Quantifying The Leadership and Social Media Predictors of Violence and Racism during the January 6th Attack on the Capitol

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Abstract

Protests involving brute force are growing in number and are now viewed as one of the mostly likely sources of collective violence in the U.S.[1] Yet our scientific understanding of how violent protests is related to leadership rhetoric and social media communications during protests remains nascent[2–6]. Here we analyze new data from the U.S. Capitol insurrection to quantify the links between leadership actions, social media communications, and levels of violence and racism during on the day of 1/6/21. Using Granger causality methods to analyze former President Trump's tweets, #StopTheSteal tweets, rally speeches, and live-action videos, we find that Trump's tweets and speech predicted rioters' levels of violence and weapons use. Trump's tweets also predicted increased levels of the #StopTheSteal tweets, which in turn predict escalations in attacks and beatings, dangerous weapons, and symbols of racism. NLP analyses indicate that a tweet's sentiment predicts different forms of violence and racism and at different levels. The findings demonstrate how the interplay of authority figure behavior and social media is predictive of shifts from peaceful protest to physical violence.

Significance Statement

We examine the predictors of violence, weaponry, and racism during the Capitol insurrection, which involved the loss of life, injury, property, and the legitimacy of the election. Using novel, high-resolution data, including 1,113 live footage videos, Trump's tweets and rally speech, other rally speeches, and 7,750 #StopTheSteal tweets, we apply Granger causality tests to identify the strong, weak, and reciprocal predictors of violence as well as the positive feedback loops that escalate violence once begins.

Introduction

Peaceful protests play a pivotal role in triggering political, legislative, and organizational change[2,7–9] by shaping law-making agendas and raising awareness about previously ignored issues. Protests can also become violent, potentially leading to the loss of life. For example, far-right protesters clashed violently with counter-protesters in Charlottesville Virginia regarding the taking down of a confederate statue, ultimately leading to the death of Heather Heyer, a peaceful protester. And a clash between protesters and armed militia of counter-protesters during a Black Lives Matters rally in Wisconsin resulted in the death of two protesters and the wounding of a third protester. In recent years, there has been an increased incidence of protesters using deadly violence, which has reduced support for causes and raised the civic costs of policing rallies[10–12]. The U.S. officially ranks social movement protests involving brute force and militias as one of the mostly likely sources of collective violence in the U.S.[1]

Although violence may arise for numerous reasons, including planned attempts to engage in violence, an important — but rarely tested — explanation for protest violence is that protestors become radicalized in real-time by movement leaders[2,13,14]. This phenomenon is one form of what early scholars of collective action referred to as emergent crowd behavior[6]. The French social theorist Gustave Le Bon described the process whereby individuals get "transformed into a crowd. . .[and develop a] collective mind which makes them feel, think, and act in a manner quite different from that in which each individual of them would feel, think, and act were he in a state of isolation" (1896: 27)[15].

Within these collective dynamics, online behavior may play a pivotal role in leaders' and protesters ability to radicalize movements[16]. Studies find a possible association between online activity and real-world violence. One investigation found that during the 2015 Baltimore protests following the death of 25-year-old Freddie Gray, the number of tweets with moralized language positively correlated with the number of arrests of protesters, suggesting a connection between tweet sentiment and protesters' civil disobedence[14]. By enabling leaders and followers to communicate their sentiment and approval of the protesters' actions, social media may also have the potential to facilitate the coordination of leaders and protesters in real-time and at an unprecedented scale[17]. Indeed, experiments that simulate violence provide evidence that when leaders give voice to grievances, demonstrators may take the rhetoric as authorization to escalate their use of bodily force[18–23]. Hypothetically, the more emotive the rhetoric is, the more it incites action[24,25], and the more disruptive and confrontational tactics can be[26–28]. These dynamics suggest that a crucial link may exist between a leader's behavior, online behavior of leaders and followers' and real-life actions that can [3,29,30] potentially turn peaceful protest to collective violence that builds on itself[31].

Despite the potential associations between leadership, crowd dynamics, and violence that have been identified, prior research has relied on proxies of violence and has not quantified their interrelationships – a condition due mostly to a lack of high-resolution data that measures how causes variously combine during peaceful protests that turn violent[2,4,14].

Here, we complement research on violent protests with novel data and methods that quantify the interrelated causes of violence using as a case study the January 6th insurrection — the most empirically documented protest-turned-violent riot in history. After months of false claims about a rigged presidential election, thousands of pro-Trump protesters assembled in Washington, D.C. on January 6th, 2021 in support of overturning the election. After listening to "Save America" rally speeches, the crowd proceeded to the grounds of the U.S. Congress. Outside the Capitol, hundreds of protestors turned violent. They smashed through barricades and sacked the Capitol in hopes of stopping the election's certification and finding Vice President Mike Pence and Senator Nancy Pelosi, whom some protesters meant to hang for treason in gallows erected beside the Capitol. After hours of destruction, the assault ended after then-President Trump tweeted for the insurrectionists to go home. Afterwards, it was determined that five people died, including one police officer. Over 140 police officers were injured. The repairs to the Capitol are projected to exceed tens of millions of dollars. One historian called it the most horrific event in modern U.S. history[32] and others see it as a paradigm for future violence[33].

A variety of entities have hypothesized that President Trump[34] (hereafter Trump), speech makers[35], or the crowd itself [6,31] caused the peaceful protest to turn violent. The U.S. Department of Justice cited Trump in fomenting the insurrection, and over a dozen rioters testified that they rampaged because of Trump's tweets[36]. For example, Mitch McConnell, the highest-ranking Senate Republican concluded that, "The people who stormed this building believed they were acting on the wishes and instructions of their president [Trump]…. shouting into the largest megaphone on planet Earth [Twitter]." The combative language used by Donald Trump Jr., former mayor Rudy Giuliani, and congressman Mo Brooks in their rally speeches is also conjectured to have incited violence[37]. Finally, theory suggests that rioters can generate positive feedback loops as violence, selective information flows[38], or the echoing of leaders' rhetoric builds on iteself[6].

Using social theory[2,15,18] and the hypotheses of authoritative observers about the precursors of the rioting to structure our analysis[34,35], we collected and coded data from a variety of sources. The high-resolution data included all the social media posts by Trump and protestors, thousands of real-time videos taken by protestors and journalists, speeches by #StopTheSteal rally speakers, and data on the timing and incidence of violence, weapons, and racism. These data were analyzed using a Granger causality model to assess the strength of leadership and social media variables in predicting changes in the levels of violence, weaponry, and racism during the riot.

Data

Our data sources include Twitter's archive of Trump's tweets and #StoptheSteal tweets[39,40]; rally speech videos[41]; and time stamped, live action video of the insurrection[42] (See Table S1 for a list of data sources). We used all 16 Trump tweets, 7550 "#StopTheSteal" tweets, 12 rally speeches, and 1113 videos from January 6th. Data on levels and timing of violence, weaponry, and racism come from videos taken in real-time and posted to websites that aggregated and coded the videos through crowdsoucing[43].

Video footage. Figure 1 shows the area of activity covered by the videos. These live-action, real-time videos were used to operationalize levels of (i) violence, (ii) weapons, and (iii) racism on January 6th. These videos were uploaded to publicly accessible websites by protesters, journalists, and bystanders located in and around the Capitol and coded through a joint effort of organizations, which included a Twitter user (@donk_enby), an archive team, and a volunteer collection of hackers and data researchers who archived the videos before Amazon Web Services stopped hosting Parler's website. In total, these websites posted 1113 recorded videos taken on January 6th, 2021 (See Methods Section).

Once uploaded, the videos were annotated for instances of violence, weapons, or racism through crowdsourcing. For example, if a video showed an instance of violence — say, a beating or a shove — the specific type of violence in the video was notated and recorded by a user in an accompanying online spreadsheet on the website[43]. Eighty-four videos were tagged for violence, weapons, or racism through crowdsourcing. Crowdsourced coders were anonymous, visited the website where the videos were posted, and coded the videos by their own accord and without pay using a coding scheme that ensured that images were being coded in a standard way across coders. We verified that the videos used in the study were correctly coded by checking the coding of each video ourselves.

Other videos contained footage of protestors walking, standing, marching, shouting, talking, or vandalizing — events that are considered non-violent crimes in the U.S.[44] (see Methods section, Table 4).

We used the crowdsourced notations to compute the severity of violence or and the display or use of various types of weaponry in the image over a five-minute interval. Separate videos covering the same five-minute period had their separate scores summed. The average length of a video is 32.80 seconds (S.D. = 57.60 seconds; max length = 547 seconds; min length =1 second).

To quantify the severity of violent acts or a weapon's potential lethality, we used the District of Columbia's criminal penalty scale, which quantifies the severity of a violent act using a point system, and in which more violent acts receive higher point scores[45]. For example, a beating is more violent than a shove and therefore has a higher penalty (higher point value) than a shove[45]. Specifically, a gunshot = 1500 points; an assault = 1000 points; other violence = 500 points. The severity of the violence or weaponry in a video was the sum of the video's separate incidents (e.g., gunshot or nightstick) times the number of instances. The level of racism in a video was measured as the proportion of anonymous crowdsourced coders who on their own accord rated the video's images as -"racist" divided by the total number of coders of the photo. The Methods section presents examples of the coding of the violence, weaponry, or racism identified in an image. Table S2 shows the details of the Washington, D.C. coding scheme and Figure S1 shows examples of still images and their coding. In addition to using the Washington, D.C. coding scheme, we did robustness checks on the results using an alternative, popular coding scheme based on TV violence ratings[46]. The results were nearly identical under both coding scheme (SI Table S5).

Trump Tweets. Donald Trump complete corpus of January 6th, 2021 tweets were archived and posted for public download at https://www.thetrumparchive.com/. In our study, Trump's tweets were operationalized in terms of their (i) positive and (ii) negative sentiment. Tweet sentiment can create emotions that motivate real-life action with positive and negative sentiment having potentially different effects[24,29]. Notably, Trump's January 6th tweets received hundreds of thousands of likes and retweets, indicating that his tweets were read and reacted to[47].

#StopTheSteal Tweets (#STS). All of the tweets with hashtag #StopTheSteal posted on January 6th, 2021 are available with the search= string "#StopTheSteal since:2021-01-06 until:2021-01-08 -filter:replies" [https://twitter.com/search?q=%23StopTheSteal%20since%3A2021-01-06%20until%3A2021-01-08%20-filter%3Areplies&src=typed_query]. We downloaded the historical data with a Python toolkits snscrape. The following fields are included in the data: Time Stamp, Tweet ID, Text, Username, and URL. Parler.com posts on January 6th were omitted from the analysis because the number of posts was de minimis relative to the number of Twitter posts, and Parler posts lacked timestamping.

Trump and #STS tweets were operationalized using the sentiment analysis toolkit VADER[48], which calculates the proportion of positive and negative words in each tweet based on tweet's lexicons. We analyzed each 5-minute interval from midnight to midnight on January 6th to create two time-series variables: "positive level of Trump's tweets" and "negative level of Trump's tweets." If a tweet had both positive and negative sentiments, the positive and negative sentiments were recorded separately in the relevant sentiment variable. The sentiment scores in the same five-minute period were combined into separate "positive" and "negative" sentiment variables. Neutral tweets received a sentiment score of zero.

Table 1 provides examples of the coding of Trump and #STS tweets. Positive and negative words are highlighted in yellow and green respectively. For example, at 1:58 PM there is a tweet with the handle #stopthesteel had the following content, "So, I've read claims that the #StopTheSteal protestors in D.C. are really #Antifa in disguises." This tweet contains one negative sentiment word, "disguises," and was given a score of 15 (total number of words) x 0.139 (negative ratio) = 2.085. When a tweet had both positive and negative sentiment, we operationalized the sentiment value of the tweet proportionately. For example, Trump tweeted at 2:38:58 PM, "Please support our Capitol Police and Law Enforcement. They are truly on the side of our Country. Stay peaceful!" In this tweet, the words "please," "support," "truly," and "peaceful" have positive sentiments and a combined score of 19 (total number of words) x 0.432

(positive ratio) = 8.208. Table S3 provides a listing of all of Trump's January 6th, 2021 tweets, their positive and negative scores, number of likes, and number of retweets.

Table 1: Tweet Sentiment Coding for Trump's Tweets and #StopTheSteal Tweets.

Variable	Time	Text	Words	Negative score	Positive score
Trump's Tweets	9:00:12 AM	They just happened to find 50,000 ballots late last night. The USA is embarrassed by fools. Our Election Process is worse than that of third world countries!	27	7.425 (= 27 x .0275)	0
Trump	2:38:58 PM	Please support our Capitol Police and Law Enforcement. They are truly on the side of our Country. Stay peaceful!	19	0	8.208 (=19 x 0.432)
Trump	12:43:42 AM	Get smart Republicans. FIGHT! https://t.co/3fs1oPVnAx	5	1.945 (= 5 x 0.389)	1.45 (= 5 x 0.29)
#STS	1:58:20 PM	So, I've read claims that the #StopTheSteal protestors in D.C. are really #Antifa in disguises.	15	2.085 (= 15 x 0.139)	0
#STS	12:55:10 PM	You want to #StopTheSteal ? There's only one man who can save America.... https://t.co/5VAzxgttOK	13	0	3.55 (= 13 x 0.273)

Rally Speeches. Per research showing that cheer length is a real-time indicator of a crowd's empowerment and collective identity due to the speech[49], we operationalized rally speeches as the length (in seconds) of cheers in each five-minute segment of the speech.

Trump and a dozen others made speeches on the stage of the "Save America March" rally in The Ellipse. Some of the rally speeches had time gaps between them (the gap to previous/next speech is 20 seconds to 1+ hour) and some speeches were contiguous (e.g., Eric Trump, welcomed Kimberly Guilfoyle who welcomed Donald Trump Jr. on the stage).

The cheer variables were defined as the length of total cheers in a single speech or a group of connected speeches that were finished in each 5-minute interval. For example, the total length of cheers during Mo Brooks's warm-up speech is 221 seconds, and Mo Brooks finished his speech at 9:16 am, we then assigned 221 seconds to the time interval 9:15 am-9:20 am in the variable "length of cheers in warmup speeches." The authors then computed the length of cheers using a CSPAN video of the speeches. Table 2 shows the rally speaker, start and stop time of each rally speech, and the total length of cheers in seconds.

Table 2: Save America Rally Speeches

Speaker(s)	**Start time**	**End time**	**Total length of cheers (seconds)**
Mo Brooks	9:06	9:16	221
Katrina Pierson, Amy Kremer	9:41	10:02	303
Vernon Jones	10:05	10:08	91
Ken Paxton	10:09	10:10	19
Eric Trump, Kimberly Guilfoyle, Donald Trump Jr.	10:15	10:30	244
Madison Cawthorn	10:39	10:41	35
Rudy Giuliani, John Eastman	10:48	10:57	164
Donald Trump	12:00	13:11	859

Figure 2 is an ensemble plot of the time-series of each data source – Trump's positive tweets, Trump's negative tweets, #StopTheSteal positive tweets, #StopTheSteal negative tweets, racism level, weaponry level, violence level, and the period of the Save America rally speeches is shaded in orange. Variables are sampled at 5-minute intervals.

Granger Causality Model. Granger causality is a widely used and validated 2003 Nobel Prize-winning innovation that infers *X*'s "Granger" causal effect on *Y* in from their time-series data[50-57]. Whereas experiments use control and treatment groups to experimentally manipulate a treatment, Granger causality tests the hypothesis that time-series *X* "Granger causes" time-series *Y*. Formally, after passing the stationary test, a time-series of *X* is considered to "Granger cause" *Y* if t-tests and F-tests on lagged values of the *X* variables and lagged values of *Y* significantly predict future values of *Y*. Thus, we present and interpret the Granger results conservatively as showing that variable X is a statistically significant predictor of outcome Y, not a cause in the controlled experiment[54].

Data Requirements of the Granger Model. To meet the data requirements for a Granger Causality analysis, we followed prior research[58-64]. There are two necessary requirements. First, the time-series must be stationary. Accordingly, we ran standard Dicky-Fuller stationarity tests. All variables passed their stationary tests with up to 2 lags (i.e., total lag of 10 min). Table 3 shows that all stationarity tests for lags of 1 and 2 passed the Dicky-Fuller tests. Second, Granger data should not be seasonal. Our data is not seasonal. -Also, Granger data may contain zeros. Our data does contain zeros. Thus, our Granger analysis follows established precedents in economics and neuroscience that use stationary, non-seasonal data that can contain zero values[58-64].

Granger causality is tested by regressing outcome variable *Y* on its own lagged values and the lagged values of predictor variables *X*. The null hypothesis test is that the estimated coefficients on the lagged values of *X* are jointly zero. Failure to reject the null hypothesis is equivalent to failing to reject the hypothesis that *X* does not Granger-cause *Y*. Our findings were obtained from the Stata commands var and vargranger. The vargranger command indicates the Granger causality bivariate relationship between each *Y* and each *X* net of the effects of other *X*s in the same equation[65]. Thus, violence level is an outcome variable and an independent variable depending on the equation. This rotating set of outcome variables allows reciprocal (or bidirectional) Granger causality among the variables in the model. Our model takes nine time series variables: violence, weaponry, racism, Trump's positive tweets, Trump's negative tweets, Trump's speech cheers, warmup speech cheers, #StopTheSteal positive tweets, and #StopTheSteal negative tweets.

Thus, there are nine models; each model has a different dependent variable that is regressed on 16 independent variables (8 variables* 2 lags). A robustness check of the Granger Model was performed with MVGC Matlab® Toolbox (SI Table S4), which produced confirmatory results. Further, for each equation and each endogenous variable that is not the dependent variable in that equation, we conducted Wald tests, which test the hypothesis that each of the other endogenous variables does not Granger-cause the dependent variable in that equation[66].

Table 3: Dicky-Fuller Test Results for Stationary.

Variable	Lag = 1 (5min)	Lag = 2 (10min)
Violence level	-9.7910, (p=0.0000)	-8.4050, (p=0.0000)
Weaponry level	-8.4380, (p=0.0000)	-5.8460, (p=0.0000)
Racism level	-9.7820, (p=0.0000)	-7.5120, (p=0.0000)
Trump's tweets (negative)	-10.9850, (p=0.0000)	-7.7070, (p=0.0000)
Trump's tweets (positive)	-11.2870, (p=0.0000)	-7.8550, (p=0.0000)
#STS tweets (negative)	-4.1190, (p=0.0009)	-3.1890, (p=0.0206)
#STS tweets (positive)	-4.8920, (p=0.0000)	-3.5840, (p=0.0061)
Cheer Length --Trump's speech	-11.9580, (p=0.0000)	-9.7470, (p=0.0000)
Cheer Length--other speeches	-10.8720, (p=0.0000)	-9.1070, (p=0.0000)

Formally, our model is written as:

$$X_{i,t} = \sum_{j=1}^{J} \sum_{\tau=1}^{L} a_{j,r} \cdot X_{j,t-\tau} + \epsilon_{j,t}$$

where $X(t) \in R^{J \times 1}$ for $t = 1, \ldots, T$ is a J-dimensional multivariate time-series. For each equation, vargranger reports Wald tests on the hypothesis that each of the other endogenous variables does not "Granger-cause" the dependent variable in that equation.

Results

Figure 3 provides a visual qualitative analysis of the chronology of variables and their intensity normalized by a variable's maximum value to permit comparisons across different measurement units. The variables in the figure are stacked to make all variables visible such that the normalized magnitude of a variable at any point is the magnitude of the variable shown on the y-axis less the sum of the magnitudes of the variables stacked below it. The figure provides several descriptive findings. First, STS positive and negative tweets have closely related temporal patterns, magnitudes, and fluctuation patterns, indicating that these variables, as expected, are highly conterminously interrelated. Variables based on the actions of specific individuals in positions of leadership or authority such as Trump and the speech makers occurred at specific times during the riot and hence appear as spikes (e.g., Trump negative tweet at 9:00am, 10:00am). The densest activity occurred at 1:10 to 5:10pm with peaks at 1:10pm, 2:20pm, 2:35pm, and 3:10pm. During these dense clusters of activity, the highest frequency and highest levels of violence (orange spikes), weaponry (green spikes), and racism (blue spikes) took place. Also, during these dense clusters of activity, we observe the highest frequency of Trump's positive tweets, which tend to occur at the beginning of a cluster. By contrast, Trump's highest density of negative tweets occur prior to the violent rioting and at the very end of the day when he tweeted for rioters to leave the Capitol. While violence, weaponry, and racism levels co-occur in these density cluster of activity, spikes in violence tend to precede spikes weaponry and racism levels, while spikes in the show of weapons tends to co-occur with spikes in racism. Finally, we observe the escalation from peaceful protest to violence attacks, weapons use, and racism initiates after Trump's 11:00 am rally speech and continues to mount as the frequency of Trump's and #StopTheSteel tweets increase until rioting peaks at around 15:30, and then begins to deescalate over the next two hours during which time Trump also stopped tweeting.

Figure 4 shows the Granger estimates of the strength and direction of effects among predictor variables and level of violence, weaponry, and racism during the January 6th insurrection. In the figure, arrow heads indicate the direction of effects, bold and normal arrows represent the statistical significance of the effects (exact p-values shown above arrows), and color of boxes represent measures of violence (blue boxes), Trump's conduct (red boxes), and the crowd's conduct (gray boxes). A null relationship is represented by an absence of a link. (See Methods section, Table 5 for full regression output and Wald tests).

The Granger mapping provides a systemic, multivariate perspective on the dynamics of the riot and indicates several broad effects. First, the conduct of Trump and the crowd are predictor of violence, use of weapons, and racism during the insurrection. Second, there is a reciprocal positive feedback loop between Trump and the rioters' behavior. For example, Trump's positive sentiment tweets and rally speech predicted the use and display of weapons, which reciprocally predicted racism, where racism was an independent predictor of increases in the positive Trump's tweets. Third, increases in violence predicted negative #StopTheSteal tweets, which predicted weapons use. When the attack on the Capitol is looked from this systemic perspective, the results suggest that the attack feeds on itself through positive feedback loops among predictor and outcomes variables such that the peaceful protest quickly escalated to violence.

Within the system, Trump's tweets and speech have three important connections in the model. First, Trump's positive tweets, and speech have a total of five strong Granger effects — more than any other variable in the model. Trump's positive tweets predicted increases in violence ($p < .000$) and weapons ($p <.000$). Second, Trump's positive tweets predicted an increase in negative #StopTheSteal tweets (p=0.002). The relationship between Trump-tweets and #StopTheSteal tweets is noteworthy because negative #StopTheSteal tweets is the second most connected Granger-causal factor driving weapons use. Third, the length of cheers of

Trump's speech predicted a burst in violence ($p<.000$) and weapons use ($p<.000$) at the beginning of the first dense cluster of rioting during the insurrection.

Trump's tweets were also predicted by other variables – indicating that Trump's behavior was not independent of the changing behavior or protesters and rioters as the insurrection unfolded. Changes in the level of positive #StopTheSteel tweets predicted ($p=0.024$) an increase in the positive sentiment of Trump's tweets, suggesting that Trump's positive tweets depended partly on the expression of positive sentiment by protesters, rioters, and others who were part of or watching the protest. We also observe a positive connection between changes in the level of racism and an increase in Trump's positive tweets ($p=0.023$), suggesting that symbols of racism were associated with the positivity of Trump's tweets.

The links between #StopTheSteal tweets, weapon displays, and racism indicate that these factors were mutually escalating. Levels of positive and negative #StopTheSteal tweets were positively and reciprocally predictive of each other (p=0.001 & p=0.019). The more positive sentiment #StopTheSteal tweets, the greater the number of negative sentiment #StopTheSteal tweets, suggesting that tweeters using the #StopTheSteal tweets approved of the unfolding events. For example, tweeter wrote, "Trump's family speaks, I feel his son's anger at the stealing of the election. They rigged it. (https://twitter.com/CarrieGeren/status/1346949246717669379)." Negative #StopTheSteal tweets predicted increases in the use and display of weapons ($p=.000$). Negative sentiment #StopTheSteal tweets predicted increases in weaponry, which predicted increases in positive sentiment #StopTheSteal tweets ($p=0.027$). For example, a tweeter posted, "BREAKING: Patriots have breached the Capitol building in Washington tearing down 4 layers of security fencing and are attempting to occupy the building (https://twitter.com/TonyToez/status/1346886695644520449)." Finally, within the set of relationships between Trump's tweets and #StopTheSteal tweets, we observe that positive #StopTheSteal tweets increased Trump's positive tweets ($p=0.024$), a connection consistent with eyewitness reports and video that showed that Trump approved of the mayhem as it unfolded on TV and social media[67].

Besides the direction of effects among variables, Granger causality regression permit an estimate of the magnitude and duration of effects. Figure 5 shows the impulse responses of Trump's tweets in relation to changes in the level of violence and weaponry. In vector autoregressive models (VAR) like Granger Causality regression, the impulse response quantifies the change in one variable(s) in reaction to a change in other variable(s). In systems like the Capitol insurrection that have stationary data, it is expected that the response of one variable to a change in another variable is impermanent as the variables response dissipates over time as the system reconverges. Methodologically, after the VAR is solved, the impulse response can be calculated by setting the input of the model as a unit impulse of $x(t=0) = 1$, $x(t=1, 2, \ldots) = 0$.

Figure 5A and 5B quantify the magnitude and length of the change in violence (5A) and weaponry (5B) in response to a change in Trump's positive tweets. The magnitude of change for the response variable is shown on the y axis and the duration of the response is shown on the x axis and is determined by the length of period for which the SE bands are above 0. The figures indicate a substantial response relationship between Trump's positive tweets and violence and weaponry levels. A one unit change in Trump's positive tweets predicts a significant increase in violence and weaponry of 100 and 150, and for a duration of two period and 3 periods, respectively, after which point the effects dissipate.

The episodic nature of the impulse responses suggests that the relationship between a leader's and rioters' behaviors are strongest when they are continuous. Because the impulse response is relatively short-lived in duration, communication must be frequent else shifts in behavior from peaceful protests to violent attacks are likely to return to the peaceful starting levels of the system as was seen in Figure 3, which shows that the escalation of rioting initiated with Trump's rally speech, continued to mount as Trump and #StopTheSteel tweets increased, and then deescalated over the period when Trump stopped tweeting and the frequency of #StopTheSteel tweets waned.

Discussion

The Capitol insurrection provide a distinctly informative case study of collective violence. Data on the Capitol Insurrection was captured in real-time on a moment-by-moment basis. Extensive videotaping allowed for the direct measurement of collective violence, tweets recorded communication among protesters and rioters, and rally speeches documented group emotion levels. Our dynamic analysis of these factors complements experiments and historical studies and provides new insights into the systemic relationships among predictor and outcomes variables that cooccur during protests that potentially lead to the escalation of collective violence.

Our analysis found evidence of direct, indirect, and reciprocal predictors of violence. Social movements research has emphasized the role of elite support in encouraging protests and other kinds of political action[68]. Our analysis found that leadership has the strongest and most diverse predictive association with violence, weapons display and use, and racism. The finding demonstrates both the importance of leaders' voices in fomenting and sustaining violence in real-time. Our analysis also finds that social media can provide an instantaneous means of communication that is directly associated with subsequent collective actions. Further, a prominent leader's use of emotive rhetoric may further stir supporters and, through the use of social media, may become a tool of radicalization for an already aggrieved crowd. There is also a reciprocal relationship between the leader's behavior and the behavior of the riots. We found that the behaviors of leaders and followers positively reinforce one another in an upward spiral of violence. Trump's rally speech and his tweets Granger-increased violence, the use and display of weapons, and the tweets of protesters and bystanders, which in turn stirred more violence and racism.

The findings have implications for the broader debate about whether social media's polarizing effects[69] and ability to spread misinformation[70-72] at an unprecedented scale enables leaders to manipulate supporters' real life violent and racist behavior[73]. Prior work showed that increases in the number of tweets with moralized language predicted later levels of arrests of protesters for civil disobedience but not outright violence or racism[14]. We found that social media posts and video are also predictive the use of lethal violence and expressions of racism and weapons use in the real-world and in real-time.

Our analysis also supports experimental research. Experimental research suggests that there is a dynamic relationship among leaders and protesters, viz., leaders and followers can escalate each other's support for more confrontational tactics. Leaders play the role of expressing positive reactions to the protesters' behavior and protesters take the leader's positive sentiments authorization to mount more aggressive attacks[18-23]. Hypothetically, the more emotive the rhetoric is, the more it incites action and the possible use of bodily force[24,25]. Our results support these experimental expectations and suggest that the positive reciprocal relationship between leaders and followers can quickly soar, changing a peaceful protest into violent attack that builds on itself.

The study's implications for the prevention of violent uprisings tentatively point in two directions. First, while this work supports the perspective that leaders have gained new power in influencing their followers through social media, social media is more than a passive communication channel. Social media companies can both enlarge or diminish a leader's impact on a crowd to the degree that they throttle the rate at wish information is communicated as well as the content of communication. Relatedly, our models indicate that the interplay between leaders, followers, and violent behavior is characterized by a system of positive feedback loops that imply can make relatively few tweets by a leader can rapidly escalate confrontational tactics by followers. However, the link between a leader's communications and violence are episodic and relatively short-lived. This suggests that reducing communications even in a real-time riot can begin a de-escalation process. While current debates over the regulation of social media companies in regard to their management of both what and how fast communications can be relayed, crucial and effective policy decisions need solid data on how the algorithms social media companies work. Consequently, future research on social movements and violent behavior would benefit from greater transparency into the algorithm used by from social media companies and how algorithms are related to bias and consumer protectionism.

Methods

Coding of Videos for Violence, Weapons, and Racism: Coding of the videos for instances and violence, weaponry, and racism was conducted through crowdsourcing. Step 1: Crowdsourcing coding was accomplished by an Internet Relay Chat channel [4] of users who watched and analyzed the Parler videos and coded each video on 14 dimensions, and added a unique video ID and timestamp of when the video was taken. These data were posted into a public Google spreadsheet called "Notable Parler Videos." https://docs.google.com/spreadsheets/d/1ThPUH5HgTcVKCoyfr2oJ21AWKTGq-dR-cRZjPOER-Q0/edit#gid=0. Step 2: All coding was manually checked by the authors for accuracy in counts and descriptions. For each video, users crowdsourced the coding of the video on 14 dimensions:

Table 4. Coding Procedures for "Notable Parler Videos" Dataset

ID	Question	Data type
1	Please copy / paste the video ID (not the sendvid.com URL)	String (url)
2	To verify your annotation, please enter the length of the video here	seconds
3	Does this video take place inside or outside?	Binary
4	Does the video focus on a person or group? (e.g., a selfie or grouping)	Boolean
5	Are any racist symbols or language present in the video?	Boolean
6	Which racist symbols are present?	String
7	Please describe any racist language used in the video and when it occurs.	String
8	Is there any physical violence in the video?	Boolean
9	Please describe any violence that is taking place.	String
10	Are there any weapons in the video?	Boolean
11	If weapons are present, please select any that appear from the list below.	String
12	Are there police or military units present in the video?	Boolean
13	If police are present, please describe what they are doing.	String
14	Is there anything else noteworthy that you want to note about this video?	String

Operationalizing Video Events as a Time-series Dataset. We built the time-series in 5-minute intervals according to the responses in the fields 1, 5, 6, 8, 9, 10, and 11. The timestamp of each video was extracted from its meta information. With the sorted timestamps, we created a variable "violence level" according to the answers to question 5-6, variable "racism level" to question 8-9, and variable "weaponry level" to question 10-11. "Violence level" and "weaponry level" are continuous variables and were constructed based on the statutory criminal punishments associated with a certain level of violence or a certain weapon. Statutory penalties are designed to be proportional to the severity of the crime https://koehlerlaw.net/criminal-defense-dc/weapons/ and https://criminallawdc.com/dc-assault-lawyer/laws/.

Table S2 lists the criminal penalty for different violent acts or weapons vary according to D.C. statutes. For example, the penalty associated with "weapons" ranges from "up to $1000". Given the fact that "firearms" were more often considered as deadly or dangerous weapons, we assign 1500 to firearms and 1000 to clubs/bats/etc. to the violence and weaponry variables. Unconventional objects used as weapons (flagpoles, etc.) that are not in the list were assigned 500.

The violence level or weaponry level for each 5-minute interval is calculated by summing up the scores of all videos taken during that interval. The racism level was calculated as the ratio of crowdsourced votes for "racism" to total responses made by crowdsources to the video and summing up all the scores within each 5-minute interval to build the time series. The mean (standard deviation) of the variables of (i) violence level, (ii) weaponry level, and (iii) racism level is 46.875 (271.255), 116.319 (489.803), and 0.070 (0.267) respectively.

Granger Regression Analysis

Wald Tests. The Wald test investigates the hypotheses that each of the other endogenous variables does not Granger-cause the dependent variable in that equation. Using a standard convention for reporting the regression results of Granger analysis, the column "**Equation**" represents the *Y* variable of the regression and the column "**Excluded**" represents the *X* variables of the regression. We set the critical value of our hypothesis test at the 5% level with lags=2. All the bivariate relationships with $p <= 0.05$ are reported in the causality map of the paper; otherwise the link is omitted.

Table 5: Granger Causality Regressions and Wald tests

Equation	Excluded	chi2	df	Prob > chi2
violencelevel	weaponrylevel	3.7969	2	0.15
violencelevel	racismlevel	2.1395	2	0.343
violencelevel	Trumps tweets_neg	6.3181	2	**0.042**
violencelevel	Trumps tweets_pos	32.532	2	**0**
violencelevel	sts_pos	1.3724	2	0.503
violencelevel	sts_neg	4.1167	2	0.128
violencelevel	cheer_length_trump	38.427	2	**0**
violencelevel	cheer_length_warmup	0.00908	2	0.995
violencelevel	ALL	107.04	16	**0**
weaponrylevel	violencelevel	3.4387	2	0.179
weaponrylevel	racismlevel	20.189	2	**0**
weaponrylevel	Trumps tweets_neg	4.2964	2	0.117
weaponrylevel	Trumps tweets_pos	18.126	2	**0**
weaponrylevel	sts_pos	5.7971	2	0.055
weaponrylevel	sts_neg	15.406	2	**0**
weaponrylevel	cheer_length_trump	26.459	2	**0**
weaponrylevel	cheer_length_warmup	0.37893	2	0.827
weaponrylevel	ALL	123.77	16	**0**
racismlevel	violencelevel	1.1035	2	0.576
racismlevel	weaponrylevel	21.756	2	**0**
racismlevel	Trumps tweets_neg	0.40681	2	0.816
racismlevel	Trumps tweets_pos	0.05327	2	0.974
racismlevel	sts_pos	2.5115	2	0.285
racismlevel	sts_neg	1.299	2	0.522
racismlevel	cheer_length_trump	5.7676	2	0.056
racismlevel	cheer_length_warmup	0.11981	2	0.942
racismlevel	ALL	75.653	16	**0**
Trumps tweets_neg	violencelevel	0.32557	2	0.85
Trumps tweets_neg	weaponrylevel	0.26036	2	0.878
Trumps tweets_neg	racismlevel	0.53725	2	0.764
Trumps tweets_neg	Trumps tweets_pos	0.62894	2	0.73
Trumps tweets_neg	sts_pos	2.0936	2	0.351
Trumps tweets_neg	sts_neg	3.4547	2	0.178
Trumps tweets_neg	cheer_length_trump	0.08231	2	0.96
Trumps tweets_neg	cheer_length_warmup	0.45627	2	0.796
Trumps tweets_neg	ALL	5.2334	16	0.994
Trumps tweets_pos	violencelevel	4.7787	2	0.092
Trumps tweets_pos	weaponrylevel	2.9604	2	0.228
Trumps tweets_pos	racismlevel	7.5206	2	**0.023**
Trumps tweets_pos	Trumps tweets_neg	1.8445	2	0.398
Trumps tweets_pos	sts_pos	7.4901	2	**0.024**
Trumps tweets_pos	sts_neg	4.4082	2	0.11
Trumps tweets_pos	cheer_length_trump	0.26565	2	0.876
Trumps tweets_pos	cheer_length_warmup	1.5742	2	0.455
Trumps tweets_pos	ALL	30.311	16	**0.016**
sts_pos	violencelevel	5.5762	2	0.062
sts_pos	weaponrylevel	7.2122	2	**0.027**
sts_pos	racismlevel	3.4485	2	0.178
sts_pos	Trumps tweets_neg	0.44931	2	0.799
sts_pos	Trumps tweets_pos	1.9085	2	0.385
sts_pos	sts_neg	14.448	2	**0.001**
sts_pos	cheer_length_trump	1.395	2	0.498
sts_pos	cheer_length_warmup	2.3308	2	0.312
sts_pos	ALL	33.998	16	**0.005**
sts_neg	violencelevel	6.6707	2	**0.036**
sts_neg	weaponrylevel	2.234	2	0.327
sts_neg	racismlevel	6.4071	2	**0.041**

sts_neg	Trumps tweets_neg	3.4058	2	0.182
sts_neg	Trumps tweets_pos	12.568	2	**0.002**
sts_neg	sts_pos	7.9437	2	**0.019**
sts_neg	cheer_length_trump	1.5448	2	0.462
sts_neg	cheer_length_warmup	1.9915	2	0.369
sts_neg	ALL	39.969	16	**0.001**
cheer_length_trump	violencelevel	0.34951	2	0.84
cheer_length_trump	weaponrylevel	0.14511	2	0.93
cheer_length_trump	racismlevel	0.50386	2	0.777
cheer_length_trump	Trumps tweets_neg	0.03878	2	0.981
cheer_length_trump	Trumps tweets_pos	0.10012	2	0.951
cheer_length_trump	sts_pos	2.6645	2	0.264
cheer_length_trump	sts_neg	0.86386	2	0.649
cheer_length_trump	cheer_length_warmup	0.02991	2	0.985
cheer_length_trump	ALL	4.0304	16	0.999
cheer_length_warmup	violencelevel	0.23913	2	0.887
cheer_length_warmup	weaponrylevel	0.45232	2	0.798
cheer_length_warmup	racismlevel	0.1218	2	0.941
cheer_length_warmup	Trumps tweets_neg	0.7191	2	0.698
cheer_length_warmup	Trumps tweets_pos	0.05828	2	0.971
cheer_length_warmup	sts_pos	2.5106	2	0.285
cheer_length_warmup	sts_neg	3.9391	2	0.14
cheer_length_warmup	cheer_length_trump	0.08158	2	0.96
cheer_length_wa~p	ALL	6.1279	16	0.987

Multivariate Granger Causality Matlab® Toolbox: Robustness Check

To test whether the Granger causality effects reported by the STATA Granger algorithm are method dependent, we ran Granger causality analyses with MVGC Multivariate Granger Causality Matlab Toolbox, which conducts numerical computation and statistical inference of Granger causality. The two approaches return the same statistically significant Granger results except that in the case of MVGC Matlab Toolbox, the link "#sts_tweets_pos by weaponrylevel" is insignificant when lag=2. The full regression results are shown in the SI Table S4.

Alternative Coding Scheme for Violence.

We conducted multiple Granger causality tests with alternative coding schemes for violence and weaponry level to test whether the results are coding dependent. For the alternative variable *violencelevel*, the coding method is derived from a rating for TV violence[46] and summarized in Table S5. The alternative rating scheme produced confirmatory results.

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Figures

Figure 1

Geographic Region of Real-time Videos and Coding example. Videos taken within the area shown by the blue rectangle (i.e., "The Capitol area") were loaded and tagged for incidents of violence, weapons, and racism through crowdsourcing.

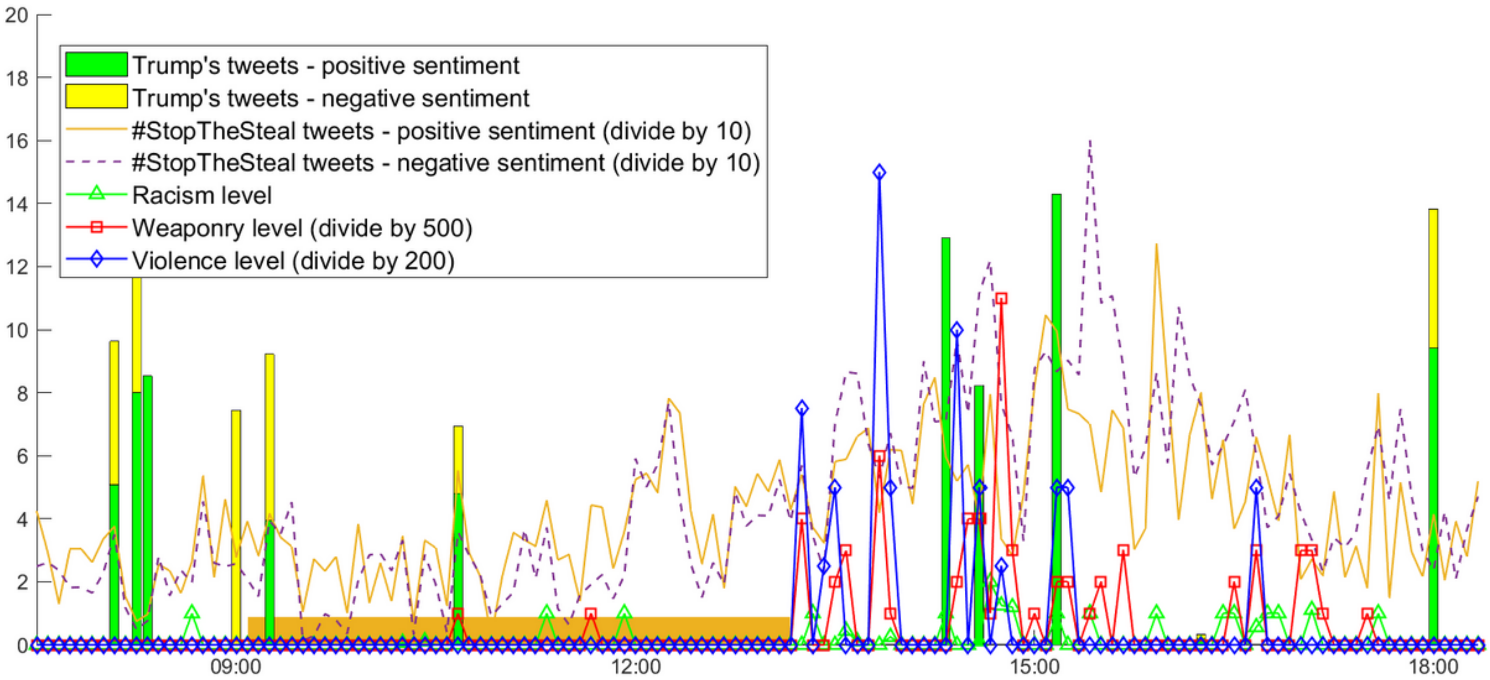

Figure 2

Time-series of Events. Figure plots the time-series of variables used in the analysis. The period during which the "Save America Rally" took place is shaded in orange.

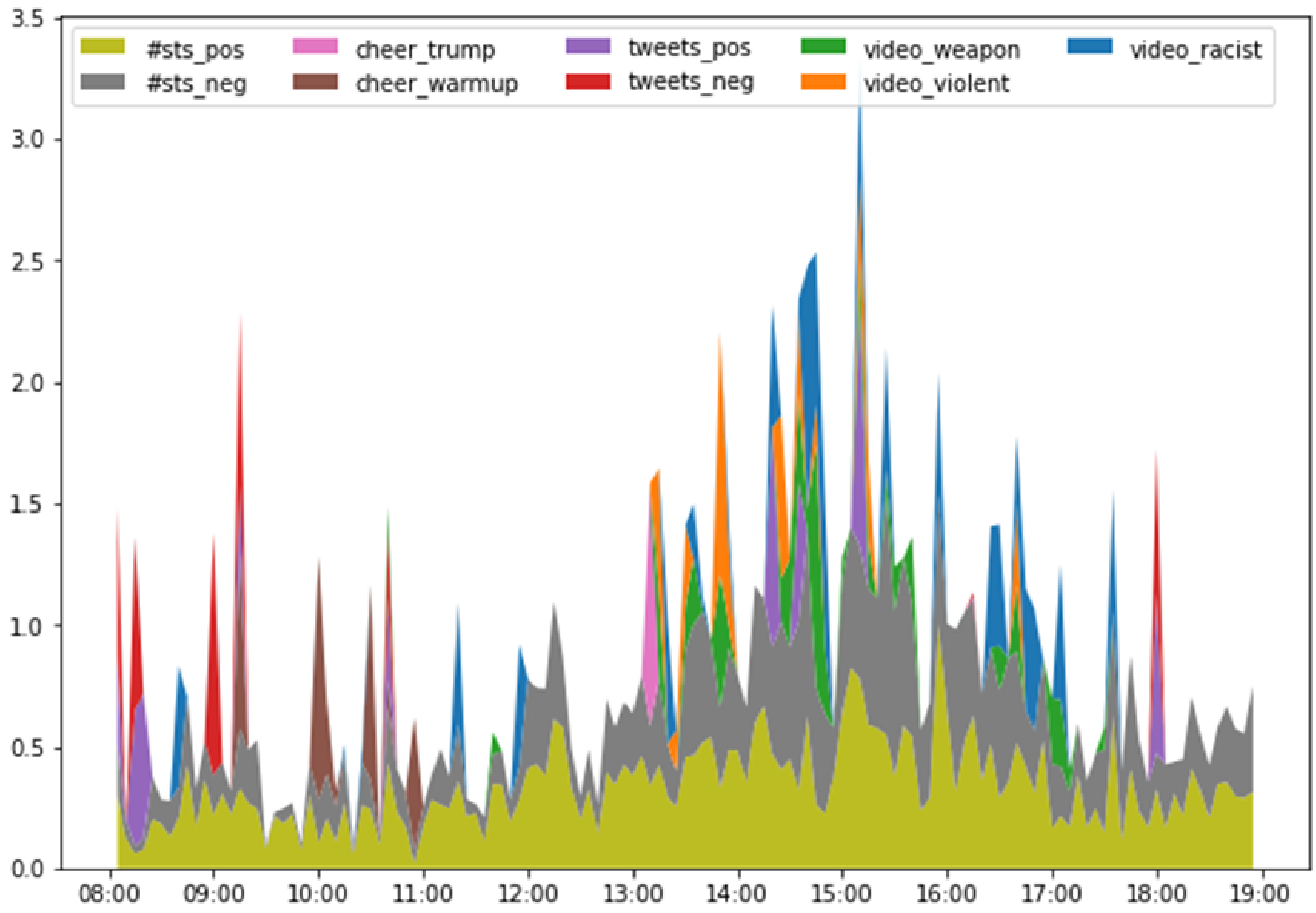

Figure 3

Steam plot of the Chronology, Cooccurrence and Magnitude of Variables in the Analysis. Variables are normalized their maximum value to permit comparisons across different measurement units and are stacked such that the normalized magnitude of a variable at any point is the magnitude of the variable shown on the y-axis less the sum of the magnitudes of the variables stacked below it.

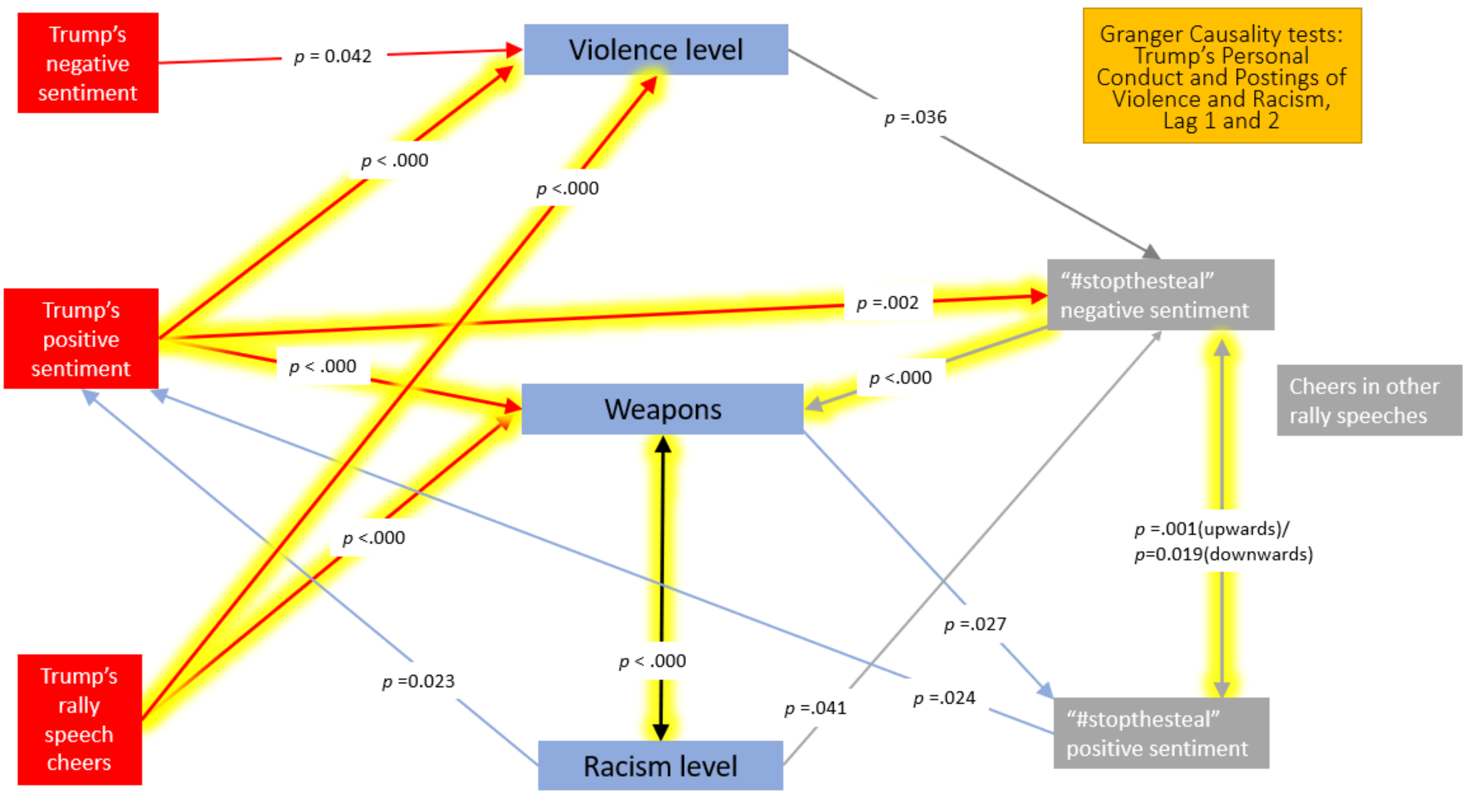

Figure 4

Granger causality estimates of the strength Trump's Tweets, #stopthesteal Tweets, and Rally Speeches in Predicting Levels of Violence, Weapons, and Racism During the Capitol Insurrection. The figure shows the "Granger-causal" predictors of violence, weaponry, and racism during the January 6th insurrection. Arrow heads indicate the direction of effects, bold and normal arrows represent the statistical significance of the effects (exact p-values shown above arrows), and color of boxes represent measures of violence (blue boxes), Trump's conduct (red boxes), and the crowd's conduct (gray boxes). The thickest arrows represent the strongest statistical relationships that can be expected to happen by changes less than 1% of the time.

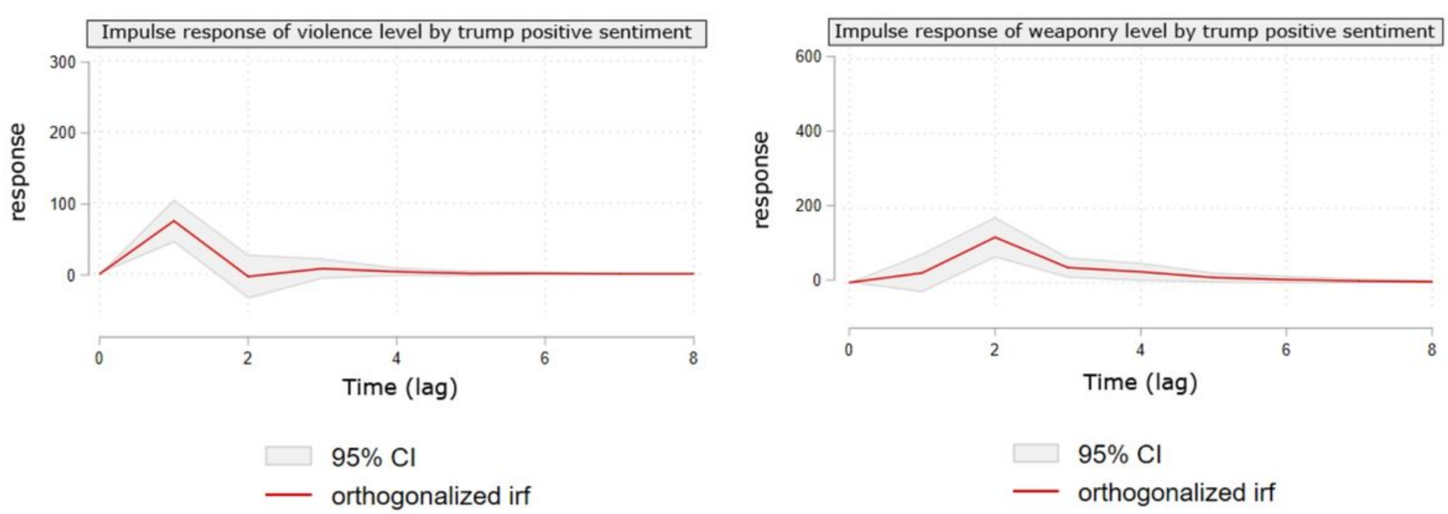

Figure 5

Var Impulse Response Function. Plots show the magnitude and duration of changes in violence level (plot A) and weaponry level (plot B) in response to Trump's positive Tweets.

Supplementary Files

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- Presidentialviolence211118SI.docx