Lives Matter protest This data comes from the crowd-sourced platform Elephrame. It provides information on the place and date of each BLM protest and estimated number of participants, as well as a link to a news article covering the protest. We extracted all protests' records from June 2014 to September 2020 and geo-coded their location.

Other protests We add information on non BLM-related protest from the US Crisis Monitor — a joint project between ACLED and the Bridging Divides Initiative (BDI) at Princeton University — that collects real-time data on different types of political violence and protest in the US from Spring 2020 up to date.

Notable Deaths data : We collect data on all notable black deaths that have occurred in the country since 2014. Not every black death at the hands of the police gets media coverage, something which is crucial for generating public discourse and action. We put together details of deaths of all black people in the hands of the local police authorities that got media coverage. Notable deaths are defined as deaths that got covered in a major national daily like the Washington Post or CNN and/or has a dedicated Wikipedia page. Descriptive statistics for these deaths is in table 1.

Use of deadly force by police We obtain this from the collaborative platform Fatal Encounters. They start in 2000 and contain the name, gender, race, and age of each victim and the specific address where the death occurred, among other variables.

2.3 Big Data

Twitter Twitter data is an important source of information when studying social events and protests. Previous work on BLM events has made use of this data into understanding this movement (Ince et al., 2017). We use the Twitter Academic Research API[7] to collect all tweets that contain at least one of the keywords "BLM", "Black Lives Matter", "Black Life Matters" or "George Floyd" with or without space and with or without hashtag excluding retweets, between the 25th of May and the 14th of June and construct our own data-set of tweets. For each tweet we can extract the time and text of the tweet, the user, the user's stated location, followers count, and account creation date. To assign tweets to a geographical location, we look at the location stated by the user in their profile and matched to coordinates using the Open Street Map database and Nominatim geo-coding engine. Not all users state a location and among those who do, not all state a valid location (e.g. "in the heart of Justin Bieber") so we restrict our sample to the users that state a valid location that can be matched to a USA county (in particular, we exclude users whose location only mentions a state). We attribute tweets to counties based on the location indicated on the author's profile, as returned by the Twitter API. For tweets collected after the fact (eg. the tweets mentioning BLM after the murder of George Floyd), this location is the current location indicated by the user, not the location at the time of posting. The location is an arbitrary text field which is not meant to be machine-readable. We use the Nominatim (https://nominatim.org/) geocoding engine to find the coordinates of the most likely match for the location. At this stage, the search is not limited to the US. We subsequently filter out all locations outside the US, and locations that map to a state (otherwise the returned coordinates are in the center of the state). Finally, we map these coordinates to counties using the US Census Bureau cartographic boundary files (https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html). We ended up with 2.76 million tweets.

Google mobility We use data on mobility provided by Google to understand the mechanism of observing protests during pandemics. This data collects information on the time a person spent on certain key mobility tasks like the time spent in parks, being at home, doing groceries, in the transit stations and finally at their workplace (as identified by Google). This information is then aggregated at the county level to measure the aggregate daily mobility.

[7] https://developer.twitter.com/en/products/twitter-api/academic-research

Safe Graph mobility We rely on two datasets provided by the SafeGraph. Both of them are based on anonymized mobile data. The SafeGraph aggregate data from around 45 million smartphones on the level of US Census Block Groups. With the help of the first dataset, Monthly Patterns (MP), we can answer such questions as: who visited each «point of interest», where they came from and where they go. The set of «points of interests» consists of millions of places such as hotels, restaurants, public parks, malls and other establishments. The MP data allows us to observe home locations on the level of the US Census Block Group, which we can use to construct our variable of tourism flows that happened during March, 2020.

2.4 County level data

County Level Controls We include *unemployment* data available on a monthly basis at the county level from the Local Area Unemployment Statistics of the US bureau of Labor Statistics and the total population, population by ethnicity, income statistics (such as Black poverty rate and median household income (all in 2018), as well as past Republican vote share (in 2012 and 2016) from the American Community Survey. Data on *community resilience* comes from the United States Census Bureau. These estimates measure the capacity of individuals and households to absorb, endure, and recover from the health, social, and economic impacts of a disaster such as a hurricane or a pandemic.[8] We use a dummy for *rural* counties which is constructed from the Office of Management and Budget's February 2013 delineation of metropolitan and micropolitan statistical areas.[9] The measure of *social capital* that we use aggregates the information on the number of the following establishments in each county: (a) civic organizations; (b) bowling centers; (c) golf clubs; (d) fitness centers; (e) sports organizations; (f) religious organizations; (g) political organizations; (h) labor organizations; (i) business organizations; and (j) professional organizations.

Survey Data We use data from the American Trends Panel survey conducted by Pew Research center to estimate the link between COVID-19 death rates and change in use of social media and public opinion on racial disparities and BLM movement. We analyse data from wave 68 that took place between June 4th and June 10th, 2020. This data set does not include information on the county of the respondent but only the exposure to COVID-19 (categorized in low, medium and high) in their county of residence at the time of the interview.

[8] https://www.census.gov/data/experimental-data-products/community-resilience-estimates.html For each county the population living under each of 11 risk factors is estimated and these factors are then aggregated into 3 composite risk factors- (i) population with 0 risk factors; (ii) population with 1-2 risk factors and; (iii) population with 3 or more risk factors. These risk factors are based on household and individual's socio-economic and health conditions. For our analysis we look at populations within each county that are classified as living under 1-2 risk factors and 3 or more risk factors.

[9] 2013 NCHS Urban-Rural Classification Scheme for Counties, Vintage 2012 postcensal estimates of the resident U.S. population. NCHS Urbanization levels are designed to be convenient for studying the difference in health across urban and rural ares. This classification has 6 categories: large "center" metropolitan area (*inner cities*), large "fring" metropolitan area (*suburbs*), median metropolitan area, small metropolitan area, micropolitan area and non-core (nonmetropolitan counties that are not in a micropolitan area).

3 Background and Motivating Evidence

The Black Lives Matter (BLM) movement was born on social media after the acquittal of George Zimmerman in the deadly shooting of a Black teenager, named Trayvon Martin. The movement was founded by three Black activists, Alicia Garza, Patrisse Cullors, and Opal Tometi in July of 2013 with the aim to end systemic racism, abolish white supremacy and state-sanctioned violence (Black Lives Matter, 2020), and more generally, to "fundamentally shape whites attitudes toward blacks" (Mazumder, 2019).

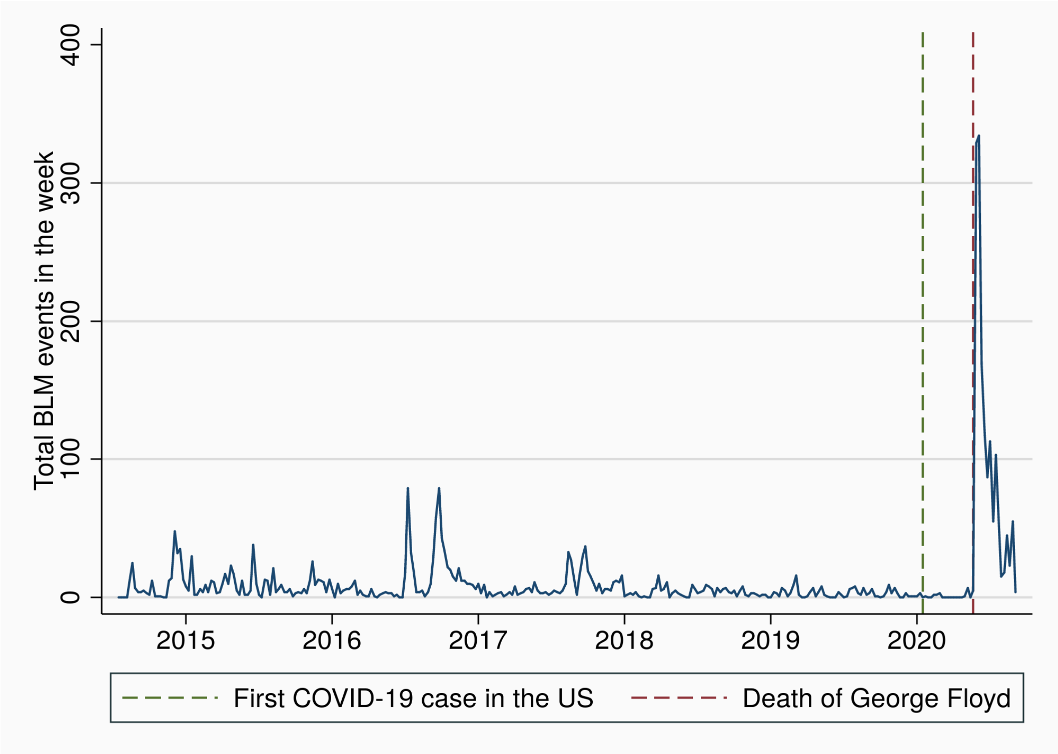
Over the following months, an ever increasing but small number of activists gathered under the hashtag #BlackLivesMatter on Twitter and Facebook. In August of 2014, after a court decision to not indite the responsible police officer in the fatal shooting of Michael Brown in Ferguson, #BLM became one of the most widely used hashtags on twitter (the hashtag was use 1.7 million times in the three weeks following the court decision, as compared to 5000 tweets in all of 2013, see Freelon et al. (2016); Anderson and Hitlin (2016)), manifesting its role as a mainstream social media phenomenon. The shooting of Michael Brown was accompanied by a large wave of protest in the city of Ferguson. The consequences of this shooting rippled through all of American society, generating counter-movements under the hashtag #AllLivesMatter and #BlueLivesMatter and mobilizing protesters (for and against the cause) far beyond the city's borders.

BLM played a crucial role in transforming localized activism into a coordinated movement across various locations within and outside of the United States. The founders state that "[...] when it was time for us to leave, inspired by our friends in Ferguson, organizers from 18 different cities went back home and developed Black Lives Matter chapters in their communities and towns — broadening the political will and movement building reach catalyzed by the #BlackLivesMatter project" (Black Lives Matter, 2020). The *Black Lives Matter Global Network infrastructure* was designed to provide decentralized actors with resources and guidelines to organize protests, receive information about the movement, and coordinate through social media.

In the subsequent years, the BLM movement expanded geographically and demographically, attracting an unprecedented number of participants after the murder of George Floyd in Minneapolis on May 25th 2020. Protesters took to the streets as a video of the murder of George Floyd (GF) went viral on social media, showing how GF suffocated under the choke-hold of police officer Derek Chauvin. The video spurred unrest in Minneapolis but the protests quickly expanded to other parts of the United States, including places that had never engaged in BLM portests before. The number of BLM protest quadrupled in May and June of 2020, compared to previous peaks in 2016 (see Figure 1).

The surge in BLM protests in the spring of 2020 is all the more remarkable as the COVID-19 pandemic was well on its way. At the time of George Floyd's murder almost 100,000 COVID-19 related deaths had been recorded in the United States and the country was just recovering from the first wave of the pandemic (see Figure 2). Tough lockdown and social distancing measures were imposed in many counties to prevent the spread of the pandemic. Average lockdown stringency peaked in the month of May (Hale et al., 2020) and the Center for Disease Control

Figure 1: BLM events over time



and Prevention urged the public to "remain out of congregate settings, avoid mass gatherings, and maintain distance from others when possible" (CDC, 2020).

A key motivating observation for our study is the exceptionally high level of participation in BLM protests after the murder of George Floyd (see Figure 1). While the outbreak of the pandemic and the peak in BLM protest coincided, the surge in protests may still be driven by counties that were less exposed to the pandemic. If we split the sample into above and below median COVID-19 related deaths at the county level and plot the BLM protest in 2020 in the left panel of Figure 3, we also find a geographical link between exposure to COVID-19 and BLM protest. In the right panel of Figure 3, we plot the evolution of tweets that mention *both* BLM and COVID-19 in the *same* tweet. Using the same tweet makes sure that users are not only tweeting about BLM and COVID-19 separately but specifically connect the two topics in their activism. Using an algorithm that assign tweets to geographic locations, we are able to assign these tweets to counties that experience above and below median COVID-19 related deaths. We find that locations that were more affected by COVID-19 increase their online protest activity and also connect the BLM activism with the pandemic. These descriptive plots suggest that - despite the fear of contagion and the stringency of social distancing measures - there is both a temporal and a geographical relationship between COVID-19 intensity and occurrence of BLM protests.

Lastly, we find that - in line with public perception - the BLM movement has broadened in scope. We divide the counties based on counties that always protest for BLM and those that protested for the first time after GF's murder. Figure 4 plots counties that had at least one BLM

Figure 2: COVID-19 (left: cumulative deaths, right: new deaths) and timing of GF's murder

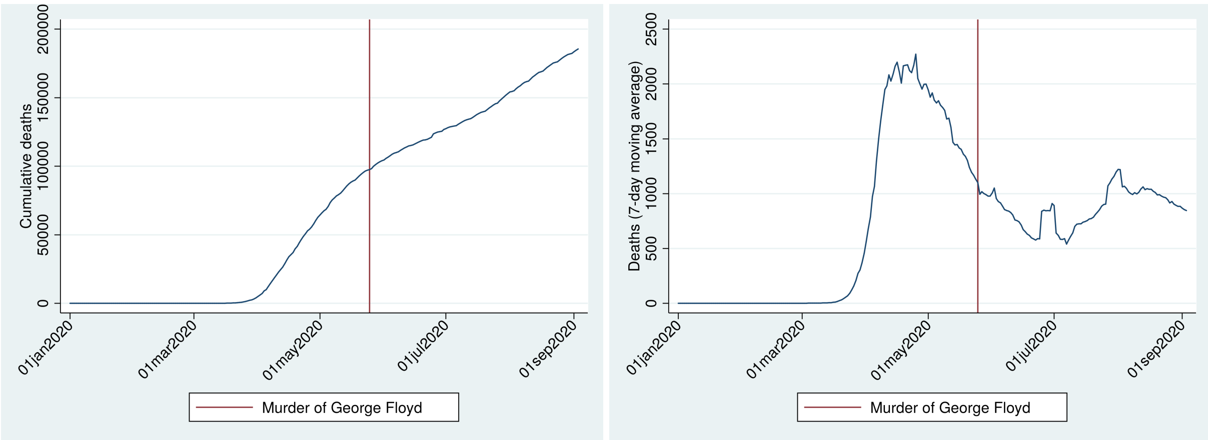
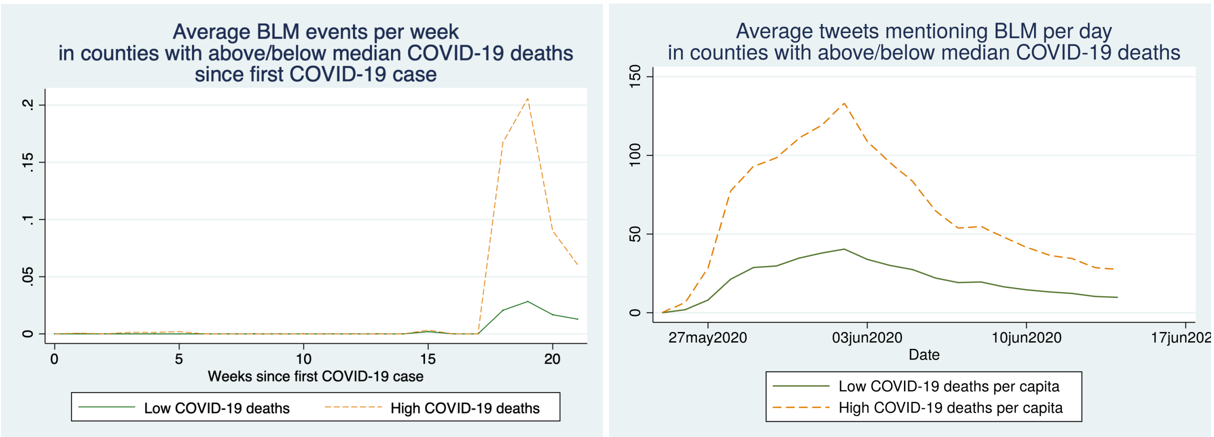


Figure 3: BLM events (left: protests, right: tweets) in counties with above and below median COVID-19 deaths per-capita

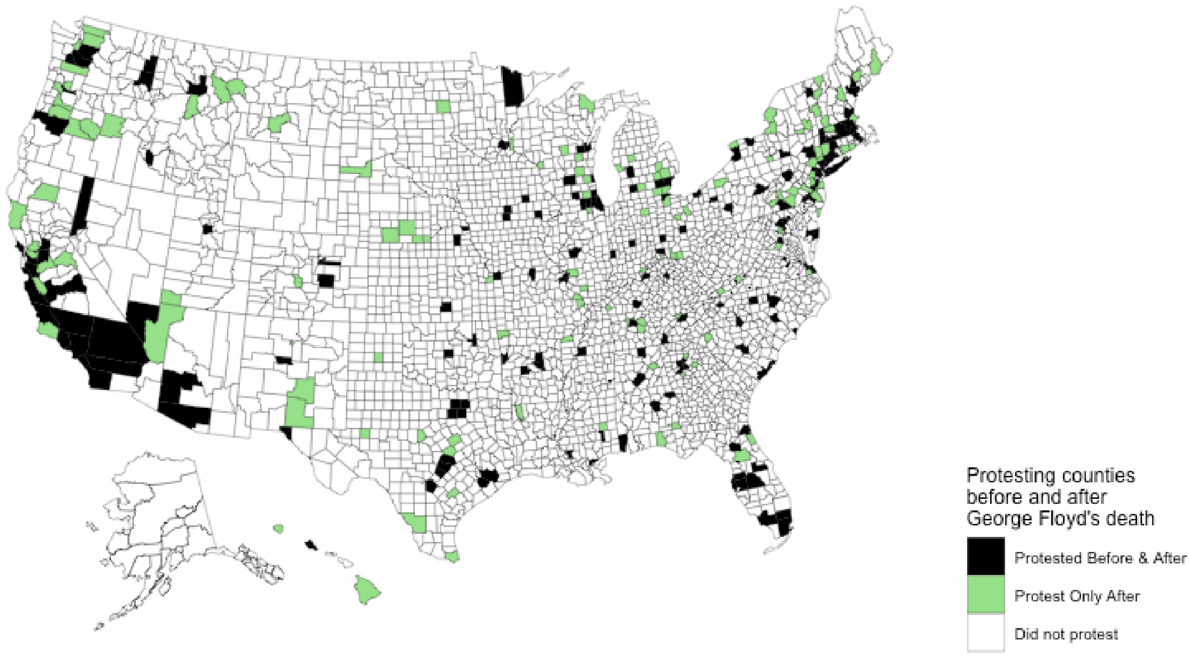


protest pre-pandemic and also protested after GF's death in black. Counties that recorded their first BLM protest only after GF's murder are shown in green. Indeed, we see that the geographic spread of first time protesters does not follow the typical coastal geographic clusters and are spreading across all of the United States.

We report detailed summary statistics for the different sub-samples in Table C2. We show four sub-samples. Those that have never protested for a BLM related cause before the pandemic and do not protest after (the vast majority of 2.636 counties, which is approximately 85% of all counties); those that protest for the first time after the pandemic (N=132) and those that are "traditional" protesters and stop protesting (N=163) and those that continue to protest (N=177). Overall, the first time protesters make up nearly 50 percent of all counties that protested during the pandemic.

In sum, this motivating evidence delivers three takeaways. First, the BLM movement has gained unprecedented scope during the pandemic. Second, there is a geographic link between COVID-19 exposure and online and offline BLM protest. Third, a meaningful proportion of protesters in 2020 come from counties that have never protested for a BLM related cause before.

Figure 4: Spatial distribution of US counties based on their BLM protest activities before and after George Floyd's death



We use these observations to guide our empirical analysis. We start by establishing a credible causal link between COVID-19 exposure and BLM protest, distinguishing between new allies and traditional protesters. Then, we move to the mechanisms to show that among these new allies, we also observe a pandemic induced increase in the use of social media. We then probe the validity of the social media channel by looking at survey data and ruling out alternative explanations.

4 Empirical Strategy

4.1 Baseline Estimating Equation

To study the effect of exposure to COVID-19 on BLM, we estimate

$$BLM_c = \beta_0 + \beta_1 Covid_{cs} + \mathbf{X}_c \beta_{\mathbf{X}} + \delta_s + \epsilon_{cs} \quad (1)$$

where Y is a dummy variable for the presence of a BLM protest in county c during the three weeks following the murder of George Floyd.[10] We are interested in the coefficient β_1, which

[10] We restrict the sample for our main outcome of interest to the three weeks after the death of George Floyd, that is the period from May 25th to June 14th for several reasons: we can capture a large share of the protest behavior (66 percent of BLM protests following GF's murder can be observed in this three week window) while limiting potential confounding factors to arise. Our results hold when we extend this window to a six or eight weeks window (see Table A3)

captures the effect of one additional COVID-19 related case per 1000 inhabitants in county c of state s at the time of George Floyd's murder on May 25th 2020. In addition to state fixed effects δ_s, the vector $\mathbf{X}_c$ includes an array of county level controls (we describe all these variables in detail in Table 1). Specifically, we include variables that are associated with the participation in the BLM movement, such as a dummy for urban counties and Black population share as well as poverty rate among Blacks. Most importantly, we also include two major determinants of BLM protest after the murder of George Floyd, namely the number of BLM events before the murder (starting 2014) and the use of deadly force by police (i.e. number of Black people that died during an encounter with the police, excluding suicides, for two time periods: from summer 2014 to 2019 and in 2020 until May 25th). We also control for underlying political and attitudinal factors and socio-economic drivers of protest and social media use, such as the vote share for Republicans in the 2012 and 2016 presidential elections, median hh income, unemployment rate, community resilience, as well as two proxies for social capital (number of civil organizations and number of religious organizations). We cluster standard erros at the state level.

4.2 IV Estimation: Super Spreader Events

A key empirical challenge in ascertaining the causal impact of exposure to COVID-19 on BLM protests is that both occurrences could be driven by third (unobserved) factors. For instance, tight-knit and socially active communities may both increase the spread of the virus and protest more for a BLM related cause. Alternatively, counties that are in favor of lax social distancing rules (and thus more aligned with the president's views at the time) are less likely to engage in BLM protests. Additionally, we may be concerned that BLM protests themselves could spur the onset of COVID-19 infections. While we can assuage the latter concern by measuring COVID-19 exposure at baseline (e.g. before the murder of George Floyd and the onset of BLM protests), we address the former concern with an instrumental variable approach.

We exploit plausibly exogenous variation in the occurrence of Super Spreader Events (SSEs) to causally identify the effect COVID-19 on BLM protest at the county level. Specifically, we construct the IV as the sum of all SSEs that occur within 50 km of the county border but not within the county until 6 weeks before the murder of George Floyd. We show the geographic spread of our instrument in Figure 8. The first stage is written as:

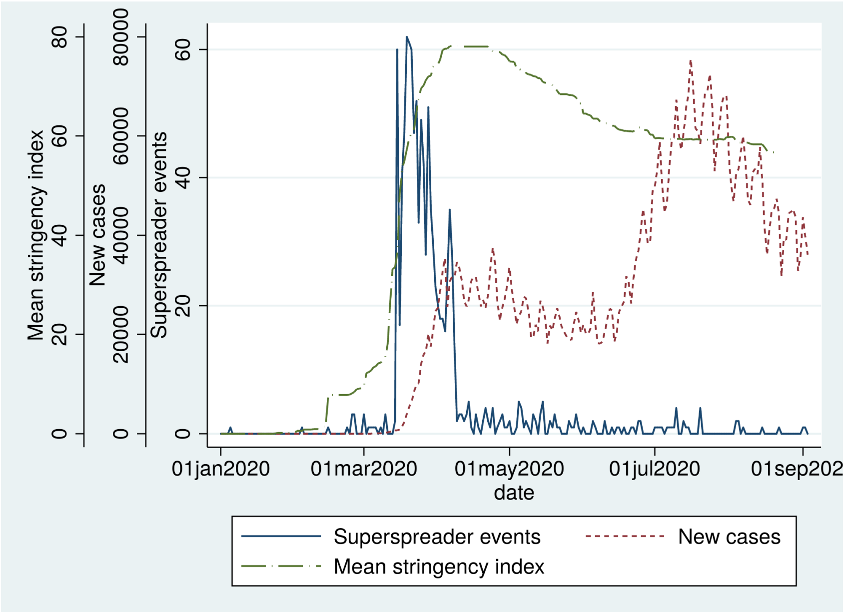
$$Covid_c = \zeta_0 + \zeta_1 Z_{cs} + \mathbf{X}_{cs}\zeta_{\mathbf{X}} + \gamma_c + \eta_{cs}, \tag{2}$$

$$Z_c = \sum_{m=1}^{t-6} SSE_{csm}^{neighbor} \tag{3}$$

4.2.1 Identifying assumption and instrument validity

The key identifying assumption of this instrument is that - given the set of controls - SSEs only affect BLM protest through an increase in exposure to COVID-19. We exploit three features of our IV to argue for the validity of the exclusion restriction: i) epidemiological features of super

Figure 5: Evolution of Super-Spreader Events, average state-level stringency and number of new COVID-19 cases (daily)



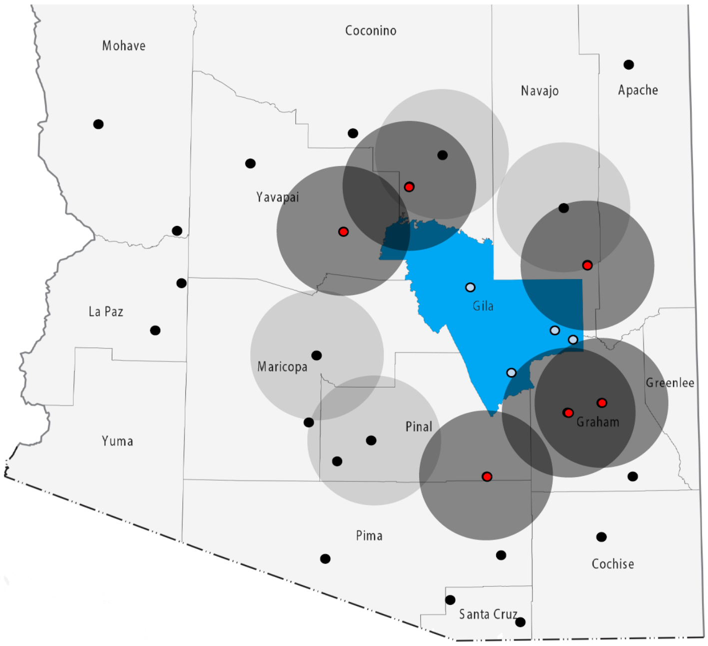
spreader events, *ii*) the temporal feature, e.g. the short window of opportunity for SSEs to arise , and *iii*) exposure to SSEs *outside* of the county.

Super Spreader Events are defined as the presence of a highly infectious person (a super spreader) in a context where they can infect a large number of people. Super-spreaders are individuals who are an order of magnitude more contagious than others. This phenomenon, well-known in epidemiology, is instrumental in infectious disease spread (e.g. Galvani and May (2005)) and of particular importance for COVID-19, where 70–80% of transmissions can be traced back to just 10–20% of cases (Adam et al., 2020; Endo et al., 2020; Miller et al., 2020). It is important to note that these events do not have to be large gatherings or mass events. The majority of the approximately 1000 SSEs in our data[11] take place in prisons, nursing homes, and at birthday parties. SSE are qualified by the presence of a highly infectious individual. The size of the event is only relevant in as much as it increases the likelihood of a super-spreading individual being present. Therefore, not all mass gatherings are SSEs and not all SSEs are mass gatherings. This is relevant for the exclusion restriction as far as it alleviates concerns about SSEs being a proxy for a county's propensity to organize large public events, including BLM events. In fact, the overwhelming majority of SSEs is recorded – as expected – in the medical care sector (see Figure 11).

Next, we illustrate in Figure 5 that the overwhelming majority of SSEs (solid blue line) occurred between the second week of March and the last week of April. This time-period presented a window of opportunity for SSEs to arise for two main reasons. First, the infectious

[11] Data recorded by scientists from the London School of Hygiene and Tropical Medicine

Figure 6: exemplary case for the construction of the super-spreading events instrument



environment was prevalent enough to bring forth a significant amount super-spreader individuals. Second, lock-down measures were not yet stringent enough (in addition to the lack of public awareness) to restrict group gatherings and encourage mask-wearing. The red dotted line of Figure 5 shows that the increase in the number of new COVID-19 cases coincided with the increase in SSEs. The green dashed line illustrates that state-issued stringency measures (as measured by the stringency index from the Oxford COVID-19 Government Response Tracker) peaked around the time that SSEs leveled off. We argue that during this time window, the occurrence of SSEs was mainly driven by the presence of a highly infectious person, rather than heterogeneity in risk preferences or other underlying factors that could drive both SSEs and BLM protest. We only include SSEs until April 13th 2020 - 6 weeks prior to Geroge Floyd's murder, to account for the fact that SSEs further into the pandemic may be more endogenous.

Lastly, we improve on the plausibility of the exclusion restriction by exploiting SSEs *outside* of the county but not within the county. Specifically, we use the number of SSEs within a 50km (or approximately 30 mile) radius from the county border in which we measure exposure to COVID-19 and BLM. We illustrate the construction of our instrument in Figure 6 using the example of Arizona. To create this instrument, we rely on the geo-location information of the super spreader events and county borders. We indicate as red dots the relevant SSEs used for our IV in this illustrating case. We first draw a circle from the location of each super spreader event and then use the SSEs whose circle intersects with the county boundary to instrument COVID-19 deaths. We argue that SSEs in geographic proximity but not in the county itself are even less likely to affect BLM events in the county other than through COVID-19 exposure.

In Figures 7 and 8 we show the geographical distribution of our instrument across US counties. In Figure 7, we show the number of SSEs 6 weeks prior at the county level. In Figure 8, we show the identifying variation of our instrument, e.g. the number of SSEs in 50 km proximity to the county border until April 13th.

4.2.2 First stage results and instrument robustness

Column 1 of Table A1 shows the first stage for our preferred specification were the instrument is the cumulative number of Super Spreader Events (SSE) in neighbouring counties within a 50km radius up until 6 weeks prior to the murder of George Floyd. An increase of one SSE increases the number of COVID-19 deaths by 0.9 per 100 000 population .

We further probe the validity of our instrument in the following columns of Table A1 with three robustness checks. First, we increase the distance to the county border to 200 km (column 2). As expected, the coefficient increases in size and the first stage becomes weaker as SSEs become less relevant for the infection trajectory of the county with distance. Second, we use the cases associated with SSEs instead of the number of SSEs (column 3) and the results hold. Lastly, we use various lags between four and eight weeks (instead of six weeks) prior to the murder of George Floyd (columns 4 to 7) and our results hold. As expected, the estimates increase in size as the lag become longer. Earlier SSE had more time to unfold their effect on COVID-19 related deaths.

Figure 7: Spread of actual SSE by counties 6 weeks prior to George Floyd's murder

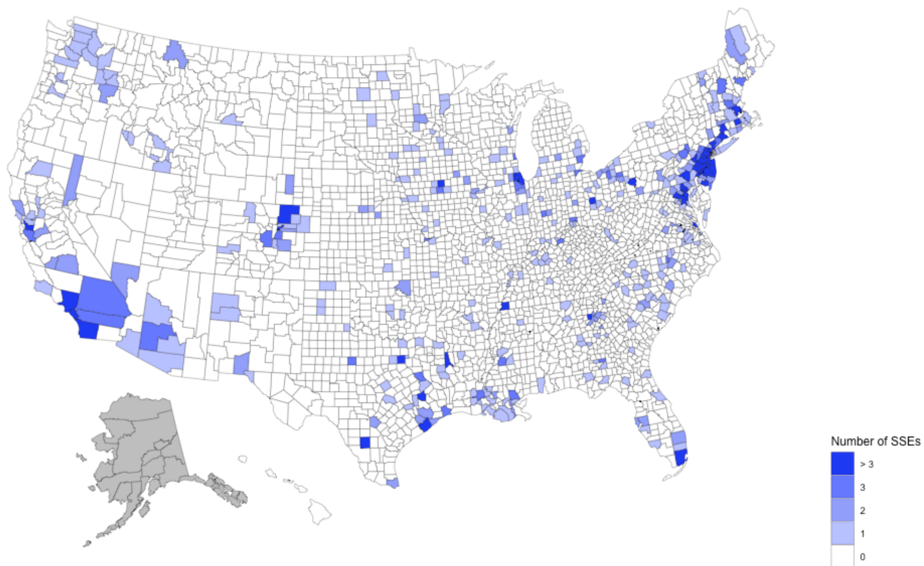
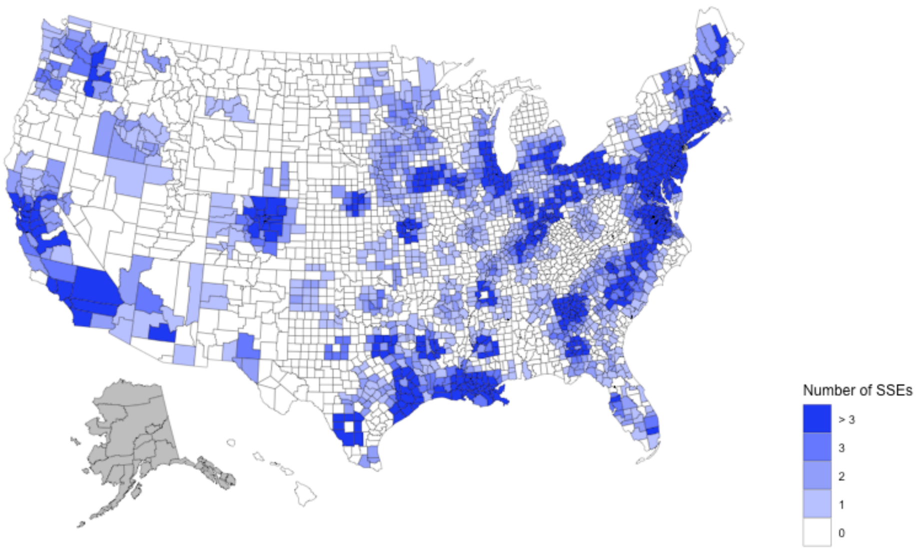


Figure 8: Variation across counties of our instrument capturing SSE within 50 kms radius of the county but excluding SSE within the county



5 Main Results

In this section, we present the results for exposure to COVID-19 and BLM protest and show whether this mobilization is in fact due to new allies joining the movement. Additionally, we provide an array of robustness checks and two alternative identification strategies.

5.1 COVID-19 and BLM

We present our main results in Table 2, showing 2SLS and OLS results for all counties, new allies and traditional protesters in panels A, B, and C respectively.[12] We successively introduce control variables, starting with our basic controls, e.g. unemployment (just before the murder of GF) and use of deadly force by police, as well as state fixed effects. We then introduce a large set of controls, most importantly past BLM events, which capture the overall propensity of BLM protest to occur, including all its underlying determinants. Interestingly, the coefficient halves when we include two indicators that capture the county's vulnerability to the pandemic: high risk factor (an indicator that measures how well prepared counties are to dampen the consequences of a health crisis, including health infrastructure, health coverage and pre-conditions) and median household income, which is an indicator for the non-institutional, individual-level economic resource counties have to deal with the pandemic.

Our preferred specification is presented in column 7 and includes the whole set of controls.

[12]We present in Appendix Table A2 the reduced form regression with the presence of BLM events as outcome.

We find that one additional death per 10 000 population increases the likelihood of at least one BLM event occurring in the three weeks following the death of George Floyd by between 2 and 6 percentage points (p.p.) depending on the specification. An increase of one standard deviation in the number of deaths per thousand increase the likelihood of at least one BLM event occurring by between 5 and 14 p.p. This magnitude is nearly doubled for the sub-sample that had never experienced a BLM protest before.

Throughout all of our estimations (including the robustness checks following in the next section) the IV estimates exhibit larger coefficient compared to the OLS. In the absence of exogenous variation in changes to the COVID-19 infectious environment, the OLS underestimates the role of COVID-19 as a trigger for BLM protests. The bias in the OLS could stem from unobserved within state county-level determinants that drive both BLM protest and lower levels of COVID-19 exposure.[13] This could be due - for instance - to underlying attitudes that disapprove of the Trump administration (beyond those that are captured in the past Republican vote shares and the inclusion of state fixed effects). For instance, more progressive counties, such as Travis county (capital Austin Texas) could be more favorable towards the BLM movement and at the same time more cautious vis a vis the pandemic outbreak and adhere to stricter social distancing rules than Montgomery, Texas. Using mobile phone mobility data, we find that counties that protested for BLM after the murder of George Floyd also decrease their workplace and leisure mobility, while increasing residential stay. This is in line with Dave et al. (2020) that show that BLM protesters adhere more to social distancing measures.

5.2 Robustness Checks

Table A3 in appendix shows the results of the robustness checks. Column 1 shows our baseline result as a comparison. In column 2 we vary the maximum distance were a SSE is expected to have an impact from 50km to 200km. In column 3 we use the number of cases associated to a SSE instead of the number of events. In columns 4 to 7 we change the lag up until which we stop counting the SSE. In column 8 we present estimates without clustering. In column 9 we use the number of COVID-19 cases instead of deaths as the explanatory variable. All the estimates remain positive and significant and in general, the magnitudes vary only marginally. In Table A4 we present additional robustness checks. Again, we present the baseline coefficient in column 1, for reference. In columns 2 and 3, we extend the time window after the murder of George Floyd to 6 and 8 weeks, respectively. Importantly, in column 4, we show that exposure to COVID-19 does not predict past BLM events between 2014 and 2019. This is important, since it validates the the plausibility of the exclusion restriction. If SSEs in neighboring were correlated with unobservables that also determine BLM protest, we should also see an effect on past BLM events. Lastly, we include the number of prisons as a control variable since a significant share of SSEs happen in prisons and it may the case that these are less relevant for our proposed mechanism. Again, our results remain robust to the various changes and iterations.

[13] Since the treatment (exposure to COVID) is measured before the protest trigger, reverse causality is not the driver behind the difference in magnitude.

5.3 Alternative Identification Strategies

We complement our preferred estimation strategy in two ways: i) we design an alternative instrument ii) we exploit the panel dimension of our data set to estimate an instrumented Differences in Differences model. We give a brief summary of the approaches here and describe the respective strategies in more detail in Appendix B. All of these approaches confirm the baseline results.

Alternative Instrument: Florida Spring Break

Instead of collecting information on multiple independent SSEs as in the previous section, we now focus on one single, large-scale event that is known to have contributed substantially to the spread of COVID-19, namely the Florida Spring Break in March of 2020 (Mangrum and Niekamp, 2020). We use *SafeGraph* mobile phone data with over 45 million data entries to identify spring break tourists and their home counties and calculate the share of devices that were present at one of the main spring break beaches in March of 2020 relative to all devices of the origin county. As expected, the first stage for this instrument (reported in Table B1 is below the conventional threshold, when we include the full set of controls the F-Stats become weak but the results qualitatively hold.

Difference in Differences: Notable Deaths Sample

We expand our data set and include BLM events at the county-week level starting in 2014. We scrape information on all police related deaths of Blacks since July 2014 that were covered in a major national newspaper like the Washington Post, that received TV coverage by CNN and/or have a dedicated Wikipedia page. We include county and state-week fixed effects to account for all time-invariant county level heterogeneity and common time varying characteristics at the state level. We interact these "Notable Deaths" (time variation) with the instrumented exposure to COVID-19 (county variation). In this instrumented Difference in Differences Approach, we exploit differences in protest behavior following a "notable" death in the presence and absence of COVID-19. We show the results in Table B2 and we find a sufficiently strong first stage and a strongly significant effect consistent with our baseline results.

6 Mechanisms

In this section, we investigate the drivers behind the COVID-19 induced increase in BLM protest. We first present our results for social media activity among those new protesters before the murder of George Floyd. Then, we combine the two analysis by using the predicted new twitter accounts in a county to see whether these are associated with a higher protest participation among new allies. We probe this mechanism further by analyzing individual-level survey data on news consumption and attitudes towards BLM before ruling out alternative explanations in the last subsection.

6.1 COVID-19 and the Use of Social Media

So far, we have shown that exposure to the COVID-19 pandemic increased BLM protest. A key hypothesis that we test in this section is that this increased activity is due to increased use of to social media during the pandemic. We first establish the direct link between exposure to COVID-19 pandemic (using SSEs as a source of exogenous variation) and the use of social media. To show this link we test if COVID-19 exposure increased creation of (i) new Twitter accounts; (ii) Google searches for Twitter; and (iii) residential stay. In Table 3, we again show results for the full sample (Panel A), new allies (Panel B) and traditional protesters (Panel C).

We find that increased exposure to the pandemic had no effect on new twitter accounts created until May 24 (just before George Floyd's murder) for the full sample, or the sample of traditional protesters but is large and significantly positive for the sub-sample of new allies. In order to find an additional proxy for the use of twitter, we use the search term Twitter on Google in the month before the murder of George Floyd, hypothesizing that interest in twitter on Google is associated with the subsequent creation of twitter accounts. We find that - again - search terms only significantly increased among new allies. Lastly, we show residential stay, using Google mobility data at the county level in the month leading up to George Floyd's murder and find that for all samples there has been an increase in residential stay - and more so among new allies. We assume that higher residential stay is likely associated with higher online activity.

Additionally, we link the increased use of social media to BLM protest more directly. To do this we predict new Twitter accounts from our IV regression shown in Table 3 column 1 for counties that had never experienced BLM protest. Using the predicted value, we estimate its effect of likelihood of a BLM protest after George Floyd's murder. Table 4 column 1 shows the result for these counties. We find that predicted new Twitter accounts created just 3 weeks prior to George Floyd's murder explain up to 0.02 percentage point increase in BLM protest in counties that had never experienced a BLM protest.

We then move on to the characteristics of the new allies that have been mobilized online. Columns 2 to 5 explore the heterogeneous effect of predicted new Twitter accounts in explaining the likelihood of BLM protest. We find that the likelihood of BLM protest significantly increases in the presence of predicted new Twitter account if the county has a higher share of non-Black population, White population, is not in a large city, and has above average household income. One explanation for this effect heterogeneity could be that those counties become new allies precisely because they have been less aware of or exposed to racial injustice before the pandemic. The increase in the use of social media, particularly twitter, and accompanying increase in exposure to BLM related content may have shifted those counties to take to the streets for the first time during the pandemic.

6.2 COVID-19, News Consumption and Attitudes towards BLM

In this sub-section we probe the social media mechanisms further by exploiting individual-level survey data. We ask whether exposure to COVID-19 at the individual level caused a shift in news consumption away from traditional media towards social media. We then investigate whether this shift is accompanied by a change in attitudes towards Blacks and the Black Lives Matter movement more generally. It is important to note, that a causal interpretation of these results not possible as we do not have information on the precise location of the respondent; we only have information on the severity of exposure to COVID-19 at their county of residence, at the time of the interview in June 2020. However, the rich set of individual-level controls and placebo checks assuage concerns about omitted variable bias. We use survey data from the Pew research center to conduct individual-level multivariate regressions on different outcomes, controlling for various characteristics of the respondent: race, whether or not they live in a metropolitan area, gender, age, education, income and whether or not they lean towards the democratic party. Table 5 shows the results. Column 1 - 3 investigate the intensity and form of news consumption in the context of George Floyd's murder. Higher levels of COVID-19 are positively and significantly associated with more news consumption about George Floyd and more social media news consumption about George Floyd. In column 3, we show that individuals in counties with higher COVID-19 exposure also consume relative more news about Geroge Floyd on social media, confirming a change in the information set - or at least their source.

Then, we analyze whether this change in mode of news consumption is accompanied by a change in attitudes. In column 4, we find that individuals are more likely to report that higher hospitalization rates of Blacks during the pandemic is caused by circumstances beyond their control, rather than personal choices or lifestyle. Respondents are also more likely to agree with the statement that the BLM protest arises because of structural racism and not as an excuse for criminal behavior. In order to rule out that exposure to COVID-19 in the earlier stages of the pandemic is just a proxy for more progressive leaning counties, we use an additional question that deals with an unrelated progressive issue: legal status for undocumented immigrants. Individuals living in counties with higher exposure to COVID-19 are not more likely to grant more rights to undocumented immigrants, alleviating some of concern on unobserved heterogeneity.

6.3 Alternative mechanisms

We have established that social media use instigated by the COVID-19 pandemic broadened the coalition for BLM movement by bringing in new allies. These new allies were more likely to be non-Black, rural and affluent. In Table 6, we now look at whether there are other mechanisms through which the pandemic could have influenced BLM protests, focusing on the sub-sample of new allies. We show equivalent results for the full sample in Appendix Table C5.

The first alternative mechanism we test is a rise in the salience of racial inequality due to the pandemic itself and not through exposure to BLM related content online. For instance, an a-priori indiscriminate virus should affect Whites and Blacks equally but if racial disparities in death rates arise, then people may be more inclined to believe in systemic disadvantages for the Black community. We therefore hypothesize that counties facing higher proportion of Black deaths due to COVID-19 are more likely to protest after the trigger of George Floyd's death. Column 1 of Table 6 shows that counties in the presence of COVID-19 are not more likely to protest due to increased death burden of Blacks. Additionally, we check whether new allies showed more interest in BLM related issues *before* the murder of George Floyd. We test this in column 2, using BLM search terms on Google in the month leading up to George Floyd's murder. We do not find that interest in racial injustice increased before the protest trigger.

The next channel that we test is the opportunity cost channel. It is possible that new allies joined the movement, particularly more affluent and white counties, because they had a lower opportunity cost of protesting during the pandemic. We proxy lower opportunity costs in two ways: first, economic opportunity costs using the unemployment rate before the protest trigger and second, social opportunity costs, e.g. stringency of social distancing measures at the state level. Columns 3 and 4 of Table 6 show the result for this channel. We find that counties experiencing higher unemployment or have stricter lock-down measures are not more likely to protest.

Lastly, we investigate whether COVID-19 has generally increased agitation in the public space. It is possible that these new allies just protest more in general and not because they have been exposed to new content and messaging online. We therefore look at the effect on other protests, using ACLED protest data. We exclude BLM-related protests from this data set and expand the observation period to 3 months post George Floyd to make sure, we do not capture a substitution effect between BLM protest and other protests right after the BLM protest trigger. We report the results in column 5 and do not find an effect of COVID-19 on other protests.

7 Conclusion

Social protests are an important tool to bring about social change and hold politicians and institutions accountable. In this paper, we investigate why the Black Lives Matter Movement became one of largest and broadest civil rights movements in US history and how it was able to build a broad coalition during the pandemic.

We exploit the recent pandemic as a shock to the underlying determinants of social protest, which in turn spark different responses to an unexpected protest trigger - the murder of George Floyds at the hands of Derek Chauvin. Using two novel instrumental variables and a difference in differences approach, we provide causal evidence for an increase in online and offline protest due to exposure to COVID-19. We find that the pandemic mobilized new allies to join the movement. Specifically, more rural counties and counties with a higher median income and higher non-Black population share - all factors that were not associated with BLM protest participation before the pandemic - start to protest for the first time after the murder of George Floyd.

We show that a key mobilizing factor was an increase in the use of social media during the pandemic. Counties that had never protested before the pandemic experienced an increase in twitter penetration and overall online activity during the pandemic. We support these results with survey evidence and rule out competing mechanisms.

Our research highlights the importance of social media presence of social movements. Changes in access to social media may increase political mobilization for those at the margin. However, our research also ties into the potential drivers of an increasing political polarization in the

United States If this effect is symmetric across the ideological spectrum, we may expect similar forms of political (and conspiratorial) mobilization in response to other protest triggers, as the attack on the capitol on January 6th 2021 illustrates.

References

Abouk, R. and B. Heydari (2020). The immediate effect of covid-19 policies on social-distancing behavior in the united states. Public Health Reports, 0033354920976575.

Acemoglu, D., T. A. Hassan, and A. Tahoun (2018). The power of the street: Evidence from egypt's arab spring. The Review of Financial Studies 31(1), 1–42.

Adam, D., P. Wu, J. Wong, E. Lau, T. Tsang, S. Cauchemez, G. Leung, and B. Cowling (2020). Clustering and superspreading potential of severe acute respiratory syndrome coronavirus 2 (sars-cov-2) infections in hong kong.

Allcott, H., L. Boxell, J. C. Conway, B. A. Ferguson, M. Gentzkow, and B. Goldman (2020, October). What explains temporal and geographic variation in the early us coronavirus pandemic? Working Paper 27965, National Bureau of Economic Research.

Anderson, M. and P. Hitlin (2016). The hashtag# blacklivesmatter emerges: Social activism on twitter. Pew Research Center 15.

Askitas, N., K. Tatsiramos, and B. Verheyden (2020). Lockdown strategies, mobility patterns and covid-19. arXiv preprint arXiv:2006.00531.

Bazzi, S., M. Fiszbein, and M. Gebresilasse (2020, September). Rugged individualism and collective (in)action during the covid-19 pandemic. Working Paper 27776, National Bureau of Economic Research.

Berman, N., M. Couttenier, D. Rohner, and M. Thoenig (2017, June). This Mine Is Mine! How Minerals Fuel Conflicts in Africa. American Economic Review 107(6), 1564–1610.

Bertocchi, G. and A. Dimico (2020). Covid-19, race, and redlining.

Besley, T. and T. Persson (2011). The logic of political violence. The quarterly journal of economics 126(3), 1411–1445.

Black Lives Matter (2020). Home - black lives matter. https://blacklivesmatter.com/. Accessed: 2020-10-31.

Bloem, J. R. and C. Salemi (2020). Covid-19 and conflict.

Borgonovi, F. and E. Andrieu (2020). Bowling together by bowling alone: Social capital and covid-19. Covid Economics 17, 73–96.

Boxell, L., M. Gentzkow, and J. M. Shapiro (2017). Greater internet use is not associated with faster growth in political polarization among us demographic groups. Proceedings of the National Academy of Sciences 114(40), 10612–10617.

Bursztyn, L., D. Cantoni, D. Y. Yang, N. Yuchtman, and Y. J. Zhang (2021). Persistent political engagement: Social interactions and the dynamics of protest movements. American Economic Review: Insights 3(2), 233–50.

Bursztyn, L., G. Egorov, R. Enikolopov, and M. Petrova (2019). Social media and xenophobia: evidence from russia. Technical report, National Bureau of Economic Research.

Bursztyn, L., A. Rao, C. Roth, and D. Yanagizawa-Drott (2020). Misinformation during a pandemic. University of Chicago, Becker Friedman Institute for Economics Working Paper (2020-44).

Campante, F., R. Durante, and F. Sobbrio (2018). Politics 2.0: The multifaceted effect of broadband internet on political participation. Journal of the European Economic Association 16(4), 1094–1136.

Campante, F. R., R. Durante, and A. Tesei (2021, September). Media and social capital. Working Paper 29230, National Bureau of Economic Research.

Cantoni, D., D. Y. Yang, N. Yuchtman, and Y. J. Zhang (2019, May). Protests as Strategic Games: Experimental Evidence from Hong Kong's Anti-Authoritarian Movement. Quarterly Journal of Economics 134(2).

CDC (2020, March). Risk Assessment and Management. Technical report, Centers for Disease Control and Prevention.

Dave, D. M., A. I. Friedson, K. Matsuzawa, J. J. Sabia, and S. Safford (2020). Black Lives Matter Protests, Social Distancing, and COVID-19. Technical report, National Bureau of Economic Research.

Dave, D. M., D. McNichols, and J. J. Sabia (2021). Political violence, risk aversion, and non-localized disease spread: Evidence from the us capitol riot. Technical report, National Bureau of Economic Research.

Della Porta, D. and M. Diani (2015). The Oxford handbook of social movements. Oxford University Press.

Della Porta, D. and M. Diani (2020). Social movements: An introduction. John Wiley & Sons.

Desmet, K. and R. Wacziarg (2020, June). Understanding spatial variation in covid-19 across the united states. Working Paper 27329, National Bureau of Economic Research.

Dube, O. and J. F. Vargas (2013). Commodity price shocks and civil conflict: Evidence from colombia. The review of economic studies 80(4), 1384–1421.

Durante, R., G. Gulino, et al. (2020). Asocial capital: Civic culture and social distancing during covid-19.

Eisinger, P. K. (1973). The conditions of protest behavior in american cities. The American Political Science Review 67(1), 11–28.

Ellis, C. and J. Fender (2011). Information cascades and revolutionary regime transitions. Economic Journal 121(553), 763–792.

Endo, A., S. Abbott, A. J. Kucharski, S. Funk, et al. (2020). Estimating the overdispersion in covid-19 transmission using outbreak sizes outside china. Wellcome Open Research 5(67), 67.

Enikolopov, R., A. Makarin, and M. Petrova (2020). Social media and protest participation: Evidence from russia. Econometrica 88(4), 1479–1514.

Enikolopov, R., M. Petrova, and K. Sonin (2018). Social media and corruption. American Economic Journal: Applied Economics 10(1), 150–74.

Falck, O., R. Gold, and S. Heblich (2014). E-lections: Voting behavior and the internet. American Economic Review 104(7), 2238–65.

Freelon, D., C. McIlwain, and M. Clark (2016). Beyond the hashtags: #Ferguson, #Blacklivesmatter, and the online struggle for offline justice. Technical report, Center for Media & Social Impact.

Friedson, A. I., D. McNichols, J. J. Sabia, and D. Dave (2020). Did california's shelter-in-place order work? early coronavirus-related public health effects. Technical report, National Bureau of Economic Research.

Fujiwara, T., K. Müller, and C. Schwarz (2021). The effect of social media on elections: Evidence from the united states. Technical report, National Bureau of Economic Research.

Galvani, A. P. and R. M. May (2005). Dimensions of superspreading. Nature 438(7066), 293–295.

González, F. and M. Prem (2020). Police repression and protest behavior: Evidence from student protests in chile. Available at SSRN 3705486.

Guriev, S., N. Melnikov, and E. Zhuravskaya (2019). 3g internet and confidence in government. Available at SSRN 3456747.

Guriev, S. and D. Treisman (2015). How modern dictators survive: an informational theory of the new authoritarianism. Technical report, National Bureau of Economic Research.

Hager, A., L. Hensel, J. Hermle, and C. Roth (2020). Political activists as free-riders: Evidence from a natural field experiment.

Hale, T., S. Webster, A. Petherick, T. Phillips, and B. Kira (2020). Oxford covid-19 government response tracker. Blavatnik School of Government 25.

Iacoella, F., P. Justino, B. Martorano, et al. (2021). Do pandemics lead to rebellion? policy responses to covid-19, inequality, and protests in the usa. Technical report.

Ince, J., F. Rojas, and C. A. Davis (2017). The social media response to black lives matter: how twitter users interact with black lives matter through hashtag use. Ethnic and racial studies 40(11), 1814–1830.

Jinjarak, Y., R. Ahmed, S. Nair-Desai, W. Xin, and J. Aizenman (2020). Accounting for global covid-19 diffusion patterns, january-april 2020. Technical report, National Bureau of Economic Research.

Lasry, A., D. Kidder, M. Hast, J. Poovey, G. Sunshine, K. Winglee, N. Zviedrite, F. Ahmed, K. A. Ethier, C. P. H. L. Program, et al. (2020). Timing of community mitigation and changes in reported covid-19 and community mobility—four us metropolitan areas, february 26–april 1, 2020. Morbidity and Mortality Weekly Report 69(15), 451–457.

Lelkes, Y., G. Sood, and S. Iyengar (2017). The hostile audience: The effect of access to broadband internet on partisan affect. American Journal of Political Science 61(1), 5–20.

Lipsky, M. (1968). Protest as a political resource. The American Political Science Review 62(4), 1144–1158.

Makridis, C. and J. T. Rothwell (2020). The real cost of political polarization: Evidence from the covid-19 pandemic. Available at SSRN 3638373.

Manacorda, M. and A. Tesei (2020). Liberation technology: Mobile phones and political mobilization in africa. Econometrica 88(2), 533–567.

Mangrum, D. and P. Niekamp (2020). Jue insight: College student travel contributed to local covid-19 spread. Journal of Urban Economics, 103311.

Mazumder, S. (2019, May). Black Lives Matter for Whites' Racial Prejudice:Assessing the Role of Social Movements in Shaping Racial Attitudes in the United States. Technical report, Harvard University.

McCarthy, J. D. and M. N. Zald (1977). Resource mobilization and social movements: A partial theory. American journal of sociology 82(6), 1212–1241.

McKersie, R. B. (2021). The 1960s civil rights movement and black lives matter: Social protest from a negotiation perspective.

Miller, D., M. A. Martin, N. Harel, T. Kustin, O. Tirosh, M. Meir, N. Sorek, S. Gefen-Halevi, S. Amit, O. Vorontsov, et al. (2020). Full genome viral sequences inform patterns of sars-cov-2 spread into and within israel. medRxiv.

Morris, A. D. (1986). The origins of the civil rights movement. Simon and Schuster.

Müller, K. and C. Schwarz (2020). From hashtag to hate crime: Twitter and anti-minority sentiment. Available at SSRN 3149103.

Müller, K. and C. Schwarz (2021). Fanning the flames of hate: Social media and hate crime. Journal of the European Economic Association 19(4), 2131–2167.

Mundt, M., K. Ross, and C. M. Burnett (2018). Scaling social movements through social media: The case of black lives matter. Social Media+ Society 4(4), 2056305118807911.

Olson, M. (1989). Collective action. In The invisible hand, pp. 61–69. Springer.

Ostrom, E. (1990). Governing the commons: The evolution of institutions for collective action. Cambridge university press.

Passarelli, F. and G. Tabellini (2017). Emotions and political unrest. Journal of Political Economy 125(3), 903–946.

Sangnier, M. and Y. Zylberberg (2017, August). Protests and trust in the state: Evidence from African countries. Journal of Public Economics 152, 55–67.

Swinkels, K. (2020). Covid-19 superspreading events database.

Tillery, A. B. (2019). What kind of movement is black lives matter? the view from twitter. Journal of Race, Ethnicity and Politics 4(2), 297–323.

Zhuravskaya, E., M. Petrova, and R. Enikolopov (2020). Political effects of the internet and social media. Annual Review of Economics 12, 415–438.

8 Tables

Table 1: Summary statistics

From 25th of May to 14th of June 2020:	N	Mean	SD	Min	Max
Presence of BLM events	3108	0.099	0.299	0.000	1.000
Number of BLM events	3108	0.265	1.474	0.000	36.000
Participants in BLM events	3108	299	6082	0	323687
Tweets mentioning BLM	3108	888	8144	0	243596
Tweets mentioning BLM and COVID	3108	15.0	151	0	5596
On the 25th of May 2021:					
COVID deaths (total)	3108	34.09	408.17	0.000	21132
COVID cases (total)	3108	588.7	4606.42	0.000	209195
COVID deaths (per 1000)	3108	0.114	0.252	0.000	2.935
COVID cases (per 1000)	3108	2.801	5.678	0.000	145.513
Superspreader events, 6+ weeks ago, neighboring counties	3108	3.119	10.035	0.000	143.000
County characteristics:					
Black police-related deaths (2014-2019)	3108	0.696	3.295	0.000	84.000
Black police-related deaths (2020)	3108	0.048	0.305	0.000	6.000
Unemployment rate (year average)	3107	4.691	1.550	0.708	19.650
Black population share	3108	0.100	0.147	0.000	0.875
Urban counties	3108	0.021	0.142	0.000	1.000
BLM events (2014-2019)	3108	0.686	5.264	0.000	174.000
Black poverty rate	3108	0.281	0.225	0.000	1.000
Population share with 3+ risk factors	3108	25.904	5.022	10.685	48.448
Vote share for republicans (2016)	3108	0.633	0.156	0.041	0.960
Vote share for republicans (2012)	3108	0.596	0.148	0.060	0.959
Median household income (2016)	3108	48810	13288	20170	129150
Social capital	3108	456	1358	0	37547
Notable Deaths	3108	0.0105	0.123	0	3

Note: Summary of main variables used in our analysis. The sample consists of 3,108 US counties. We report the number of observations, the mean, the standard deviation as well as the minimum and maximum value of each of the variables.

Table 2: Covid-19 exposure and BLM protest

	Presence of BLM events						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: All counties							
IV: COVID	0.556***	0.559***	0.573***	0.578***	0.258**	0.222*	0.215*
(deaths/1000)	(0.140)	(0.140)	(0.147)	(0.142)	(0.115)	(0.119)	(0.121)
OLS: COVID	0.0948**	0.0904**	0.0725*	0.0662	0.0366	0.0346	0.0323
(deaths/1000)	(0.0434)	(0.0436)	(0.0416)	(0.0406)	(0.0264)	(0.0268)	(0.0264)
Observations	3,106	3,106	3,106	3,106	3,106	3,106	3,106
F first stage	40.63	40.56	36.09	35.01	38.10	37.44	36.05
Mean dep. var.	0.0988	0.0988	0.0988	0.0988	0.0988	0.0988	0.0988
Panel B: *new allies* (counties with no BLM protest before)							
IV: COVID	0.549***	0.549***	0.595***	0.665***	0.425**	0.405**	0.404**
(deaths/1000)	(0.164)	(0.164)	(0.179)	(0.178)	(0.178)	(0.184)	(0.187)
OLS: COVID	0.0469*	0.0469*	0.0484*	0.0527*	0.0423*	0.0398*	0.0385*
(deaths/1000)	(0.0276)	(0.0276)	(0.0266)	(0.0274)	(0.0233)	(0.0225)	(0.0221)
Observations	2,767	2,767	2,767	2,767	2,767	2,767	2,767
F first stage	43.48	43.48	40.31	28.01	26.83	27.35	27.04
Mean dep. var.	0.0477	0.0477	0.0477	0.0477	0.0477	0.0477	0.0477
Panel C: *traditional protesters* (counties with BLM protest before)							
IV: COVID	0.416*	0.431*	0.378	0.423*	0.123	0.0495	0.0104
(deaths/1000)	(0.221)	(0.220)	(0.248)	(0.220)	(0.293)	(0.268)	(0.266)
OLS: COVID	0.314***	0.305***	0.251**	0.229**	0.0705	0.0743	0.0682
(deaths/1000)	(0.0915)	(0.0938)	(0.110)	(0.0977)	(0.106)	(0.100)	(0.102)
Observations	333	333	333	333	333	333	333
F first stage	36.32	37.34	37.37	37.23	28.87	28.55	28.09
Mean dep. var.	0.514	0.514	0.514	0.514	0.514	0.514	0.514
Past BLM events		Y	Y	Y	Y	Y	Y
Black population			Y	Y	Y	Y	Y
Black poverty			Y	Y	Y	Y	Y
Urban				Y	Y	Y	Y
3+ risk factors					Y	Y	Y
Median hh income					Y	Y	Y
Past Republican vote						Y	Y
Social capital							Y
Use of deadly force	Y	Y	Y	Y	Y	Y	Y
Unemployment	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y

Note: Estimation of the effect of COVID-19 deaths per 1000 population on the presence of at least one Black Lives Matter event during the three weeks following the murder of George Floyd. Panel A presents 2SLS estimation, using number of super-spreader events in neighbouring counties (50km radius) six weeks prior as an instrument and OLS results for all US counties. Panel B presents these results for the sub-sample of counties with no BLM protest before the murder of George Floyd. Panel C presents these results for the sub-sample of counties with at least one BLM protest before the murder of George Floyd. All specifications include state fixed effects and control for the unemployment rate of the county and the number of Black people that died during a police encounter. Each column include sequentially different sets of additional controls. We report Kleibergen-Paap rkWald F statistic. Standard errors (in parentheses) are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 3: COVID-19 exposure and social media use

	New Twitter accounts	Google searches for Twitter	Residential stay
	(1)	(2)	(3)
Panel A: all counties			
IV: COVID (deaths/1000)	-0.709	14.32**	3.155***
	(20.17)	(3.200)	(0.592)
Observations	3,106	3,056	1,351
F first stage	36.05	35.71	27.49
Mean of dependent variable	4.586	60.64	12.08
Panel B: *new allies* (counties with no BLM protest before)			
IV: COVID (deaths/1000)	17.88**	21.33*	3.895***
	(7.871)	(10.64)	(1.191)
Observations	2,767	2,733	1,025
F first stage	27.04	26.05	20.20
Mean of dependent variable	1.808	59.98	11.45
Panel C: *traditional protesters* (counties with BLM protest before)			
IV: COVID (deaths/1000)	-37.13	5.784	2.447**
	(62.07)	(6.165)	(0.980)
Observations	333	317	320
F first stage	28.09	26.54	26.13
Mean of dependent variable	27.47	66.43	14.12
All controls	Y	Y	Y
State fixed effects	Y	Y	Y

Note: Estimation of the effect of COVID-19 deaths per 1000 population on use of social media. Column 1 shows estimates for new twitter accounts created between April 13 to May 24. Column 2 shows results for Google searches for twitter during the same period and column 3 for residential stay. Panel A presents 2SLS estimation, using number of super-spreader events in neighbouring counties (50km radius) six weeks prior as an instrument and OLS results for all US counties. Panel B presents these results for the sub-sample of counties with no BLM protest before the murder of George Floyd. Panel C presents these results for the sub-sample of counties with at least one BLM protest before the murder of George Floyd. All specifications include state fixed effects and standard controls. Each column include sequentially different sets of additional controls. We report Kleibergen-Paap rkWald F statistic. Standard errors (in parentheses) are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Predicted social media use and BLM protests

	Presence of BLM				
	(1)	(2)	(3)	(4)	(5)
***New allies*: counties without BLM events before**					
Predicted new Twitter accounts	0.00215*	-0.00371*	-0.00350**	-0.00926***	-0.00724**
	(0.00123)	(0.00186)	(0.00167)	(0.00229)	(0.00341)
... × Non-black population share		0.00838**			
		(0.00362)			
... × White population share			0.00866**		
			(0.00344)		
... × Not large cities				0.0115***	
				(0.00264)	
... × Median household income					2.20e-07**
					(9.33e-08)
Interacting variable		-0.0313**	0.0610*	0.340***	2.30e-06***
		(0.0146)	(0.0335)	(0.0484)	(8.48e-07)
Observations	2,767	2,767	2,767	2,767	2,767
All controls	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y

Note: Note: Estimation of the effect of predicted new twitter accounts as explained by COVID-19 deaths per 1000 population on first time BLM protest. We present results for the sub-sample of counties with no BLM protest before the murder of George Floyd. All specifications include state fixed effects and all standard controls. We report Kleibergen-Paap rkWald F statistic. Standard errors (in parentheses) are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Survey data: COVID-19, news consumption and attitudes towards BLM, Blacks and COVID-19

	News consumption			**Attitudes towards Blacks, BLM & COVID-19**			**Placebo**
	Follow news about GF (1)	Receive news about GF on social media (2)	Ratio social media to overall GF news (3)	Higher Black COVID hospitaliz. not their fault (4)	Protest because structural racism (5)	Protest because criminal behaviour (6)	Illegal immigration (7)
COVID-19 deaths per capita (category)	0.0480***	0.0343**	0.0225*	0.0115*	0.0259***	-0.0254**	-0.00641
	(0.00964)	(0.0152)	(0.0134)	(0.00645)	(0.00907)	(0.0109)	(0.00540)
Black	Y	Y	Y	Y	Y	Y	Y
Metropolitan area	Y	Y	Y	Y	Y	Y	Y
Female	Y	Y	Y	Y	Y	Y	Y
Age	Y	Y	Y	Y	Y	Y	Y
Education	Y	Y	Y	Y	Y	Y	Y
Income	Y	Y	Y	Y	Y	Y	Y
Democrat	Y	Y	Y	Y	Y	Y	Y
Observations	9,201	9,121	9,111	9,212	9,190	9,183	9,212

Note: Relation between living in a county with different levels of COVID-19 deaths per capita on different outcomes related to news consumption and attitudes towards Blacks, BLM and COVID-19. Columns 1 to 3 present the estimates for outcomes related to news consumption. In particular, column 1, 2 and 3 show respectively: the interest in George Floyd related news, the amount of GF related news received through social media and the ratio of the variable of column 2 over the variable of column 1. Columns 4 to 6 show the results for the outcomes related to attitudes towards BLM and racism awareness. Column 4 corresponds to the likelihood of answering that the higher COVID-19 mortality rate faced by Blacks is due to their disadvantaged circumstances instead of to their personal life style choices. Columns 5 and 6 correspond to the likelihood of answering that the protest following George Floyd's death is related with structural racism or to criminal behaviour respectively. Finally, column 7 shows a placebo result. The exact framing of the questions is as follows: column 1: *"How closely have you been following news about the demonstrations around the country to protest the death of George Floyd, a black man who died while in police custody?"*; column 2: *How much, if any, news and information about the demonstrations to protest the death of George Floyd have you been getting on social media (such as Facebook, Twitter, or Instagram)?*; column 4:*Do you think the reasons why black people in our country have been hospitalized with COVID-19 at higher rates than other racial or ethnic groups have more to do with... Circumstances beyond people's control*; column 5: *How much, if at all, do you think each of the following has contributed to the demonstrations to protest the death of George Floyd? Longstanding concerns about the treatment of black people in the country*; column 6: *Some people taking advantage of the situation to engage in criminal behavior*; column 7: *Which comes closer to your view about how to handle undocumented immigrants who are now living in the U.S.? There should be a way for them to stay in the country legally, if certain requirements are met* All columns include controls for various characteristics of the respondent: race, whether or not they live in a metropolitan area, gender, age, education, income and whether or not they lean towards the democratic party. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Alternative Mechanisms

	Presence of BLM				Other Protests
	(1)	(2)	(3)	(4)	(5)
***New allies*: counties with no BLM protest before**					
COVID (deaths/1000)	0.444**	0.585	0.507	0.0347	0.279
	(0.1994)	(0.342)	(0.536)	(1.4901)	(0.224)
...×Black_death_burden	-0.003				
	(0.054)				
...×Google_BLM_search		-0.004			
		(0.022)			
...×Unemployment			-0.003		
			(0.054)		
...×Stringency				0.005	
				(0.0211)	
Interacting variable	-0.257	0.0006	0.0047	-0.0003	
	(0.176)	(0.001)	(0.008)	(0.0014)	
Observations	2,767	2,647	2,767	2,768	2,767
F stat COVID	31.95	19.09	24.93	85.33	41.12
F stat Interaction	3.89	25.33	13.61	94.27	
Mean of dependent variable	0.0477	0.0477	0.0477	0.0477	0.0321
All controls	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y		Y

Note: Estimation of the effect of COVID-19 deaths per 1000 population on presence of BLM protest. Column 1 shows estimates for instrumented COVID deaths. Columns 2 to 4 show heterogeneous effects for Black death burden weeks prior to GF's murder, Google searched for BLM 3 weeks prior to GF's murder, unemployment and stringency 3 weeks after GF's murder. Column 5 presents results for other protests. We present these results for the sub-sample of counties with no BLM protest before the murder of George Floyd. All specifications include state fixed effects and standard controls. We report Kleibergen-Paap rkWald F statistic. Standard errors (in parentheses) are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Online Appendix

A: Robustness Checks

Table A1: First stage: robustness checks.

	Covid deaths per thousand						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SSE measure	0.00930***	0.00132***	0.0000634***	0.00900***	0.00919***	0.00962***	0.0112***
	(0.00155)	(0.000379)	(0.0000124)	(0.00155)	(0.00154)	(0.00164)	(0.00208)
Distance	50 km	200 km	50 km	50 km	50 km	50 km	50 km
Measure	SSEs	SSEs	SSE cases	SSEs	SSEs	SSEs	SSEs
Lag	6 weeks	6 weeks	6 weeks	4 weeks	5 weeks	7 weeks	8 weeks
Past BLM events	Y	Y	Y	Y	Y	Y	Y
Black population	Y	Y	Y	Y	Y	Y	Y
Black poverty	Y	Y	Y	Y	Y	Y	Y
Urban	Y	Y	Y	Y	Y	Y	Y
3+ risk factors	Y	Y	Y	Y	Y	Y	Y
Median hh income	Y	Y	Y	Y	Y	Y	Y
Past Republican vote	Y	Y	Y	Y	Y	Y	Y
Social capital	Y	Y	Y	Y	Y	Y	Y
Use of deadly force	Y	Y	Y	Y	Y	Y	Y
Unemployment	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y
Mean of dependent variable	0.113	0.113	0.113	0.113	0.113	0.113	0.113
Observations	3,106	3,106	3,106	3,106	3,106	3,106	3,106
R^2	0.162	0.123	0.155	0.160	0.161	0.162	0.160
F statistic	36.05	12.08	26.23	33.79	35.66	34.63	28.91

Note: Estimation of the effect of different SSE measures on COVID-19 deaths per 1000 population. Column 1 correspond to our baseline specification: number of SSEs in a 50km radius from the border of the county up until 6 weeks prior to George Floyd's death. In column 2 we change the radius to 200km instead of 50km. In column 3 we use the number of cases attributed to each SSE instead of the number of SSEs themselves. Columns 4 to 8 use different lags at wich we stop counting the SSEs: 4, 5, 7 and 8 weeks prior to the death of George Floyd respectively. All columns include state fixed effects and the whole set of controls. We report Kleibergen-Paap rkWald F statistic. Standard errors (in parentheses) are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Reduced form: superspreader events on the presence of BLM events.

	Presence of BLM events						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cumulative SSE 6 weeks ago, not in county, less than 50km away	0.00577***	0.00581***	0.00560***	0.00566***	0.00242**	0.00209	0.00200
	(0.00132)	(0.00133)	(0.00129)	(0.00136)	(0.00117)	(0.00128)	(0.00128)
Past BLM events		Y	Y	Y	Y	Y	Y
Black population			Y	Y	Y	Y	Y
Black poverty			Y	Y	Y	Y	Y
Urban				Y	Y	Y	Y
3+ risk factors					Y	Y	Y
Median hh income					Y	Y	Y
Past Republican vote						Y	Y
Social capital							Y
Use of deadly force	Y	Y	Y	Y	Y	Y	Y
Unemployment	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y
Mean of dependent variable	0.0988	0.0988	0.0988	0.0988	0.0988	0.0988	0.0988
Observations	3,106	3,106	3,106	3,106	3,106	3,106	3,106
R^2	0.167	0.175	0.178	0.203	0.228	0.254	0.254

Note: Estimation of the effect of the number of SSE in neighbouring counties (50km radius) six weeks prior to the death of George Floyd on the presence of at least one Black Lives Matter event during the three weeks following the murder of George Floyd. All specifications include state fixed effects and control for the unemployment rate of the county and the number of Black people that died during a police encounter. Each column include sequentially different sets of additional controls. We report Kleibergen-Paap rkWald F statistic. Standard errors (in parentheses) are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Robustness checks - I

	Presence of BLM events during 3 weeks after May 25th								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: IV									
COVID	0.215*	0.373*	0.213*	0.202	0.209*	0.225*	0.240*	0.215**	
(deaths/1000)	(0.121)	(0.207)	(0.121)	(0.121)	(0.121)	(0.119)	(0.120)	(0.0883)	
COVID									0.0135*
(cases/1000)									(0.00694)
Panel B: OLS									
COVID	0.0323	0.0323	0.0323	0.0323	0.0323	0.0323	0.0323	0.0323	
(deaths/1000)	(0.0264)	(0.0264)	(0.0264)	(0.0264)	(0.0264)	(0.0264)	(0.0264)	(0.0220)	
COVID									0.000147
(cases/1000)									(0.000843)
Panel C: First stage									
SSE measure	0.00930***	0.00132***	0.0000634***	0.00900***	0.00919***	0.00962***	0.0112***	0.00930***	0.149***
	(0.00155)	(0.000379)	(0.0000124)	(0.00155)	(0.00154)	(0.00164)	(0.00208)	(0.000647)	(0.0539)
Distance	50 km	200 km	50 km	50 km	50 km	50 km	50 km	50 km	50 km
Measure	SSEs	SSEs	SSE cases	SSEs	SSEs	SSEs	SSEs	SSEs	SSEs
Lag	6 weeks	6 weeks	6 weeks	4 weeks	5 weeks	7 weeks	8 weeks	6 weeks	6 weeks
Cluster	state	state	state	state	state	state	state		state
All controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean of dep var	0.0988	0.0988	0.0988	0.0988	0.0988	0.0988	0.0988	0.0988	0.0988
Observations	3,106	3,106	3,106	3,106	3,106	3,106	3,106	3,106	3,106
F stat	36.05	12.08	26.23	33.79	35.66	34.63	28.91	206.6	7.633

Note: Variations of the baseline specification of the effect of the number of SSE in neighbouring counties on the presence of at least one Black Lives Matter event during the weeks following the murder of George Floyd. Column 1 correspond to our baseline specification. Columns 2 to 7 show the results when varying the definition of the instrument. In column 2 we change the radius to 200km instead of 50km. In column 3 we use the number of cases attributed to each SSE instead of the number of SSEs themselves. Columns 4 to 8 use different lags at which we stop counting the SSEs: 4, 5, 7 and 8 weeks prior to the death of George Floyd respectively. Column 8 shows the results without clustering. Column 9 uses the number of COVID cases instead of deaths as explanatory variable. All specifications include the whole set of controls and state fixed effects. We report Kleibergen-Paap rkWald F statistic. Standard errors (in parentheses) are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Robustness checks - II.

	Presence of BLM events				
	Baseline	6 weeks	8 weeks	Past BLM	Prisons
	(1)	(2)	(3)	(4)	(5)
Panel A: IV					
COVID	0.215*	0.289**	0.244**	-0.807	0.208*
(deaths/1000)	(0.121)	(0.108)	(0.119)	(0.148)	(0.1200)
	[1.598]				
Panel B: OLS					
COVID	0.0323	0.0649*	0.0618*	0.273	0.031
(deaths/1000)	(0.0264)	(0.0355)	(0.0336)	(0.0369)	(0.0256)
Panel C: First stage					
SSE measure	0.00930***	0.00930***	0.00930***	0.00930***	0.00930***
	(0.00155)	(0.00155)	(0.00155)	(0.00155)	(0.00065)
Past BLM events	Y	Y	Y		Y
Prisons					Y
All other controls	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y
Mean of dep var	0.0988	0.123	0.134	0.686	0.0988
Observations	3,106	3,106	3,106	3,106	3106
F stat	36.05	36.05	36.05	36.05	36.01

Note: Variations of the baseline specification of the effect of the number of SSE in neighbouring counties on the presence of at least one Black Lives Matter event during the weeks following the murder of George Floyd. Column 1 correspond to our baseline specification, bootstraped t statistics is shown in parentheses. In columns 2 and 3 we change the number of weeks where we measure the presence of BLM events to 6 and 8 weeks after May 25th respectively. Column 4 shows the effect of instrument COVID-19 deaths on past BLM events. Column 5 includes the total number of prisions in each county as additional control. All specifications include the whole set of controls and state fixed effects. We report Kleibergen-Paap rkWald F statistic. Standard errors (in parentheses) are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

B: Alternative Estimation Strategies

Alternative Instrument: Florida Spring Break

In our preferred empirical strategy, we chose smaller and decentralized SSEs to argue for a causal relationship between COVID-19 and BLM. Here, we add another cross-sectional instrumental variable: the spatial distribution of touristic flows originating in major Florida Spring Break destination during March of 2020. Instead of collecting information on multiple independent SSEs as in the previous section, we now focus on one single, large-scale event that is known to have contributed substantially to the spread of COVID-19 (Mangrum and Niekamp, 2020).

Despite the fact that COVID-19 infections had surged in Florida's main spring break destinations and despite the fact that the Center for Disease Control had issued multiple warnings, Florida Governor DeSantis failed to implement social distancing orders until April 1st 2020[14]. We exploit this unique, large scale event to track the diffusion of COVID-19 infections that originated in Florida during spring break and then spread across the United States. In order to track these movements, we benefit from exceptionally rich data on cell phone mobility provided by SafeGraph. We can identify spring breakers' home counties – locations where they most likely have returned after vacationing in highly infectious spring break locations.

Specifically, we pick three Florida vacation destinations: Miami Beach, Panama Beach and Fort Lauderdale. These three destinations caught the attention of the media in early March which reported congestion of tourists who did not respect social distancing measures (BBC, CNN). We are using anonymised mobile data for the period from March, 1, 2020 to April 1, 2020, covering the majority of spring break periods across the country. With the help of the Monthly Patterns data (MP), we measure unique devices that visited specific «points of interest» in one of three popular spring break destinations mentioned above.

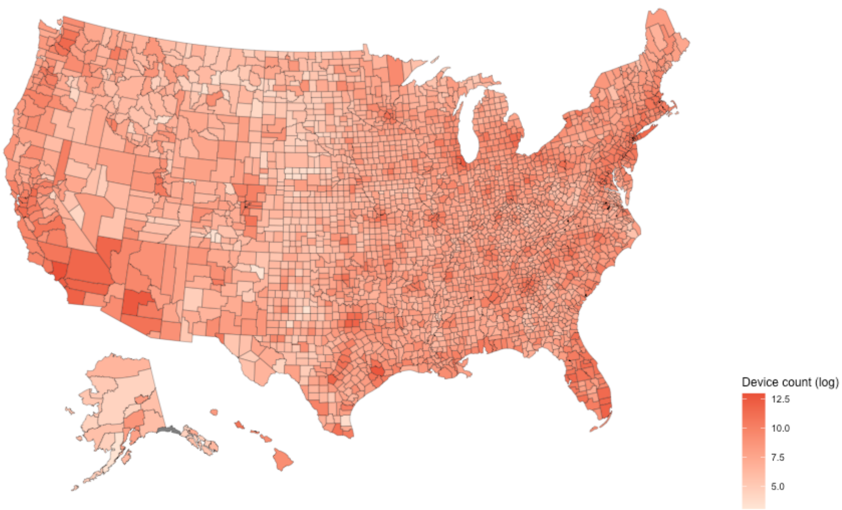


Figure 9: Number of devices (log) by US counties pinged during March 1st, 2020

The SafeGraph data provides us with a rich set of points of interests, which include more than 3000 places such as restaurants, bars, hotels, gyms, public parks, malls and other establishments. Using this data, we measure the Number of devices that «pinged» in each of point of interests during March, 2020. The MP data also allows us to observe home locations on the level of the US Census Block Groups (CBG). An individual "home" is defined as a place where user's devices

[14]Local officials had started to close some of the beaches for public access in mid March

pinged most often in the night time between 6 PM and 7 AM during the baseline 6-week period determined by the SafeGraph.

Using this information, we calculate the number of unique visitors to points of interests in three cities in Florida and group this number by device home counties. Given that cell phone data is anonymized, each device is counted as many times as it has visited different places (such as restaurants and shops) in a given touristic destination. Therefore, this measure captures both intensity of tourism flow from the county and mobility of these tourists during their spring break. Since higher mobility is associated with higher chances of disease contraction, our variable captures both extensive and intensive margins of COVID-19 spread. We see this variable as an improvement over ones used in literature examining stay at home behaviour (Abouk and Heydari (2020); Lasry et al. (2020); Friedson et al. (2020); Dave et al. (2020); Dave et al. (2021)). The exposure to COVID-19 is therefore instrumented by the number of spring-break tourists.

$$Z_c = \frac{\sum_{POIs} pings_{POI,c}}{devices_c} \tag{4}$$

We normalise this variable calculating a ratio of the total number of devices detected in spring breakers' home counties at March , 1, 2020 to account for differences in population size and differences in resident device coverage between counties in the SafeGraph data. In Figure 9 the map of (log) number of devices by counties is presented. Figure 10 shows our resulting measure of "spring breakers" inflow split into five categories: high flow, moderate-high flow, moderate-low flow, low flow, no flow (missing).

We use the same set of controls and connotations as in our baseline cross-sectional estimation. Our estimating equation writes as:

$$BLM_c = \beta_0 + \beta_1 \widehat{Covid}_{cs} + \mathbf{X}_c\beta_{\mathbf{X}} + \delta_s + \epsilon_{cs}$$

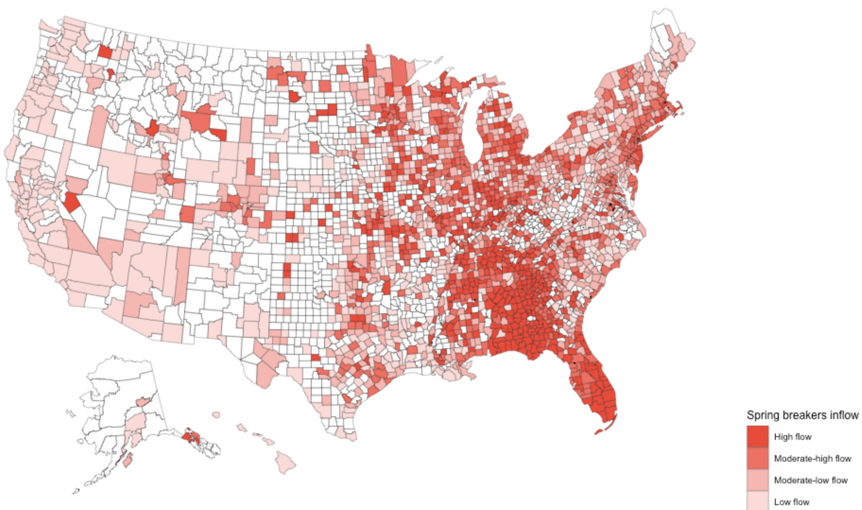


Figure 10: Spring Breakers by US counties. Own visualization based on SafeGraph data.

We present our 2SLS results in Table B1. We use the same set of controls as in the previous cross-sectional estimations, successively introducing socio-economic, demographic and political control variables. The inclusion of the Black population rates and Black poverty index in column 3 substantially decreases the F-Statistic (see First Stage results in Table B1). When including

Table B1: Spring breakers IV: Covid-19 deaths on the presence of BLM events, 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Presence of BLM events						
Panel A: IV							
Covid deaths per thousands	1.513***	1.472***	1.714**	1.717**	1.392**	0.828	0.832
	(0.550)	(0.550)	(0.733)	(0.731)	(0.645)	(0.514)	(0.533)
Panel B: OLS							
Covid deaths per thousands	0.0972***	0.0931***	0.0736***	0.0669***	0.0375*	0.0356	0.0333
	(0.0222)	(0.0221)	(0.0227)	(0.0224)	(0.0223)	(0.0219)	(0.0219)
Panel C: First stage							
Visits per device	0.558***	0.548***	0.448***	0.449***	0.446***	0.445***	0.430***
	(0.164)	(0.164)	(0.160)	(0.160)	(0.158)	(0.159)	(0.159)
Past BLM events		Y	Y	Y	Y	Y	Y
Black population			Y	Y	Y	Y	Y
Black poverty			Y	Y	Y	Y	Y
Urban				Y	Y	Y	Y
3+ risk factors					Y	Y	Y
Median hh income					Y	Y	Y
Past Republican vote						Y	Y
Social capital							Y
Deadly forces	Y	Y	Y	Y	Y	Y	Y
Unemployment	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y
Observations	3,039	3,039	3,039	3,039	3,039	3,039	3,038
F first stage	11.53	11.14	7.898	7.916	7.985	7.791	7.305

Cross-sectional 2SLS estimation of the effect of the cumulative number of COVID-19 related deaths per thousand population the day before the death of George Floyd on the likelihood of having at least one BLM event during the first three weeks after George Floyd's death. All specifications include state fixed effects, the cumulative number of black police-related deaths since 2014 and the mean unemployment rate for to period May 2019- May 2020. Columns (1) is the baseline specification. Column (2), (3), (4), (5), (6), (7), (8) include one by one additional set of controls and column (9) include all controls together. Cross-sectional data at the county level. We report Kleibergen-Paap rkWald F statistic. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

the full set of controls, the instrument remains at 7.3, well below the conventional threshold. However, for all specifications we find a positive coefficient for COVID-19 on the presence of a BLM event and where the first stage is sufficiently strong, we find a positive and statistically significant sign.

Difference in Differences: Notable Deaths Sample

With this empirical approach, we use data on BLM at the county-week level starting in 2014 and exploit differences in protest behavior following what we call a "notable" death. Deaths of Blacks at the hands of the police have been - not only in the case of George Floyd - a trigger for BLM protests across the country. Roughly, more than 300 Blacks die each year in the US either due to police brutality or under police custody. However, not all of these deaths result in media coverage, which is crucial for generating public discourse or action. Many of these events only received public traction since they were - mostly by chance - recorded through a phone camera. We construct a data set of all police related Black deaths since July 2014 covered in a major national daily newspapers like the Washington Post, received TV coverage by CNN and/or has a dedicated Wikipedia page.

We now exploit the full potential of our panel data by interacting out main COVID-19 variable with a dummy variable for a notable death occurring in a certain week. Following the sample selection of our baseline estimation, we use information on BLM orotest ub counties in the 3 weeks after the recorded notable death (we can reduce this to 2 weeks and expand it to 4 weeks without significantly changing the first and second stage results). This data set structure allows us to observe counties' protest behavior after a protest trigger. Following a difference in differences logic, we then look at whether the reaction following this trigger differs in counties that were more exposed to the COVID-19 pandemic. Again, we use the SSE IV to account for the fact that COVID-19 exposure may be endogenous to past and present protest behavior.

$$Covid_{ct} = \zeta_0 + \zeta_1 Notable\_deaths + \zeta_2 Z_{cst} + \zeta_3 Notable\_deaths \times Z_{cst} + \mathbf{X}_{cs}\zeta_{\mathbf{X}} + \gamma_c + \theta_{st} + \eta_{cst}, \quad (5)$$

$$Z_{cst} = \sum SSE^{neighbor}_{cst} \quad (6)$$

The second stage is written as:

$$\begin{aligned} BLM_{cst} = \beta_0 + \beta_1 Notable\_deaths_t + \beta_2 \widehat{Covid}_{cst} \\ + \beta_3 Notable\_deaths_t \times \widehat{Covid}_{cst} + \mathbf{X}_{cs}\zeta_{\mathbf{X}} + \mu_c + \delta_{st} + \epsilon_{cst} \end{aligned}$$

where, $Notable\_deaths_{cst}$ is a dummy variable that takes the value of one in the three weeks following a nationally covered deaths and zero otherwise. We include county and state-week fixed effects, as well as all Black police-related deaths at the county level. This is a crucial control as it allows us to exploit the "extra" trigger that nationally covered deaths create, above and beyond the local level of deadly force used by local police. The key coefficient of interest is β_3.

Table B2 shows the results of this estimation. Columns 1 and 3 report the effect of notable deaths up to 4 weeks since it occurred and columns 2 and 4 report for up to 3 weeks. In both cases we find that the effect of notable deaths in predicting the likelihood of observing a BLM protest is significantly higher in the presence of COVID death burden. The results control for county specific time trends as shown in columns 3 and 4.

Table B2: Notable Deaths Regression

	(1)	(2)	(3)	(4)
		Presence of BLM		
Covid deaths per thousand	0.0595***	0.0597***	0.0450***	0.0451***
	(0.0166)	(0.0166)	(0.0116)	(0.0116)
Notable deaths × Covid deaths	1.4926***	2.0714***	1.4935***	2.0707***
	(0.1053)	(0.1095)	(0.1057)	(0.1102)
Notable deaths	-0.0389***	-0.0391***	-0.0410***	-0.0412***
	(0.0125)	(0.0128)	(0.0127)	(0.0130)
Black police-related deaths	Y	Y	Y	Y
Unemployment	Y	Y	Y	Y
Weeks post Notable Death	4	3	4	3
County FE	Y	Y	Y	Y
State-Week FE	Y	Y		
County Week Trend			Y	Y
Observations	96286	96286	96329	96329
F First Stage (COVID)	18.03	17.92	32.23	32.09
F First Stage (Interaction)	13.05	13.87	14.59	14.97

Note: Estimation of the effect of Notable deaths and COVID-19 deaths on different Black Lives Matter measures. This table presents 2SLS results, using the cumulative number of all super-spreader events in neighbouring counties (50km radius) as an instrument. Columns (1) and (3) presents the effect of instrumented cumulative number of COVID-19 deaths and notable deaths on the likelihood of having a BLM event in the county within 4 weeks of the notable death. Column (2) and (4) presents the effect of instrumented cumulative number of COVID-19 deaths and notable deaths on the likelihood of having a BLM event in the county within 3 weeks of the notable death. All specifications include county fixed effects and two time varying controls (the number of black police-related deaths and the unemployment rate both at a county level) along with either state-week fixed effects or county week time trend to increase precision. Weekly data by county from year 2014 until the 14th June 2020. Standard errors clustered at the county level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

C: Additional Tables

Table C1: Alternative outcomes: intensive and extensive margin of online and offline protest

	Presence of BLM events (1)	Number of BLM events (2)	Participants per 1000 (3)	Environmental protests (4)	Residential stay (5)	Tweets BLM (6)	New Twitter Users (7)
IV: COVID (deaths/1000)	0.215*	0.558	-1.356	0.00737	2.222***	2,318	2.430
	(0.121)	(0.662)	(1.649)	(0.0947)	(0.817)	(1,948)	(45.17)
OLS: COVID (deaths/1000)	0.0323	0.0270	0.0239	0.0117	1.789***	-220.2	-9.966
	(0.0264)	(0.0886)	(0.148)	(0.0151)	(0.249)	(465.9)	(12.39)
Mean of dependent variable	0.0994	0.265	0.442	0.00740	12.10	888	12.12
Observations	3,106	3,106	3,106	3,106	1,351	3,106	3,106
F first stage	36.05	36.05	36.05	36.05	27.49	36.05	36.05
All controls	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y

Note: Estimation of the effect of COVID-19 deaths per 1000 population on different outcomes capturing the intensive and extensive margin of offline and online BLM protest. Columns 1, 2, 3 and 4 correspond to offline protest outcomes. Columns 1,2 and 3 correspond respectively to: the presence, the number and the number of participants to BLM events during the three weeks following the murder of George Floyd. Column 4 shows the number of environmental related protest during the period May 25th until August 29th. Column 5 shows the result for residential stay (relative to pre-pandemic baseline). Columns 6 and 7 show results for online protest outcomes and correspond respectively to: the number of tweets mentioning BLM of George Floyd and of new accounts created after the pandemic and before George Floyd's death that are tweeting about BLM in the three weeks following George Floyd's deaths. All columns include state fixed effects and the same set of controls as Table **??**. We report Kleibergen-Paap rkWald F statistic. Robust standard errors are clustered at the state level and are shown in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table C2: Descriptive statistics of selected variables on different sub-samples

	All counties			No events before						Has events before						Counties with tweets		
				No ev. after			Has ev. after			No ev. after			Has ev. after					
	mean	sd	p50	mean	sd	p50	mean	sd	p50	mean	sd	p50	mean	sd	p50	mean	sd	p50
COVID deaths before May 25th (per 1000)	0.114	0.252	0	0.096	0.228	0	0.173	0.266	0	0.162	0.223	0	0.296	0.449	0	0.115	0.254	0
SSEs less than 50km away	3.119	10.035	1	1.998	5.533	1	8.894	23.389	2	6.337	13.324	2	12.542	24.620	3	3.153	10.187	1
BLM events (May 25th to June 14th)	0.265	1.474	0	0.000	0.000	0	1.333	0.695	1	0.000	0.000	0	3.655	4.945	2	0.267	1.474	0
Population	103656	356931	25878	41000	69407	20696	203668	222705	122808	205312	186958	156819	868564	1201478	558905	107006	364129	27416
Urban counties	0.021	0.142	0.000	0.001	0.028	0.000	0.000	0.000	0.000	0.012	0.110	0.000	0.339	0.475	0.000	0.021	0.142	0.000
Black population share	0.100	0.147	0.032	0.094	0.149	0.025	0.067	0.070	0.038	0.140	0.140	0.097	0.175	0.144	0.128	0.100	0.147	0.032
Black poverty rate	0.281	0.225	0.258	0.285	0.239	0.260	0.260	0.153	0.234	0.276	0.108	0.277	0.251	0.089	0.249	0.284	0.223	0.261
Unemployment rate (2019-2020)	4.691	1.550	4.425	4.718	1.593	4.450	4.618	1.158	4.442	4.529	1.541	4.325	4.493	1.089	4.263	4.721	1.547	4.450
Population share with 3+ risk factors	25.904	5.022	25.602	26.075	5.075	25.778	23.602	4.262	22.765	24.310	4.087	24.030	26.554	4.860	26.340	25.893	5.016	25.598
Median household income (2016)	48810	13288	47017	46920	11737	45645	59520	17453	54007	55469	14321	52648	62838	16148	59122	48795	13180	47029
Intergenerational mobility	0.431	0.062	0.421	0.434	0.064	0.424	0.426	0.038	0.426	0.405	0.042	0.402	0.404	0.043	0.404	0.429	0.060	0.421
Stringency index	68.454	8.514	69.440	68.064	8.567	68.520	71.131	7.500	72.220	70.347	8.273	69.440	70.527	7.781	71.760	68.464	8.504	69.440
Black death burden	1.346	0.962	1.317	1.348	0.987	1.317	1.259	0.939	1.356	1.424	0.767	1.356	1.308	0.738	1.312	1.362	0.960	1.356
Vote share for republicans (2012)	0.596	0.148	0.608	0.618	0.139	0.629	0.536	0.140	0.526	0.499	0.128	0.489	0.413	0.124	0.420	0.594	0.146	0.606
Vote share for republicans (2016)	0.633	0.156	0.663	0.661	0.139	0.688	0.549	0.146	0.565	0.505	0.140	0.500	0.388	0.126	0.397	0.632	0.154	0.662
Black people killed by police (2014-2019)	0.696	3.295	0.000	0.187	0.681	0.000	0.606	1.259	0.000	1.626	2.704	1.000	7.480	11.219	4.000	0.706	3.307	0.000
Black people killed by police (2020)	0.048	0.305	0.000	0.013	0.127	0.000	0.038	0.192	0.000	0.153	0.409	0.000	0.475	1.006	0.000	0.050	0.312	0.000
Observations		3108			2,636			132			163			177			2966	

Note: Descriptive statistics (mean, standard deviation and median) of selected variables on different sub-samples depending on the presence or absence of BLM events before and after George Floyd's death. First sub-sample (first three columns) correspond to counties that did not had any BLM event from the beginning of the movement until the end of the study period on the 14th of June. Second sub-sample (columns four to six)correspond to counties that did not had any BLM event before George Floyd's death but did had at least one event in the three weeks following it. Third sub-sample correspond to counties that did had a BLM before May 25th 2020 but that do not have any event after that date. Finally, the fourth sub-sample correspond to counties that did had BLM events both before and after George Floyd's death.

Figure 11: Distribution of Super Spreader Events in the US by their type

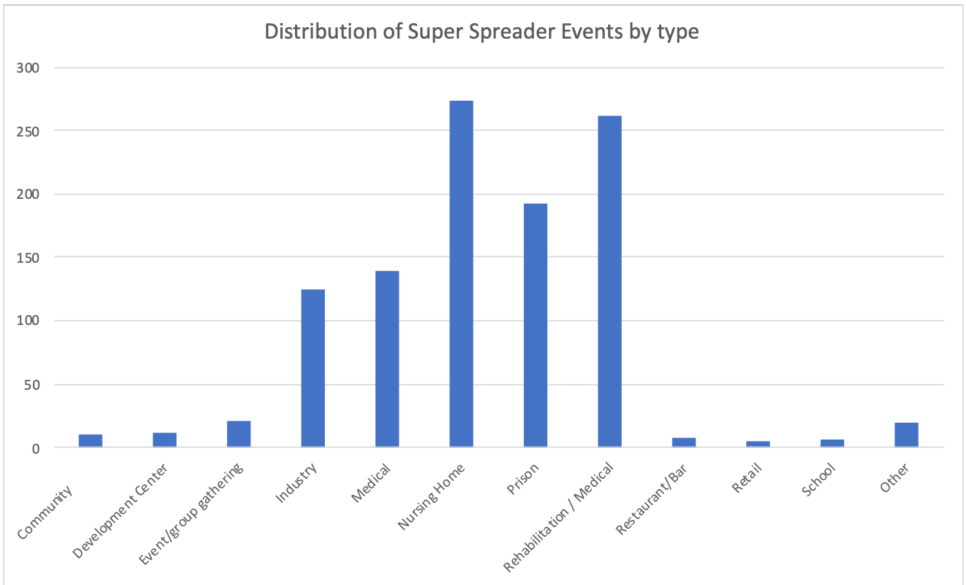


Table C3: Summary statistics for super spreading events by their type

Type of SSE event	Total events	Total Events 6 weeks before GF's murder	Mean	Standard Deviation	Total Cases
Community	11	9	1.364	0.505	504
Development Center	12	12	3.833	1.404	1612
Event/group gathering	21	13	3	1.549	1083
Industry	125	87	15.656	8.642	17825
Medical	140	134	36.586	17.037	13731
Nursing Home	273	261	80.597	37.073	26684
Prison	193	187	45.487	19.674	49747
Rehabilitation / Medical	262	251	89.618	41.009	26979
Restaurant/Bar	8	4	1.5	0.535	1306
Retail	5	0	1	0	68
School	7	2	1.286	0.488	218
Other	20	15	2.5	1.051	1592

All super spreading (SSE) in the USA by their type. Total events are total number of SSE event of each type occurring till 29 August. Total Events 6 weeks before GF's murder is sum of all SSE events by their type that occurred 6 weeks before GF's death. Total cases is sum of all reported COVID-19 positive cases attributed to each type of SSE event.

Table C4: Predicted social media use and BLM protests

	Presence of BLM				
	(1)	(2)	(3)	(4)	(5)
Panel A: All counties					
Predicted new Twitter accounts	-0.0171	-0.0170	-0.0192	-0.0159	-0.0169
	(0.0235)	(0.0236)	(0.0237)	(0.0243)	(0.0229)
... × Non-black population share		-9.84e-05			
		(0.000670)			
... × White population share			0.000237		
			(0.000774)		
... × Not large cities				-0.000470	
				(0.000506)	
... × Median household income					-3.31e-08**
					(1.48e-08)
Interacting variable		-0.374	0.0847**	-0.692	4.01e-06**
		(0.664)	(0.0339)	(1.249)	(1.92e-06)
Observations	3,106	3,106	3,106	3,106	3,106
Panel B: *New allies* (counties without BLM events before)					
Predicted new Twitter accounts	0.00215*	-0.00371*	-0.00350**	-0.00926***	-0.00724**
	(0.00123)	(0.00186)	(0.00167)	(0.00229)	(0.00341)
... × Non-black population share		0.00838**			
		(0.00362)			
... × White population share			0.00866**		
			(0.00344)		
... × Not large cities				0.0115***	
				(0.00264)	
... × Median household income					2.20e-07**
					(9.33e-08)
Interacting variable		-0.0313**	0.0610*	0.340***	2.30e-06***
		(0.0146)	(0.0335)	(0.0484)	(8.48e-07)
Observations	2,767	2,767	2,767	2,767	2,767
All controls	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y

Note: Note: Estimation of the effect of predicted new twitter accounts as explained by COVID-19 deaths per 1000 population on first time BLM protest. We present results for all counties (Panel A) and the sub-sample of counties with no BLM protest before the murder of George Floyd (Panel B). All specifications include state fixed effects and all standard controls. We report Kleibergen-Paap rkWald F statistic. Standard errors (in parentheses) are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table C5: Alternative Mechanisms

	Presence of BLM				Other Protests
	(1)	(2)	(3)	(4)	(5)
Panel A: All counties					
COVID (deaths/1000)	0.279**	0.570*	0.252	0.890	0.170
	(0.119)	(0.289)	(0.424)	(1.066)	(0.138)
...×Black_death_burden	1.017				
	(0.888)				
...×Google_BLM_search		-0.015			
		(0.010)			
...×Unemployment			0.006		
			(0.030)		
...×Stringency				-0.007	
				(0.0146)	
Interacting variable	-0.195	0.001	0.008*	0.001	
	(0.176)	(0.001)	(0.005)	(0.0013)	
Observations	3,106	3,056	1,351	3107	3,106
F stat COVID	25.59	22.14	27.49	96.71	31.4
F stat Interaction	12.46	58.19	27.49	96.04	
Mean of dependent variable	0.099	0.099	0.099	0.099	0.081
All controls	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y		Y

Note: Estimation of the effect of COVID-19 deaths per 1000 population on presence of BLM protest. Column 1 shows estimates for instrumented COVID deaths. Columns 2 to 4 show heterogeneous effects for Black death burden weeks prior to GF's murder, Google searched for BLM 3 weeks prior to GF's murder, unemployment and stringency 3 weeks after GF's murder. Column 5 presents results for other protests. Panel A presents 2SLS estimation for all counties. Panel B presents these results for the sub-sample of counties with no BLM protest before the murder of George Floyd. All specifications include state fixed effects and standard controls. We report Kleibergen-Paap rkWald F statistic. Standard errors (in parentheses) are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1