Operation gridlock: opposite sides, opposite strategies

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Abstract

Twitter and other social media platforms are important tools for competing groups to push their preferred messaging and respond to opposing views. Special attention has been paid to the role these tools play in times of emergency and important public decision-making events such as during the current COVID-19 pandemic. Here, we analyze the Pro- and Anti-Protest sides of the Twitter discussion surrounding the first few weeks of the anti-lockdown protests in the United States. We find that these opposing groups mirror the partisan divide regarding the protests in their use of specific phrases and in their sharing of external links. We then compare the users in each group and their actions and find that the Pro-Protest side acts more proactively, is more centrally organized, engages with the opposing side less, and appears to rely more on bot-like or troll-like users. In contrast, the Anti-Protest side is more reactive, has a larger presence of verified account activity (both as actors and targets), and appears to have been more successful in spreading its message in terms of both tweet volume and in attracting more regular type users. Our work provides insights into the organization of opposing sides of the Twitter debate and discussions over responses to the COVID-19 emergency and helps set the stage for further work in this area.

Keywords Social network analysis · Twitter · Protests · Case study

Introduction

Online social media platforms have proved to be powerful tools in the dissemination of information, expression of opinion, and in the shaping of public discourse. Political campaigns, advocacy groups, and the public all use these platforms in parallel with traditional venues of TV, radio, print media, community and organization meetings, rallies, and protests to vie for attention and promote their views. It is

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important to understand how this all is accomplished, especially in periods leading up to important public decisions such as elections, or during emergencies such as the ongoing COVID-19 crisis.

In the case of Twitter, much of the attention from academics, politicians, pundits, news media, and the public has focused on issues of political, policy, and electoral discourse, crisis communications during natural disasters and other important events, and to the use of Twitter in relation to offline protests. With respect to collective action, social media in general, and Twitter in particular, plays a role as an organizing mechanism [1] and as a reporting mechanism [2, 3]. Today when protests occur, they co-occur in the streets and on social media. Phrases such as "Twitter Revolutions" give voice to the role of these social media technologies in anti-government protests [4]. In protest after protest, from the Arab Spring [5, 6] to the Occupy protests [7], social media has been an integral part of the protest story. The ability of users to use social media to shape and coordinate these protests using disinformation, bots, cyborgs and trolls is seen as a fundamental issue of our time, and is the subject of an emerging area of science referred to as social cybersecurity [8].

Prior studies have shown that discourse in Twitter reflects the changing dynamic of the collective action movement and can be used as part of the gatekeeping process [1]. Before, during, and after protest events, platforms like Twitter are used by participants and observers to plan, inform, coordinate, and to advocate for their positions [9]. Moreover, protesters can operate as a networked organization using Twitter to support and enable coordination [10–12]. Twitter can be used to provide tactical support such as when telling people where to meet, and as a tool for symbolic association when the sender of the tweet links themselves with a public critic or authority (e.g., by quoting, retweeting, or mentioning them) [13]. The populous periphery agents on Twitter have been found to play important roles in spreading messages from the core conversation relating to protests [14]. On-the-ground protests also serve as jumping off points for conversation, debate, and coordinated political activity on Twitter by non-active observers, reporters, and commenters [15]. When there is a serious opposition to the protest, social media can be employed to curtail protests as well as to provide evidence for arresting protesters [16].

During a protest, social media makes possible the broadcast of first-hand evidence as "citizen reporters" post news, images and videos, but also allows a space for manipulation and the broadcast of disinformation about the protests that may be spread by more intentional "troll" and automated bot accounts. Such activity can create, build, or bridge groups thereby affecting the organization of possible protest or Anti-Protest groups. For example, bot accounts on Twitter were used to create a group of potential EuroMaidan revolutionaries by linking individuals who did not know each other together and were used to create bridges between groups in the 2016 election [17].

The prior research demonstrates that protests groups and discussions about protests on Twitter have organization and that both the narrative and the organization can be manipulated by bots and other actors. While the "war of ideas" has been shown to rage in social media over the course of a protest, less is known about how the opposing sides in such discussions are organized. For example, do opposing sides of a collective action event use social media in the same way? Are the types of

actors involved in opposing sides similarly present and active (e.g., are the number of and actions of bots, trolls, verified accounts, and news agencies similar between groups)? Are the narratives in opposition or focused on different issues? How does all this activity change over time?

In this work, we explore these research questions through descriptive and network analysis approaches and seek to better understand the role of social media in a collective action event. Our specific concern is with the COVID-19 protest-related messaging on Twitter. We summarize and analyze the Twitter discussion surrounding the first weeks of the anti-lockdown protests organized against state-imposed restrictions to manage the ongoing COVID-19 pandemic in the United States. We utilize a network analysis approach to compare the Pro- and Anti-Protest groups and their actions in the Twitter discussion to answer the following:

1. Does the Twitter conversation reflect the partisan divide over the anti-lockdown protests?
2. Do the Pro- and Anti-Protest groups contain similar types of users and do such users act in the same way?
3. Over the course of the first weeks of the protests, how does the Twitter conversation change and what does that indicate about the organization of the Pro- and Anti-Protest groups?

By answering these questions through this case study, we hope to provide insight into how opposing sides are organized around protests during a time of national emergency. The next section provides background information on the anti-lockdown protests and recent research on COVID-19 and Twitter. Next, we discuss our data collection and annotation methods. We then summarize our results and conclude with a discussion of what they may indicate about the nature of such Twitter discussions with considerations for future work.

Background

In response to the COVID-19 pandemic, most state governments in the United States implemented various restrictions with the aim of slowing the pace of new cases of the disease, ranging from voluntary shelter in place orders to the mandatory closing of businesses and public spaces. A few small public protests against these restrictions occurred in March 2020, but starting the week of April 12 larger and more numerous protests began taking place. The start of the increase in the size and number of protests coincided with the #OperationGridlock protest in Michigan on April 15 and the release of Trump administration guidelines for opening up on April 16. President Trump also tweeted a series of "Liberate" tweets in support of the protest efforts in Michigan, Virginia, and Minnesota on April 17.

The COVID-19 crisis and governmental responses to it in the United States have been marked by divisive rhetoric and partisanship, and the anti-lockdown protests appeared to be no different. There was media reporting on the numerous conservative

political groups, anti-gun control advocacy groups, local elected officials, and individuals with close ties to Trump campaign organizations and administration that organized, promoted, and/or supported these protests. Many local organizers of subsequent protests mentioned being inspired by the April 15 OperationGridlock protest that was organized and funded by conservative political groups. Hundreds of web domains with names linked to the protests were set up over the week of April 12–18, including many directly after President Trump tweeted his support of the protestors on April 17. Both Reddit users and internet security researchers determined that many of these pages were set up by anti-gun control groups and other conservative organizations and several were linked to Facebook pages promoting the protests [18–20]. Some of these pages also appear to have been set up by those trying to sell protest-themed merchandise or the domains themselves, and in one case by someone trying to prevent their use by pro-protestor groups [21]. Anti-vaccine advocates and right-wing militias were also visibly part of the anti-lockdown protests.

Mainstream conservative media and individual pundits in the United States promoted the protests, whereas more liberal media pundits questioned or attacked the protests [22]. The majority of the public polled by Pew Research during this uptick in protests stated that they are more worried about opening up too quickly than not quickly enough, though partisan differences related to this subject grew over the period of interest [23].

Early research work on the Twitter conversations around COVID19 generally found that the level of partisanship in US politicians' Twitter communications rose in February and remained elevated into March [24]. Other early work suggested that bot-like accounts are more involved in spreading misinformation or ideology than human-like accounts [25]. A recent unreviewed analysis of tweets using "openup" in late April/early May by Samuel et al. claims that more positive sentiment was used to discuss opening up state restrictions than negative sentiment Samuel et al. Questions remain as to how closely the Twitter conversation regarding the protests mirrors the on the ground support of the protests and how different views on the protests are expressed and organized on the social media platform.

Data collection and annotation

Using the public Twitter REST API v1.0, we collected tweets containing the keywords, "operationgridlock", "openup", and "liberate" from April 12 through May 10. We deduplicated the raw collected tweets and pulled out additional tweets not already in our data from the retweets, quotes, or replies where possible. As some of the keywords used in collection are general terms, we removed tweets that had no relation to the anti-lockdown protests or general "open up" conversation in the United States.

We annotated the user accounts present in our data in three ways. First we ran BotHunter, a machine learning bot detection tool, and obtained a bot score for each user account [27, 28] The bot score is from 0 to 1, and higher scores indicate that the account appears to act more similarly to certain types of automated accounts (is more "bot-like", if not necessarily an automated account itself).

Second, we labeled user accounts as News Agencies based upon a list of known news organization accounts.

After deduplication, our data set contained a total of 1,251,895 tweets from 470,567 unique user accounts. As is typical of event-based Twitter datasets, a large majority of the tweets in our data are retweets (86%). Figure 1 below shows the number of tweets, including retweets, over time, with the largest spikes in activity coinciding with the day of the first large demonstration in Michigan and directly after President Trump's "Liberate" tweets. For part of our analysis, we divide up the overall timeline into three periods to analyze changes in networks and activity: Period 1 is April 12 to April 17, Period 2 is April 17 to April 24, and Period 3 is April 24 to May 11. We based these divisions on both the timeline of offline events and the Twitter activity timeline from our collected data. Period 1 represents the period in which the administration announces their openup agenda and the first OperationGridlock protest in Michigan occurs, but before President Trump weighs in directly. The second period represents the week in which President Trump tweets, the reactions to it occur, and the first larger protests after the first OperationGridlock occur. The last period is the remainder of our data that covers the following 2 weeks in which there were additional protests but the level of Twitter activity in our collection was consistently lower.

To find Pro- and Anti-Protest communities we investigated the retweet network between user accounts. While retweeting does not necessarily indicate support, such a network may still provide a helpful starting point in finding communities. A preliminary inspection of the retweet network revealed two large groups that dominated the network (Fig. 2a).
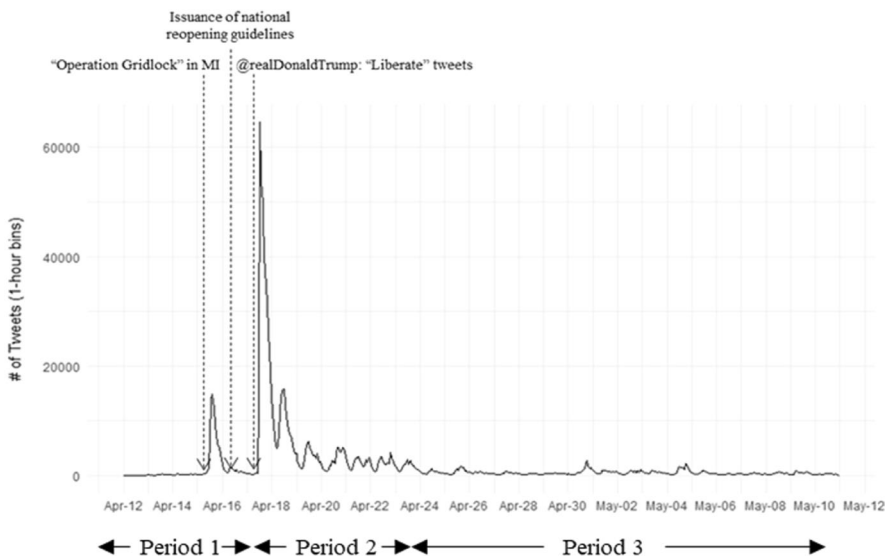

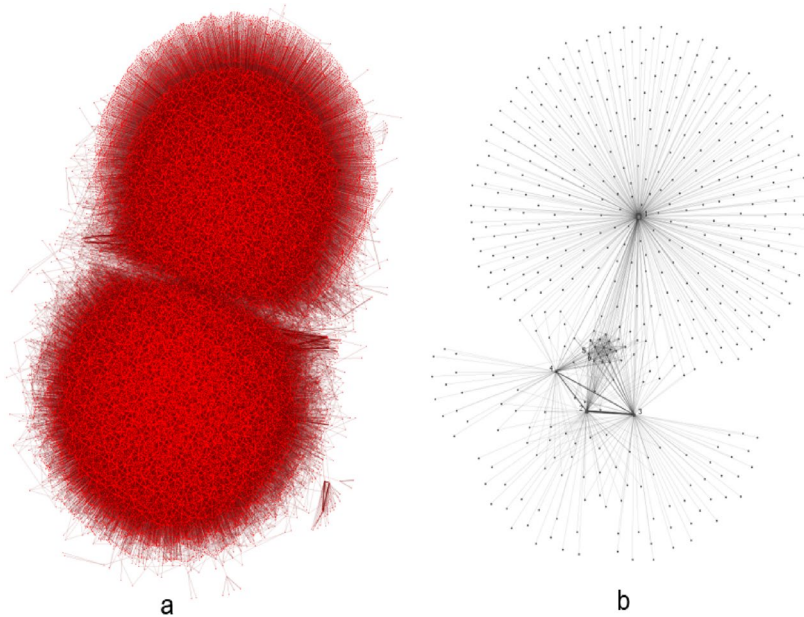**Fig. 1** Collected tweets containing keywords "operationgridlock", "liberate", and/or "openup" over time

Fig. 2 General structures of Retweet Network a. User × User retweet network. K-core of 3 shown for clarity (each user is connected to at least 3 others and/or is connected to 1 other with a weight of 3 or more). **b** Leiden Group × Leiden Group retweet network

We performed Leiden clustering [29] on the full User x User retweet network to find less obvious community structure and created a Leiden Group × Leiden Group retweet network (Fig. 2b). We manually inspected the most retweeted tweets and found that those sourced from Leiden Group 1 were in favor of the anti-lockdown protests whereas those from Groups 2–4 were against the protests and/or against President Trump's promotion of the protests (see Table 9 in the appendix). This result suggests that the Pro-Protest group is more cohesive and more coordinated than the Anti-Protest group. Using the Leiden Group network we assigned a label to each Leiden Group based on the ratio of retweets from that group that retweeted tweets from Group 1 versus Groups 2–4. Users in groups with a ratio of 0.75 or above were labeled "Pro-Protest", users with a ratio of 0.25 or less were labeled "Anti-Protest", and the rest were labeled as "Mixed" (users accounts not in the retweet network were labeled as "NotLabeled").

As the Pro-Protest groups are dominated by connections to the realDonaldTrump account, we reran the Leiden clustering without that account to see if there were substantial changes in the cluster. Without the realDonaldTrump account, the results of Leiden groupings were similar: Group 1 was still very Pro-Protest and insular, Groups 2–4 were still very Anti-Protest and interactive with each other. We therefore decided to analyze the full networks including the realDonaldTrump account.

Our analysis is focused on comparing the users, tweets, and networks of the Pro-Protest conversation with that of the Anti-Protest conversation. The results are summarized in the next section.

Table 1 Summary of tweets and users by group

	Pro-Protest	Anti-Protest	Mixed	Not labeled	Total
# of Tweets	431,045	721,452	6541	92,857	1,251,895
# of Users	131,470	264,306	3330	71,461	470,567

Table 2 Summary of tweet activity by group

	Pro-Protest	Anti-Protest	Mixed	Not labeled	Total
# of tweets	431,045	721,452	6541	92,857	1,251,895
% Original tweets	3.1%	3.1%	7.2%	32.2%	5.2%
% Retweets	91.9%	92.4%	85.5%	12.6%	86.2%
% Comments (Replies and Quotes)	5.0%	4.5%	7.3%	55.2%	8.5%
Number of unique mentions	1548	1,662	89	2776	4904
Avg. # of mentions per tweet	0.02	0.01	0.02	0.13	0.02
Avg. # of mentions per tweet w/mentions	1.6	1.5	1.7	1.5	1.5
Number of unique hashtags	6500	6039	483	9303	17,611
Avg. # of hashtags per tweet	0.51	0.12	0.43	0.43	0.27
Avg. # of hashtags per tweet w/hashtag	1.7	1.6	1.9	2.2	1.7

Results

Overall characteristics of the pro- and anti-protest groups

Table 1 summarizes the number of tweets and users present for each group. There are approximately double the number of Anti-Protest users as Pro-Protest users and very few users that fit our definition of "Mixed". The Anti-Protest users tweeted approximately 1.7 times more tweets than the Pro-Protest users.

Table 2 summarizes the tweets by tweet type and group label. It shows how similar the Pro- and Anti-Protest groups are in terms of the percentage of their tweets that are original tweets, retweets, and comments. It also shows that the Pro- and Anti-Protest groups are similar in the number of other accounts they mention and hashtags they use though the Anti-Protest users use hashtags less often. Together the results from Tables 1, 2 are suggesting that although the anti-protest group is using Twitter more to push their message, this message is less coordinated and more varied. In contrast the Pro-Protest group are all pushing a more cohesive similar message as evidenced by the higher use of hashtags.

We next considered three different aspects of community: (1) what types of actors are present, (2) the structure of the communications network, and (3) the structural position of the most central actors in those networks. Table 3 summarizes information about the accounts present in the Pro- and Anti-Protest groups. There are low levels of verified users and news organizations with the lowest numbers in the Pro-Protest group. The Pro-Protest group also had the highest levels of accounts with default profiles and suspended accounts (as of May 20, 2020). Default profiles and

Table 3 Summary of user accounts (*default and suspended information gathered May 20, 2020)

	Pro-Protest	Anti-Protest
# of users	131,470	264,306
% verified users	0.32%	1.26%
% news orgs	0.01%	0.04%
% default profiles[*]	9.25%	5.16%
% suspended accounts[*]	0.83%	0.27%
% bot score > .75	26.3%	22.9%
% bot score between .5 and .75	36.4%	30.6%
% bot score < .5	37.4%	46.5%

suspended accounts can signal actors new to Twitter, or actors that violated the terms of service, including bots. We also find that accounts that cannot be labeled as either Pro- or Anti- the protest, have a surfeit of news agencies and verified actors. This supports our observation that this group is largely made up of those reporting on the protest. These results suggest that by and large news agencies are acting in a more objective fashion in their lack of retweeting activity. In addition, they suggest that the Pro-Protest group is more supported by bots and less credible actors.

We next compared the full Pro- and Anti-Protest communities on general network metrics for the combined User × User communication network (retweets, comments, and mentions) as summarized in Table 4. The Pro-Protest network was found to be slightly denser than the Anti-Protest network. This suggests there is slightly more cohesion and coordination within the Pro-Protest group.

We also compared the degree and eigenvector centrality of the top 50 most central users in each group, as summarized in Fig. 3. The top Pro-Protest users measured higher on total degree centrality metrics than the top Anti-Protest users. As users outside of the top 50 are looked at, the users in both groups have similar measures. This higher degree centrality among the top actors in the Pro-Protest group suggests that these actors are more tied to other Pro-Protestors and/or are spending more of their messages mentioning and attacking actors on the Anti-Protest side.

One possible indicator of organized activity related to protests is the creation of new accounts to push narratives around such protests. Figure 4 shows the creation dates of the users involved in the conversation by group for those accounts that started since 2019. The creation of what are labeled Pro- and Anti-Protest accounts appear to be similar until March 2020, when there is a spike in Pro-Protest account creation. This result provides further evidence of a possible type of orchestration on the Pro-Protest side of the debate.

Table 4 Comparison of network metrics by group

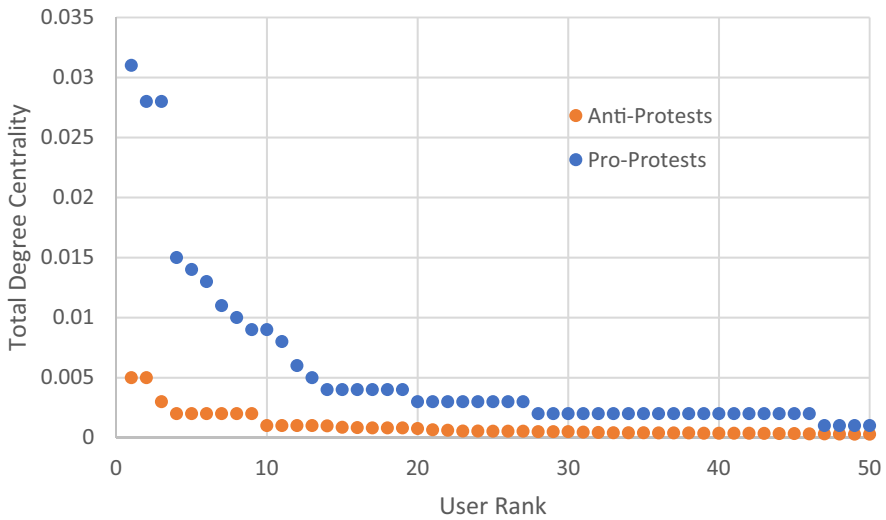|	Pro-Protest	Anti-Protest
Density	0.000023	0.000009
Echo-chamberness	0.004	0.002
Reciprocity	0.003	0.002

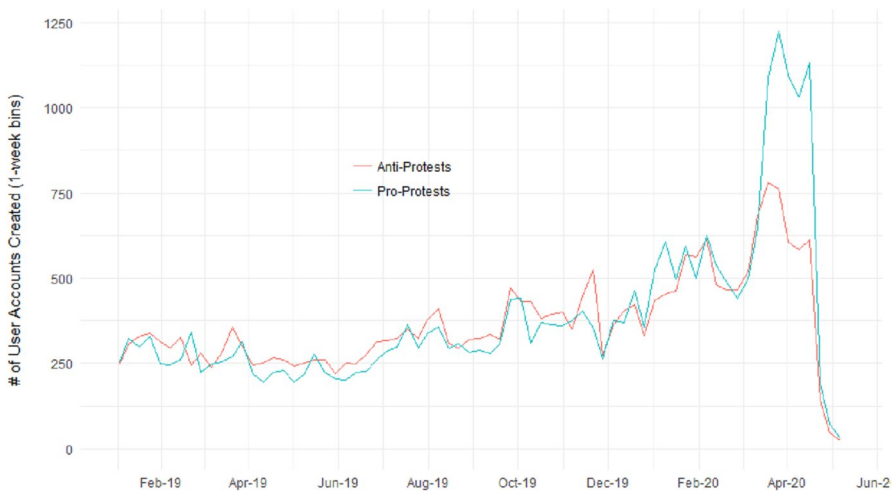**Fig. 3** Total degree centrality of top 100 most central users

Fig. 4 Involved user accounts' creation over time by group from Jan 1, 2020

Table 5 summarizes characteristics of these newer accounts. Approximately 60% of the newer accounts and tweets from newer accounts are from the Pro-Protest group, otherwise, the newer accounts looks relatively similar between the two groups.

Figure 5 details the retweet network between these younger user accounts. The majority of newer accounts are not interacting with each other, but for those that do, it appears that the Pro-Protest accounts are interacting with each other more as

Table 5 Summary of new user accounts created since March 1, 2020 (*default and suspended information gathered May 20, 2020)

	Pro-Protest	Anti-Protest
# of Users	8886	5514
# of Tweets	20,581	13,476
% retweets	86.2%	88.6%
% default profiles*	13.0%	11.8%
% suspended accounts*	3.6%	2.8%
% bot score > .75	13.3%	15.1%
% bot score between 0.5 and 0.75	69.3%	66.6%
% bot score < 0.5	17.3%	18.2%

Fig. 5 User x User retweet network for users whose accounts were created after March 1, 2020. Isolates removed for clarity. Nodes are sized by number of tweets from that user
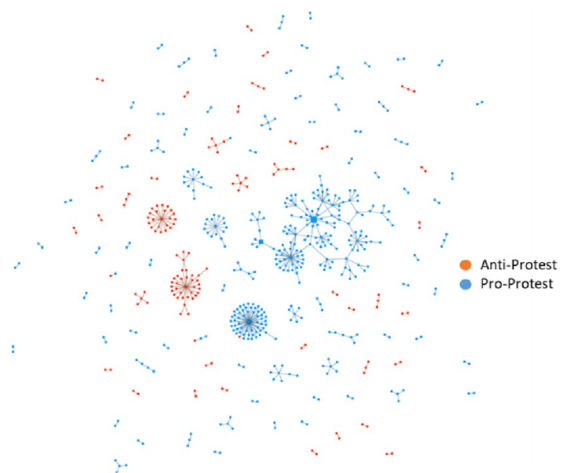
can be seen by the largest component. It is also of interest that the two most active accounts on the Pro-Protest side overall are located in this main component (one of which is now suspended by Twitter, and both of which have bot scores above 0.75). These two accounts as well as many others shown in Fig. 5 appear to be troll-like accounts upon manual inspection: they are consistently retweeting attacks on the opposite group or praise for their own. These results indicate that both groups have troll-like new accounts active in the conversation, but the Pro-Protester group appears to have more coordination of such accounts.

Narrative differences (shared hashtags and URLs)

To broadly investigate the differences in content shared by the Pro-Protest and Anti-Protest groups, we obtained the top five most used hashtags and top five most shared website domains (both including retweets) for each group as shown in Tables 6, 7. In terms of hashtags, we can see an emphasis on certain states and the Trump MAGA slogan on the Pro-Protest side and an emphasis on COVID and attacking President

Table 6 Top five used hashtags per group by user type

	All	Verified	Bot score > 0.75
Pro-protest	OperationGridlock	OperationGridlock	OperationGridlock
	LiberateMichigan	MAGA	MAGA
	MAGA	LiberateIllinois	Michigan
	LiberateIllinois	Shutdown	LiberateIllinois
	Michigan	Chicago	LiberateMichigan
Anti-Protest	OperationGridlock	OperationGridlock	OperationGridlock
	COVID19	COVID19	COVID19
	25thAmendmentNow	CoronaVirus	25thAmendmentNow
	Liberate	China	Trump
	Trump	Liberate	Democratic

Table 7 Top five shared domains per group by user type

	All	Verified	Bot Score > .75
Pro-protest	thegatewaypundit.com	thegatewaypundit.com	thegatewaypundit.com
	breitbart.com	bit.ly	breitbart.com
	youtu.be	trib.al	youtu.be
	foxnews.com	dailycaller.com	mlive.com
	facebook.com	waynedupree.com	foxnews.com
Anti-Protest	nbcnews.com	trib.al	washingtonpost.com
	washingtonpost.com	bit.ly	nbcnews.com
	rawstory.com	washingtonpost.com	rawstory.com
	cnn.com	hill.cm	huffpost.com
	thenation.com	nbcnews.com	dailykos.com

Trump (e.g., #25thAmendmentNow) on the Anti-Protest side. There does not seem to be much difference in the use of hashtags between verified and high-bot-score accounts compared with the overall group.

In terms of shared domains, the top five for the Pro-Protest side are dominated by either center to far right news sites or social media, while the Anti-Protest side are dominated by center/center left news media, demonstrating the apparent partisan divide. For both sides it appears that verified accounts share link-shortened addresses to a greater degree.

Tables 8, 9 show the changes to the top five most shared hashtags and websites by group over the three time periods of interest. The top hashtags shared by Pro-Protest follow the states in which protests were occurring in each time period. The first period also contains pro-Trump hashtags (MAGA and TheGreatAwakening, a reference to pro-Trump conspiracy, QAnon). COVID19 is prominently used throughout by the Anti-Protest users as well as anti-protest/anti-Trump hashtags such as "Covidiots" and "25th AmendmentNow". It should be noted that in the last period the DropOutBiden hashtag appears to have been an attack on the Democratic nominee

Table 8 Top five most used hashtags by group and time period

	Period 1	Period 2	Period 3
Pro-protest	OperationGridlock	OperationGridlock	OperationGridlock LiberateCalifornia
	Michigan	LiberateMinnesota	LiberateIllinois
	MAGA	LiberateMichigan	Unconstitutional
	MichigandersAgainstExcessiveQuarentine	OperationGridlockNJ	LiberateMichigan
	TheGreatAwakening	WeThePeople	
Anti-Protest	OperationGridlock	25theAmendmentNow	DropOutBiden
	COVID19	COVID19	MichiganProtest
	Michiganshutdown	OperationGridlock	COVID19
	Michigan	Liberate	Liberate
	Covidiots	Democratic	MAGA

Table 9 Top five most shared websites by group and time period

	Period 1	Period 2	Period 3
Pro-protest	youtu.be	breitbart.com	youtu.be
	thegatewaypundit.com	thegatewaypundit.com	thegatewaypundit.com
	facebook.com	youtu.be	foxnews.com
	youtube.com	foxnews.com	breitbart.com
	americanthinker.com	mol.im	facebook.com
Anti-Protest	youtu.be	nbcnews.com	washingtonpost.com
	facebook.com	washingtonpost.com	medium.com
	bit.ly	rawstory.com	thedailybeast.com
	citypages.com	cnn.com	bit.ly
	washingtonpost.com	thenation.com	nbcnews.com

from progressives. Similarly, the use of MAGA in the last period is in tweets attacking President Trump, his supporters, or the protests.

The top five web domains shared by the two groups reiterate their apparent partisan leanings and both groups prominently shared other social media links in the first period. Pro-Protest users continued to do so while the Anti-Protest group shared additional news/opinion sites.

Dynamic change in groups, activity and targets

Figure 6 again shows the tweets over time throughout the three periods of interest, but now grouped by what cohort is the source of the tweet. Period 1, which coincides with the original OperationGridlock protest in Michigan, is dominated by Pro-Protest activity. The second period instead shows an original spike in activity from
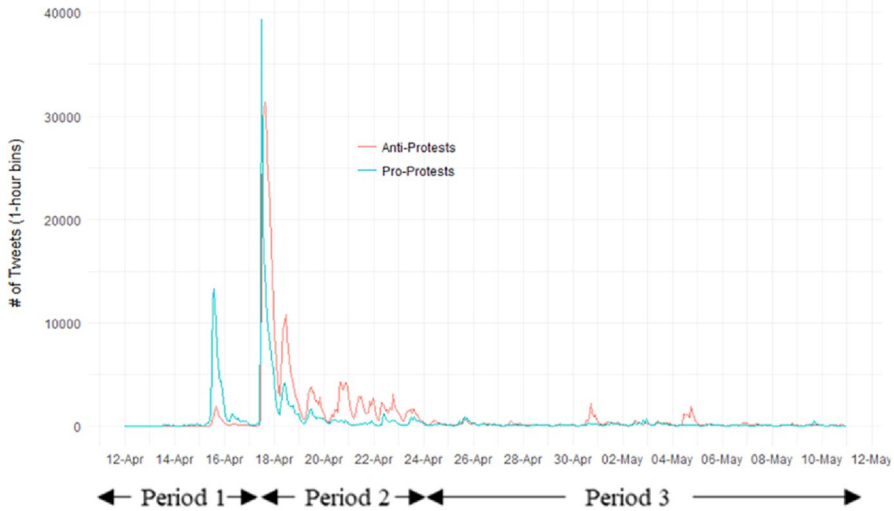
Fig. 6 Tweets over time by group. The tweets from Anti-Protest users appear to follow and overwhelm (in terms of volume) those of the Pro-Protest accounts in Period 2 (April 17–April 24)

the Pro-Protest group (focused mostly on retweets of realDonaldTrump's "Liberate" tweets) and then the response from the Anti-Protest group against both President Trump and the protests, which overtake the Pro-Protest side in volume. This can be seen in the change in number of users with the Pro-Protest side only increasing from 46,056 unique users in Period 1 to 106,575 users in Period 2, while the Anti-Protest side increases from 12,404 to 244,193 users. Additionally, 26.0% of the Pro-Protest users in Period 2 were present in Period 1, whereas for the Anti-Protest side, only 3.5% of the users in Period 2 were from Period 1. These results suggest a higher level of consistent and continued coordination and participation among the Pro-Protest group, while the Anti-Protest group is able to attract a larger number of newer users between periods.

We compared the users within each group that are doing the targeting as shown in Figs. 7, 8. In contrast to their targets, there is a much lower level of verified users involved in retweeting, commenting, and mentioning in both groups. The

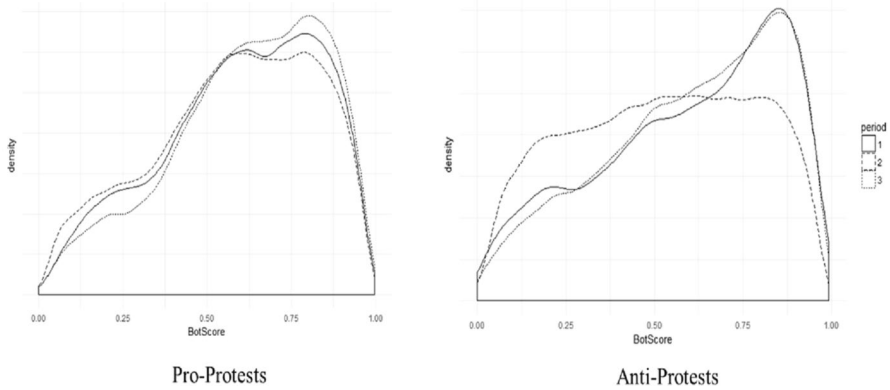**Fig. 7** Characteristics of the active users from each group by period
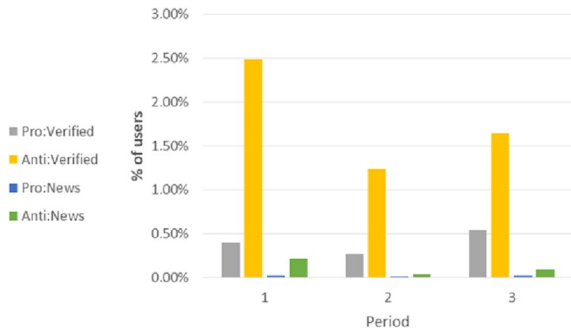
Fig. 8 User bot score distributions by group and period

Anti-Protest group has a higher presence of verified accounts in all time periods than the Pro-Protest group. The bot score distributions summarized in Fig. 8 present an interesting comparison between the Pro- and Anti-Protest users. While the Pro-Protest user distributions are very similar across all time periods, the Anti-Protest distribution flattens out in period 2 (the period with the most activity and attention). This indicates a higher relative presence of users with low bot scores. This could indicate that the Anti-Protest group is more successful at attracting activity from the general public during the most active period than the Pro-Protest group. It also suggests that the Pro-Protest group's composition is less organic than that of the Anti-Protest group.

To obtain an understanding of any differences in how these Pro- and Anti-Protest users operated over time, we also explored the most targeted accounts for each group for each time period (Appendix for Table 11). "Most targeted" in this context refers to the accounts that were most retweeted or had the most comments (replies and quotes) directed at them, or which were most mentioned by Pro- or Anti-Protest users. The top five most targeted accounts within each period are dominated by government, political group, pundit, journalist, and news organization accounts. For the retweet and comment networks, the focus is on a mix of verified and unverified accounts for both Pro- and Anti-Protest groups. The top five mentions in both groups are all verified accounts. In looking at the top five targets across the comment and mention networks and all time periods, the most apparent difference between the Pro- and Anti-Protest activity is that the none of the top five targets for the Pro-Protest side are labeled as Anti-Protest, whereas many of the top five targets of Anti-Protest users are Pro-Protest (Pro-Protest users do target NotLabeled user accounts of the Democratic governors of states where protests took place, and such accounts are most likely Anti-Protest though they are not labeled as such due to not being in the retweet networks).

To get a wider perspective on which types of accounts were being targeted by each group, we compared the top 100 targets for each group at each time period through the percentage of verified accounts, news organization accounts and high-bot-scoring (> 0.75) accounts. As Fig. 9 shows, there are higher percentages of verified accounts in the top 100 most retweeted accounts for the Anti-Protest group in contrast to the Pro-Protest group, especially in the second and third periods. *The most* commented on and mentioned accounts for both groups have similar percentages of verified accounts, though there are more new organizations being targeted by the Anti-Protest group in some periods. The percentage of targets for the Pro-Protest group that have high-bot scores hovers around 10% in all time periods, whereas for the Anti-Protest group the percentage is between 2 and 5%. This further supports the argument that the Pro-Protest was a less organic coordinated activity; rather, it appears more as a bot amplified and highly coordinated activity.

Discussion and conclusions

As governments, organizations, and publics continue to respond to and communicate about the COVID-19 crisis it will be helpful to investigate how social media platforms are extending or facilitating debate over policy. In this work we took a broad look at the Twitter conversation around the beginnings of the anti-lockdown protests in the United States. After determining that the overall Twitter discussion does mirror the partisan divide over the protests based on the opposing sides retweet activity, use of hashtags, sharing of external links, and support of popular tweets, we then contrasted the organization of these groups in terms of their members and their activity. Our results suggest that there were different strategies at play and that these differences can be summarized as having to do with the presence and attention paid to verified and high-bot-scoring accounts and with the levels of network centralization.

Automated accounts, trolls, and booster accounts have come to be ubiquitous in political discussions on Twitter, and the debate over OperationGridlock and early anti-lockdown protests was no different. While in raw numbers there were more high-bot-score accounts in the Anti-Protest community, the Pro-Protest side had a higher percentage of and appeared to put more attention on such accounts. The
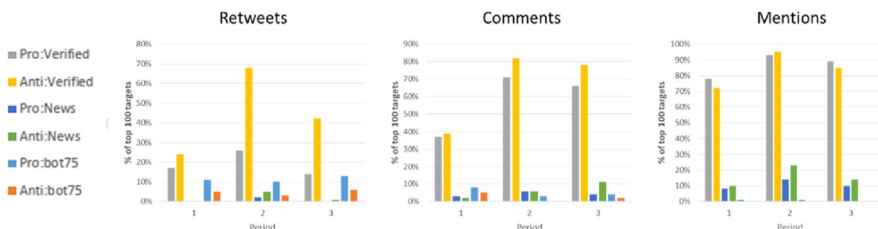

Fig. 9 Characteristics of top 100 users being retweeted, commented, or mentioned by group and period. For example, approximately 70% of the top 100 accounts retweeted by Anti-Protest users in the 2nd period were verified accounts

most striking result related to this is the lack of flattening of the bot score distribution of the Pro-Protest group in Period 2 compared to that of the Anti-Protest group. Throughout all time periods the Pro-Protest group appears to engage similar types of accounts, whereas the Anti-Protest group appears to engage a much larger share of less bot-like accounts during the most active period (Fig. 8). Additionally, a consistently higher percentage of the accounts being retweeted by the Pro-Protest group are those with higher bot scores. Similarly, the apparent coordination of some of the most newly created accounts in the discussion also suggests additional organization on the part of some of the Pro-Protest group.

In terms of verified accounts, the Anti-Protest group appears to utilize larger numbers of such accounts to a greater extent than the Pro-Protest group, both in terms of active users and in terms of the number of targets for retweeting. The Pro-Protest group does push content from verified accounts (and in fact the top most retweeted users by Pro-Protest users are verified accounts), but they do so from a smaller number of accounts, especially in Periods 2 and 3. In contrast, the Anti-Protest group retweets content from a much larger number of verified accounts in those same two periods; almost 70% of the unique users retweeted by the Anti-Protest side are verified compared to about 25% by Pro-Protest users. Additionally, while both low, the percentage of active verified users on the Anti-Protest side is consistently over four times as great as for the Pro-Protest side. A commonality between both groups is the similar attention paid to verified accounts through comments or mentions, both of which are more likely to be discussions or attacks rather than the passive or active spreading of messages through retweets.

This phenomenon of the Pro-Protest group concentrating attention on a smaller number of important users than the Anti-Protest group is reiterated when looking at the full communication networks and the centrality of the users in those networks. Higher centrality scores for the top users in the Pro-Protest group indicate more attention on them from their own group, whereas the Anti-Protest side appears to focus on a larger number of central users. The reliance on multiple central agents has previously been found as a distinguishing factor in how Democrat politicians operate on Twitter, though in this case, it could also be driven by the different types of attacks (some anti-protest, and some more directed at attacking President Trump's support than the protests themselves).

In looking at effectiveness, it appears based on simply the volume of tweets and types of users involved that the Anti-Protest group was more effective at spreading their messaging during the second period (which is where the majority of the discussion occurred) than the Pro-Protest group. This may in part be due to the Anti-Protest group's ability to engage larger numbers of more normal-looking accounts and/or their reliance on more activity and content from verified accounts (who typically have large follower bases). The Pro-Protest group appears to be more

concentrated around President Trump and a small group of allied users but did not increase engagement as effectively. Future work could explore how misinformation and/or corrective information are passed on by the different organizational states or strategies as alternative measures of effectiveness to the number of engaged or the volume of tweets.

Overall, these results suggest that the Pro-Protest side was more centrally coordinated and less organic than the Anti-Protest side. This is supported by the larger role of bot-like or troll-like accounts, the involvement of newer accounts, and the more central role of top users. In contrast, the Anti-Protest side was characterized by being more organic, less centrally coordinated, larger, and less cohesive. This is seen in the lesser role of bot and troll-like accounts, the higher number of verified actors, the high temporal volatility in membership, and the lower level of interaction among members. Similarly, we note that the Pro-Protest side had a single focused agenda; whereas, the Anti-Protest side had a more scattered agenda.

This work is a broad look at the Twitter conversation around the start of the anti-lockdown protests. It is limited by the fact that the data are based on specific keyword searches and therefore may miss part of the overall conversations, especially in the later time period. We also lack data on the friends/followers networks and "likes", both of which may help to provide clearer separation between the Pro- and Anti-Protest sides. Overall, it appears that our retweet-based approach to exploring communities did enable us to find general distinctions to use as the basis of our analysis. We find many ways to coordinate, but the level and type of coordination is different for both sides of the protest. Further insights about how Twitter is used to report on and support or detract from the anti-lockdown protests and the general open-up debate in the United States could be gleaned from additional work focusing on state to state comparisons and the timing of real world and twitter events. This would further our understanding of how partisan battles over policy during times of crisis are conducted on Twitter, which in turn can help inform how the public and others participate in such debates.

Appendix

See Tables 10, 11.

Table 10 Text of top three most retweeted Tweets by Leiden Group

Leiden Group	Text of top three tweets from Leiden Group	# RTs
1	"LIBERATE VIRGINIA, and save your great 2nd Amendment. It is under siege!"	43,305
	"LIBERATE MICHIGAN!"	39,552
	"LIBERATE MINNESOTA!"	34,436
2	"Never forget this day, when the U.S. president called on citizens — some displaying swastikas, and many armed — to "liberate" their states. This would have been treason in 1861. It would have been treason in 1941. It is treason now."	10,815
	"LIBERATE AMERICA!!! Just wondering, what elected member of the GOP is ok with this lunatic tweeting this shit and inciting violence. https://t.co/CNYRBnZXOj"	7558
	"Days after trump supporters in Michigan dangerously prevented emergency workers from reaching hospitals, trump is screaming LIBERATE VIRGINIA, and citing the 2nd Amendment. He's inciting violence and civil unrest during a pandemic. Time for #25thAmendment. NOW."	5676
3	"The president's statements this morning encourage illegal and dangerous acts. He is putting millions of people in danger of contracting COVID-19. His unhinged rantings and calls for people to "liberate" states could also lead to violence. We've seen it before. 1/7"	18,914
	"Former head of DOJ's Nat'l Security Div Mary McCord: "it's not at all unreasonable to consider Trump's tweets about "liberation" as at least tacit encouragement to citizens to take up arms against duly elected state officials of the party opposite his own" https://t.co/a6IcEAvHDT"	7649
	"Republicans are good at stoking outrage and bad at governing. So instead of deploying tests we get angry mobs trying to "liberate" states from life-saving governance."	7101
4	"A lot of the "liberate" footage is meant to make these events look big. Here's what the protest in Ohio today really looks like.\r\n\r\n https://t.co/0uxRuG0lxS"	30,182
	"Three nurses showed up to counter-protest the Arizona "liberate" rally. They stood silently. And the "liberate" crowd didn't leave them alone. They stood in their faces and berated them. These women are heroes, and deserve so much better. https://t.co/h3NrLfvN13"	17,792
	"I don't understand how these nurses protesting in front of the White House today didn't get 10×as much attention as the "liberate" lunatics.\r\n\r\n https://t.co/SePKbTPVW8"	17,503

Table 11 Top five most targeted accounts by group, period, type of response

For tweets from pro-protest users

	Most targeted accounts	Type of account	Verified?	BotHunter probability	Cohort of targeted account	# of tweets by target	# targeting tweets
Period 1 Retweets	A2	Journalist	True	0.03	Pro	10	8,036
	B1	Journalist	True	0.01	Pro	4	7,707
	MI_Republicans	Government	False	0.09	Pro	1	6,301
	C1	Political	True	0.06	Pro	10	4,788
	D1	Other	False	0.51	Pro	2	4,446
Period 2 Retweets	realDonaldTrump	Government	True	0.05	Pro	3	116,031
	C2	Other	False	0.33	Pro	3	13,585
	D2	Political	True	0.04	Pro	9	12,485
	IngrahamAngle	Pundit	True	0.02	Pro	1	11,440
	G1	Pundit	True	0.00	Pro	1	6,011
Period 3 Retweets	F1	Other	False	0.38	Pro	2	3,094
	F2	Other	False	0.36	Pro	5	2,482
	F3	Pundit	True	0.08	Pro	4	2,092
	C2	Other	False	0.33	Pro	4	1,330
	E1	Other	False	0.65	Pro	1	937
Period 1 Comments	B1	Journalist	True	0.01	Pro	5	130
	A2	Journalist	True	0.03	Pro	4	77
	C1	Political	True	0.06	Pro	7	70
	MI_Republicans	Government	False	0.09	Pro	2	61
	E2	Other	False	0.51	Pro	1	56

Table 11 (continued)

For tweets from pro-protest users

	Most targeted accounts	Type of account	Verified?	BotHunter probability	Cohort of targeted account	# of tweets by target	# targeting tweets
Period 2 Comments	realDonaldTrump	Government	True	0.05	Pro	58	1,823
	F4	Journalist	True	0.13	Mixed	2	192
	benshapiro	Pundit	True	0.15	Mixed	8	172
	IngrahamAngle	Pundit	True	0.02	Pro	15	89
	C2	Other	False	0.33	Pro	11	58
Period 3 Comments	realDonaldTrump	Government	True	0.05	Pro	101	393
	F5	Political	True	0.17	Pro	24	70
	GovTimWalz	Government	True	0.01	NotLabeled	27	69
	dbongino	Pundit	True	0.04	Pro	24	64
	IngrahamAngle	Pundit	True	0.02	Pro	25	47
Period 1 Mentions	GovWhitmer	Government	True	0.00	NotLabeled	na	279
	realDonaldTrump	Government	True	0.05	Pro	na	115
	gatewaypundit	NewsOrg	True	0.40	Pro	na	71
	POTUS	Government	True	0.10	Pro	na	20
	FoxNews	NewsOrg	True	0.55	NotLabeled	na	14
Period 2 Mentions	realDonaldTrump	Government	True	0.05	Pro	na	793
	gatewaypundit	NewsOrg	True	0.40	Pro	na	280
	BreitbartNews	NewsOrg	True	0.22	Pro	na	213
	GovWhitmer	Government	True	0.00	NotLabeled	na	125
	POTUS	Government	True	0.10	Pro	na	124

Table 11 (continued)

	Most targeted accounts	Type of account	Verified?	BotHunter probability	Cohort of targeted account	# of tweets by target	# targeting tweets
For tweets from pro-protest users							
Period 3 Mentions	realDonaldTrump	Government	True	0.05	Pro	na	341
	GovWhitmer	Government	True	0.00	NotLabeled	na	120
	GavinNewsom	Government	True	0.01	NotLabeled	na	76
	GovTimWalz	Government	True	0.01	NotLabeled	na	73
	GovPritzker	Government	True	0.03	NotLabeled	na	66
For tweets from Anti-Protest users							
Period 1 Retweets	A1	Other	False	0.26	Anti	2	2,856
	D22	Political	False	0.36	Anti	12	2,345
	D23	Other	False	0.19	Anti	1	1,388
	D24	Journalist	False	0.06	Anti	9	882
	F54	Other	True	0.33	Anti	2	782
Period 2 Retweets	A1	Other	FALSE	0.26	Anti	12	79,050
	GovInslee	Government	True	0.00	Anti	1	18,798
	F34	Political	FALSE	0.25	Anti	13	16,012
	LightfootForChi	Government	True	0.02	Anti	1	15,226
	B22	Other	False	0.57	Anti	1	14,720

Table 11 (continued)

	Most targeted accounts	Type of account	Verified?	BotHunter probability	Cohort of targeted account	# of tweets by target	# targeting tweets
	For tweets from Anti-Protest users						
Period 3 Retweets	A1	Other	False	0.26	Anti	19	8,570
	R2	Political	False	0.31	Anti	1	5,582
	R4	Other/political	True	0.10	Anti	3	4,524
	R5	Political	True	0.09	Anti	8	4,080
	R6	Other	True	0.04	Anti	1	2,464
Period 1 Comments	MI_Republicans	Government	False	0.09	Pro	2	62
	A2	Journalist	True	0.03	Pro	5	33
	D55	Journalist	False	0.06	Anti	5	31
	A1	Other	False	0.26	Anti	5	24
	Y7	Journalist	False	0.22	Pro	2	23
Period 2 Comments	realDonaldTrump	Government	True	0.05	Pro	68	6,324
	IngrahamAngle	Pundit	True	0.02	Pro	13	752
	PressSec	Government	True	0.01	NotLabeled	6	220
	A1	Other	False	0.26	Anti	16	192
	A5	Political	True	0.01	Anti	4	156
Period 3 Comments	realDonaldTrump	Government	True	0.05	Pro	103	788
	AA2	Government	True	0.01	Anti	6	75
	AA3	Political	True	0.14	NotLabeled	1	45
	A1	Other	False	0.26	Anti	14	43
	PressSec	Government	True	0.01	NotLabeled	9	41

Table 11 (continued)

For tweets from Anti-Protest users

	Most targeted accounts	Type of account	Verified?	BotHunter probability	Cohort of targeted account	# of tweets by target	# targeting tweets
Period 1 Mentions	GovWhitmer	Government	True	0.00	NotLabeled	na	41
	realDonaldTrump	Government	True	0.05	Pro	na	24
	GOP	Government	True	0.05	NotLabeled	na	6
	MSNBC	NewsOrg	True	0.62	Anti	na	6
	maddow	Journalist	True	0.02	Anti	na	5
Period 2 Mentions	realDonaldTrump	Government	True	0.05	Pro	na	1,449
	NBCNews	NewsOrg	True	0.61	Anti	na	193
	GOP	Government	True	0.05	NotLabeled	na	156
	HuffPostPol	NewsOrg	True	0.41	Anti	na	123
	JoeBiden	Political	True	0.19	NotLabeled	na	108
Period 3 Mentions	realDonaldTrump	Government	True	0.05	Pro	na	169
	GOP	Government	True	0.05	NotLabeled	na	32
	thedailybeast	NewsOrg	True	0.23	Anti	na	29
	POTUS	Government	True	0.10	Pro	na	25
	thenation	NewsOrg	True	0.05	Anti	na	21

Non-celebrity/public figure or organizational accounts have been anonymized

Data availability Tweet IDs can be made available.

Code availability ORA analysis software is available.

Declarations

Conflict of interest The authors declare that there are no conflicts of interest presented in this work.

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