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Samuel Planck

# Where We Go One, We Go All: QAnon and Violent Rhetoric on Twitter

Samuel Planck
Seton Hall University

**Abstract**

*This study concerns the rhetoric of the QAnon conspiracy theory as it appears on Twitter, and compares that rhetoric to that of mainstream conservatives on the same platform. By coding individual tweets' content for specific instances of violent, religious, economic, or paranoid rhetoric, and comparing samples of both of these populations, the study aims to determine what differences there are between the QAnon community's uses of rhetoric, particularly violent rhetoric, and that of the mainstream conservative community. The results demonstrate that the QAnon movement is more likely to use violent terminology in their tweets, but is not able to find strong correlations between violent rhetoric and other forms of speech, such as paranoia or religiosity. Likewise, the QAnon movement frequently focuses on ritualistic cults or on accusations of satanism, but not in sufficient numbers to demonstrate a correlation between such accusations and violence.*

## 1. Introduction

The far-right movement known as QAnon has become an increasingly potent phenomenon on social media, and in real life. Dedicated to a conspiracy theory centered around President Donald Trump and a mysterious figure in the administration known as 'Q', the theory began on anonymous messaging board 4Chan in 2017, offering explanations for the lack of arrests of figures like Hillary Clinton or Barack Obama. The movement was one of many listed as part of an FBI intelligence bulletin concerning conspiracy theory-related violence (*Fringe Political Conspiracy Theories*). Followers of the theory have committed several violent crimes: from murder attempts, both successful (Watkins) and failed (Haag and Salam), to trespassing, to vandalism (McIntire and Roose). How does the rhetoric of these movements on social media sites, for instance Twitter, differ from the conservative movement as a whole? What specific topics do these conspiracy theorists concern themselves with?

This paper will seek to explore these questions by conducting an analysis of QAnon Twitter data and comparing it to a sample of mainstream conservative tweets. The author will then perform content analysis on both samples, to determine where the QAnon theory fits into the Conservative Twitter landscape. Principally, the paper seeks to prove that the amount of paranoia in a tweet is predictive of the amount of violence that tweet will display.

## 2. Literature Review

The first issue debated by scholars is that of collection methodology. Most scholarship falls into three categories in this regard. The first two concern networks and clusters of individual accounts, attempting to map relationships so that researchers may better understand the greater pictures of how individual accounts interact with each other. The two types I have identified for

these purposes are follow-based or activity-based. The first is demonstrated in the paper "The Australian Twittersphere in 2016: Mapping the Follower/Followee Network". The authors proposed to identify Twitter accounts from a massive sample of "accounts which meet any one of a number of criteria for 'Australianness,' rather than snowballing out from a set" (Bruns et al. 3). Using the application program interface (API) provided by Twitter, the team measured the outward connections of a sample of the Australian accounts. By coding these accounts and grouping them based on common interests through an algorithm, the researchers were able to place them in communities based on topic and follower clusters. This research demonstrates a very clear cluster effect on Twitter, what many call an 'echo chamber' when relating to politics especially. On the other hand, one can attempt to use an Activity-based methodology for measuring communities, as in the paper "Influential Spreaders in the Political Twitter Sphere of the 2013 Malaysian General Election". This process begins with clustering accounts in opinion communities, but takes the further step of measuring interactions (likes, retweets) in order to determine which accounts are the most influential in their given communities (Hong-liang et al. 57-58). This is particularly effective for short-term analysis, as in this paper, which collected data over two non-consecutive weeks, to study the relationship between tweets and election data. Given this information regarding temporal effectiveness (long-term vs. short term data analysis), it may be better to use the short-term analysis to make up for the short amount of time available to conduct this research.

These papers have useful general principles for Twitter research, but concern unrelated political issues. The far-right, specifically on Twitter, and specifically within the United States, may have sufficiently different characteristics to Malaysian General Election networks or Australian society as a whole. The article "Researching Far Right Groups on Twitter: Methodological Challenges 2.0" presents possible solutions. Specifically, the paper discusses 'Traces' (Crosset et al. 941). By performing basic algorithmic content analysis, accounts can be identified related to the alt-right. Particularly, the paper identifies that the far-right hides behind a great deal of euphemism and irony in order to recruit and spread propaganda. The methodology, particularly identifying euphemisms frequently used by the far-right, will be useful in my own research, since groups like QAnon have a very specific vocabulary that they use.

"The Alt-Right Twitter Census" by J. M. Berger presents a number of methodological techniques that will certainly prove useful in current research. The goal of the paper was to conduct a simple data gathering of the Twitter data of the Alt-Right, and their associated mainstream right counterparts. The report identifies several categories into which Alt-Right Twitter accounts fall, based on their principle issue: immigration, support for Trump, white nationalism, or general harassment. These groups came into occasional conflict with one another. The research analyzed the 200 most recent tweets from more than 29,000 accounts. The accounts were identified through the Follower-Followee system of the Australian Twitter Landscape paper, creating a map of Alt-Right groups and their interactions with one another. They then created a control group of approximately 30,000 accounts. The researchers gathered data concerning account biographies, text in tweets, and hashtag use. The goal of the paper was quantitative, simply to measure the overall presence of the Alt-Right online and to survey which topics they discussed, where this study will be qualitative. While this research does allow for interesting collection techniques, content analysis will require more investigation.

## 3. Research Design

First, we must discuss the possibilities for collecting the data on Twitter. However, using the

Twitter search function in and of itself is not sufficient to the task, since Twitter is not a random site, but influenced by thought leaders of clusters of people. This Network-based analysis is what is used in most examinations of Twitter data. In order to judge the feelings of the community, we give weight to the most popular figureheads in the movement, accounts such @prayingmedic, an established leader of the conspiracy theory with over 273,000 followers, and at least one retweet by the President himself, on 21 February, 2020 (@prayingmedic). By analyzing the accounts of accepted and influential leaders in the community, we can minimize the amount of non-real Twitter accounts entering into our sample and jeopardizing the validity of the sample.

@Prayingmedic will act as our 'leader account', the nexus of our network. Having identified a leader, we take a sample from their follower base, equal to 25 followers, screening each for possibilities of being false accounts. From these accounts we will screen the 10 most recent tweets, whether retweets or original content. The reasons for this small sample are twofold: firstly, that the time required to screen thousands of tweets is not within the bounds of this paper, and second, that by automating the procedure, we risk the inclusion of bot accounts or non-QAnon accounts. Following this I will code the content of the tweets, as explained in Section 3: Coding. This process will then repeat for mainstream conservative tweets, to compare the two's rhetoric. On the part of Conservative Twitter, there are a number of possible thought leader accounts, such as Ben Shapiro, Tucker Carlson, Mitch McConnell, among various others. Various factors come into play in determining which is most like @prayingmedic in kind, if not in content, meaning that, for example, Mitch McConnell's rhetoric as Senate Majority Leader will be quite different from that of Ben Shapiro, a talk show host, or @prayingmedic, a private citizen. I decided to use the account of House Minority Leader Kevin McCarthy, reasoning that he was mainstream enough to attract a large following, while not being a figurehead around which conspiracy theorists or alt-right figures congregate.

Specifically, we will be looking for violent or dehumanizing rhetoric, searching for things such as referring to groups of people (immigrants, Muslims, LGBT people) as insects, vermin, plague, or the like. This dehumanizing language is a primer for violence against such groups (Luna 253). Likewise, we will code for references to religion and to the economy, and consider sentiment more generally: whether the tweets on the whole express positive or negative emotions. This gives us more than one factor with which to compare the QAnon movement with mainstream conservatives. Do they focus more on violent rhetoric, while conservatives focus on economic policy and news more generally? By comparing these multiple categories, we can better determine divergences between the two.

Some may object that I am focusing only on theoretical violence, rather than immediate threats. In response, I posit that the question of actualizing violent rhetoric is beyond the scope of this particular paper, but presents interesting avenues for future researchers to explore—how can we accurately predict the likelihood of violent rhetoric being actualized, and can that prediction be capitalized upon by intelligence agencies and police forces while respecting civil liberties? This paper is merely designed to measure rhetoric and the differences in rhetoric between the two groups, conspiracy theorists and mainstream conservatives.

## 4. Coding

Each of five different measures: Violence, Religiosity, Economy, Paranoia, and Sentiment, will be measured on an interval scale of real numbers, beginning at zero. Every violent word, for example, will raise the violence scale by one. Likewise for mentions of "Christ", "Dollar", "Love", or any QAnon-specific acronyms or initialisms, like "WWG1WGA", for religiosity, economy, positiv-

ity, and paranoia respectively. A word in ALL CAPS receives double counting, as does a word used as part of a hashtag, since both of these point to particularly important information to the author. If a word is both capitalized and part of a hashtag, it is only counted twice, coded as part of a hashtag, since the hashtag is what is meant to draw attention, not the capitalization. For example, CHRIST would count for Religiosity=2. Some may take issue with using integers alone for the non-dichotomous variables, and not scaling the variables as, for example, number of violent words per hundred. The objection is waived, however, since all tweets are of roughly uniform size. Were this piece researching blog posts, which may vary from a Tweet-sized piece to a manifesto in length, then scaling for length would be appropriate. However, in this case, the very data with which we work has essentially solved this problem.

Each Tweet will also be coded on a scalar variable of Positivity, Negativity, and Sentiment, measuring the relative positive or negative emotions of the tweets. In many ways, these are very context-specific variables. For every positive word or phrase in a tweet, "Good job", for instance, that variable will be increased by one. Likewise, for words like "hate", the Negativity variable will be decremented by one. Once these two variables have been coded, they will be summed, and that value will be entered as Sentiment. This variable will provide a holistic measure of the overall positive or negative feelings of the tweets.

Further, each measure will have a paired nominal scale measuring only the presence of each of the variables within the tweets. If there is any kind of violent rhetoric in a tweet, the Presence_Violence variable, for instance, will measure "1" for yes. If the opposite, it will measure "0" for no. This variable allows for comparison between the Conservative sample and the QAnon sample, judging an absolute number of violent or religious tweets, and comparing them.

Coders will be two of my undergraduate colleages, and will be instructed to code not only the tweet itself, but the photo it is associated with or the tweet to which it is replying if they seem to be in agreement. As we are attempting to measure Conservative or Conspiracist viewpoints alone, it would be counterintuitive to code, for instance, a tweet by Congresswoman Alexandria Ocasio-Cortez, as the subject of a taunting reply. However, if an account tries to support an idea, it will be coded as part of the sample, considered as representative of the subject account's opinions, and thus worthy of measurement. The contents of videos have been excluded from the sample, but where there is significant textual commentary in the tweet, with a video attached, coders will be instructed to count the commentary in the sample. The process of coding will use two coders. Each will be assigned a random sample of the data. Since the sample is 500 total tweets, each individual coder will be given 300 tweets total. This is to accounts for 1.) their share of the coded tweets (250), and 2.) intercoder reliability, an overlap of 10% of the sample between coders to test whether methods are accurate and valid across different people.

## 5. Example

As an example of the coding process, we will use the top QAnon tweet on Twitter as of 4:00 PM, 20 March, 2020, displayed in Figure 1. This tweet is a particularly good example, as it provides a number of extremes for our coding system to measure. The tweet is long and full of text, ideal for the methodology. How best would we code this Tweet? "FIGHTING" is used twice, counting for a total of 4 in Violence, two for each mention of the word, doubled since both are in caps. Add on 2 for "WAR". "NOT...CLEAN" likewise receives two. Finally, a single point for the inclusion of the "U.S. Military". The "Chain of Command" comment is not typically used by QAnon in reference to the U.S. Military's Chain of Command, but rather to the President and White House


**Figure 1. Example coding tweet.**

specifically, so it does not receive a rating on the violence measure. Thus, the Pres_Viol variable = 1, and the Deg_Viol = 9.

Let us turn to an examination of Religious aspects. "Have FAITH...HAVE FAITH" are the explicitly religious references in the tweet, coding at two each, for its religious reference and use of capitals. Some may point to the first line "We are FIGHTING for LIFE" as a possible example, perhaps referring to religious-based pro-life advocacy, but there is insufficient evidence in the remainder of the tweet to substantiate this claim. Therefore, the Pres_Rel variable = 1, and the Deg_Rel variable = 4. The tweet does not seem to mention economics in any meaningful way. Thus, it would receive a 0 in both the Pres_Econ and Deg_Econ variables. Paranoia is a more difficult metric, as it is even more subjective than its counterparts. However, some aspects, such as "[SCARE] NECESSARY EVENT" or "WE ARE IN CONTROL" point each to the certain paranoid conspiracy-mongering that we're looking for, so a total of Pres_Par=1 and Deg_Par=4.

Finally, we examine overall sentiment. The overall process, using all of the above variables, eventually brings the total of sentiment to +8. A total of 10 negative sentiment and 18 positive sentiment. Despite advocating for violence, the tweet primarily uses positive sentiment to do so, much like a rallying cry.

## 6. Intercoder Reliability

Using the open source statistical software Gretl, I was able to analyze the data that my coders provided. First, I wanted to establish whether the methodology was reliable between coders. For this, I utilized two-sample t-tests, testing the difference of means between the coders' ratings on Degree of Violence and Degree of Paranoia.

First, an examination of Degree of Violence. My coders did not have a significant difference in either measuring Degree or Presence of Violence. In order to statistically test this, I performed a t-test on the means of each coder's samples. First, the tests for Presence Variables, both of Paranoia and of Violence. The p-value of the Pres_Paranoia test was equal to .547, a good indicator that the test for paranoia held a good amount of intercoder reliability. The other test garnered remarkable results. The test for Pres_Violence yielded a p-value equal to 1. In this case, we see that the coders identically identified the number of tweets in the intercoder test for the Presence of Violence, an excellent indicator that intercoder reliability is strong.

Having established that my coders had similar results for identifying tweets containing violent and paranoid rhetoric, and found independent agreement with one another, I moved on to establish that their methods of gauging the amount of violence or paranoia in any given tweet correlated similarly. Running the same tests, for the same variables' Degree counterparts, I was able to determine that the coders had a strong correlation in their identification of degrees of paranoia throughout the sample, with a $p = .84$. While they had some divergence on identifying which tweets were paranoid, when they did identify paranoid tweets, they were able to do so in highly similar manners. Contrast this with the Deg_Violence test. This test had a p-value of .56, a much stronger difference than the other variable. This indicates that, while

the coders were able to identify violent tweets in a highly similar manner, they still had some divergence on their methods of coding the violence contained within each tweet. While not significant enough to bring the intercoder reliability into question, it indicates that, in the future, consideration must be taken by researchers as to the way that their coders rate violence, to ensure the utmost validity. In conclusion, the high intercoder reliability my research demonstrates is a positive sign both for the validity of this paper and for future work concerning the content analysis of tweets using this method.

## 7. Paranoia

The QAnon movement, like many conspiracy theories, is considerably characterized by paranoia. The movement folds in a number of different theories, possibly as part of its nature as a decentralized internet following. Various ideas can be proposed and other conspiracy theories can be brought into the grander narrative. What is more, various groups can disagree with each other on the specifics of who exactly is to blame in the theory, while still maintaining a cohesion around the figure of 'Q'. One finds a number of people are to blame, depending on the individual asked. Some blame extraterrestrials, others blame Jews, and still others blame, for example, the Cult of Moloch, an ancient mythic religion. However, they are all united in the thought that a nebulous 'other' is to blame for the problems of the world at large.

Some examples of this behavior were demonstrated in our sample, which included a number of different conspiracy theories, from the adrenochrome conspiracy, centering around the extraction of a random hormone form trafficked children on behalf of Hollywood elites, to Pizzagate, the theory that the 'deep state cabal' uses codes such as 'Cheese Pizza' in emails to refer, once again, to trafficked children. The paranoia of the movement is particularly troubling. It demonstrates a deep institutional distrust on the part of a not-insignificant population of Americans.

When studying the Paranoia of the movement, I decided to provide my coders with a glossary of terms, in order to help them decipher the many terms which the movement tends to use in order to communicate its paranoia. As already discussed in Section Five: Intercoder Reliability, I found that my coders had a high amount of reliability between each other when determining the amount of Paranoia present in each tweet. Let us now discuss the interpretation of the data collected on Paranoia.

First, I conducted another difference of means test on the samples, this time between tweets from QAnon associated accounts and Conservative associated accounts. While I suspected that the answer would be somewhat obvious, that a conspiracy theory would demonstrate more paranoia than a mainstream political movement, it was still necessary for two reasons. First, it was necessary to determine whether or not our samples had significant crossover between each other. This helped to determine whether or not the methodology, of collecting followers from a thought leader and then sampling their tweets, provided an accurate picture of two different communities, rather than either one community with some variation, or two communities with a great deal of crossover, thus making data collection and interpretation difficult and possibly invalid.

I compared the two samples' means of Degree of Paranoia, including those with a Degree measurement of 0. The first sample, that represented the QAnon movement, had an average Degree of Paranoia of 2.54, while the Conservative sample's mean was 1.95. Conducting a standard two tailed t-test, I found that the test statistic was 2.36, with a p of .018. The results of the test are displayed in Figure 2.

The test demonstrates that there does indeed exist a significant difference between the two samples. While conservatives do demonstrate some amount of paranoia, the QAnon tweeters were

```
Null hypothesis: Difference of means = 0

Sample 1:
 n = 250, mean = 2.548, s.d. = 3.31476
 standard error of mean = 0.209644
 95% confidence interval for mean: 2.1351 to 2.9609

Sample 2:
 n = 248, mean = 1.95968, s.d. = 2.08289
 standard error of mean = 0.132264
 95% confidence interval for mean: 1.69917 to 2.22019

Test statistic: t(496) = (2.548 - 1.95968)/0.248313 = 2.36928
Two-tailed p-value = 0.0182
(one-tailed = 0.009102)
```

**Figure 2. Difference of means, degree of Paranoia.**

considerably more so, almost two and a half standard deviations away from the Conservative mean. This confirms that the samples were, at least in some regard, significantly different from one another, demonstrating that these are two separate communities, with different ideals and ways of thinking, or at least, of expressing that thought.

What I believe accounts for the difference between the two samples is the much higher level of paranoia that some QAnon accounts have, bringing the overall average up. In order to test this, I ran a Binary Logistic Regression, using Presence of Paranoia Variable against the dummy variable that determined whether a specific tweet was part of the QAnon sample. The results are displayed in Fig. 3.

```
Function evaluations: 30
Evaluations of gradient: 10

Model 2: Ordered Logit, using observations 1-498
Dependent variable: Pres_Paranoia
Standard errors based on Hessian

             coefficient   std. error      z      p-value
  --------------------------------------------------------
  Qanon      -0.230417     0.184385     -1.250   0.2114

  cut1       -0.591536     0.132329     -4.470   7.81e-06 ***
  cut2        6.09980      1.00457       6.072   1.26e-09 ***

Mean dependent var    0.620482   S.D. dependent var   0.498026
Log-likelihood       -337.4952   Akaike criterion     680.9905
Schwarz criterion     693.6223   Hannan-Quinn         685.9480

Number of cases 'correctly predicted' = 306 (61.4%)
Likelihood ratio test: Chi-square(1) = 56.3634 [0.0000]
```

**Figure 3. Binary logistic regression, QAnon dummy variable and Presence of Violence.**

Here, one sees that there is not a significant enough correlation between any given tweet demonstrating the presence of paranoia and being in the QAnon sample. In absolute numbers, 149 QAnon tweets, 59% of their sample, demonstrated paranoia. Contrast with 160 Conservative tweets, 64% of the sample. If the QAnon sample does not simply have a much larger number of tweets with paranoia in them, and rather has a similar amount of observations to their counterparts, the only logical explanation for the difference between the two in terms of Degree must be that the tweets which do demonstrate the presence of paranoia in the QAnon sample must have a higher degree of paranoia within them. The highest QAnon tweets rated as 16's and 17's, generally consisting of heavy usage of hashtags and of capitals, denoting a particular commitment to getting out the message via hashtags, discussing topics already named in this paper, see Fig. 4 for an example of this kind of 'evangelizing' tweet. These tweets would generally focus on the repetition of topics in said hashtags, likely focusing on casting a broad net for possible casual searchers to find a QAnon tweet and be dragged into the community as a whole.


**Figure 4. Example high Paranoia tweet.**

Many of the more paranoid tweets focused on Numerology, the process of translating words into number, and those numbers back into words. These tweets generally focus on attempting to decode messages from the President or other sources, as seen in Figure 5, which attempts to construct a connection between the President's May 2017 tweet and the COVID-19 pandemic. It

helps to demonstrate as well, the leaps of logic that defines the paranoia of these tweets, making assumptions and connections with no evidence behind them.

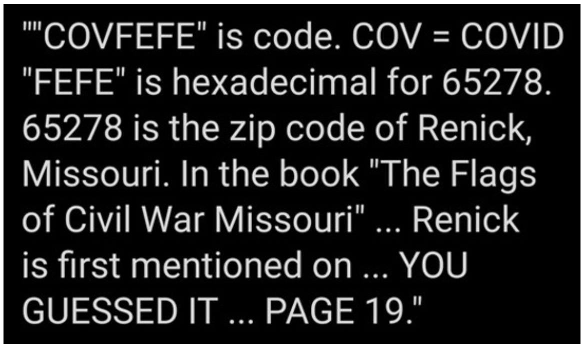


**Figure 5. A QAnon tweet demonstrating numerology.**

However, the most paranoid tweets in the QAnon sample did not focus on either decoding messages or on evangelizing, but rather on target identification and accusations. Of the 8 tweets above the 95th percentile of observations for degree of paranoia, 5 named specific individuals or groups of people responsible for crimes which they likewise outline in their tweets. Individuals are not only politicians, but also mainstream celebrities, while organizations tend to be the Democratic Party, tech companies, and the business side of the Military Industrial Complex, while the military itself is beyond reproach. See, for example, Figure 6 and Figure 7. The first concerns the data collection practices of Google and other tech companies, claiming both that they are associated with the Mark of the Beast, and that they are colluding with Communist China. Here, we see target identification of specific companies, based on an accusation with no evidence behind it, and further, the baseless tie, the leap of logic, to something like a shibboleth of 'the enemy', a figure around which hate can be easily directed, and a figure who is so universally hated by the community as to make mutual identification easy.

Figure 7 depicts another of these tweets, but one which focuses on accusing individuals rather


**Figure 6. Paranoia towards organizations.**

than organizations. These tweets are particularly concerning, as they provide actionable targets for potential violent actors to move against, as demonstrated by the 2018 'Magabomber', who targeted people such as George Soros or Hillary Clinton, commonly named in these kind of conspiracy theories. This, paired with the specific accusations about child abduction and murder, make for a possibly dangerous formula where theorists not only have specific targets, but believe them to be guilty of heinous crimes and going unpunished.


**Figure 7. Paranoia towards individuals.**

Contrast this with the Conservative sample, where the highest outlier was rated a 12, while all

other observations were rated 10 or lower. Further, the primary focus of the paranoia in the Conservative sample was not on violent cabals or on governmental plots, but primarily the theory that the news media, inclusive of every major channel, even including Fox News, were conspiring to underreport the successes of President Trump and overreport his failures. These were counted as part of a paranoid mindset, since such rhetoric betrays a form of unfounded distrust in an institution, even if, instead of a governmental body, it is the fourth estate.

When examining the outliers of the Conservative sample, those above the 95th percentile, there begins to be cross-contamination between the two samples. There were only 5 outliers in this population, and three of them concerned QAnon or theories related to QAnon. One of the other two focused on the theory that the Coronavirus was fake, using #filmyourhospital to try and get people to prove that hospitals were not, in fact, overrun, and were deceiving the public to some as yet unknown end. The other concerned the conspiracy theory concerning Joe Biden and his son's involvement in the gas company Burisma.

The fact that the most paranoid tweets in the Conservative sample, more often than not, included QAnon references or rhetoric, provides a signal that the movement has a significant amount of paranoia separate from the Conservative sample, and which has not quite become a significant presence in the Conservative movement as a whole.

## 8. Violence

Now we will discuss the principle variables for this paper, measuring the Presence and Degree of Violence within a given tweet. For the purposes of measuring Violence, it is worth reminding the reader that this paper is merely measuring violent rhetoric, and what potential insights can be gleaned into the mindset of the community. The probability of that rhetoric being actualized into real-world violence against any particular people is out of the scope of this paper, but presents interesting avenues for future research.

How comfortable are these populations with, at least in their own anonymous echo chamber, expressing a desire to inflict violence on other people? In accord with this goal, I instructed my coders to code not only for direct and actionable threats (i.e. "I'll kill you") but also for support of state agencies being deployed to use the monopoly the state has on the means of violence (i.e "Arrest Ilhan Omar"), and also to code slurs and other degrading language (i.e. "Maggot", and others less mentionable here). This last qualification for rating a word or phrase as violent may be unintuitive at first, but is included in the data based on the notion that hate speech is a vector for violence, identifying potential groups as targets and furthering an us vs. them mentality that makes violence come more easily. The thought runs that hate speech increases bias, "bias converts into discriminatory thoughts and behavior and in some may lead to acts of direct violence, as above, like a mass shooting" (Zakrison 674).

Likewise, I instructed the coders to code rhetoric which attempted to paint the potential enemies identified by the theory as violent. The reason for this is that painting a potential enemy as violent is a primer for violence. As outlined in the paper "Understanding Conspiracy Theories", "[conspiracists] use conspiracy theories to create the ideological conditions for extremism and political violence. These include fear of Muslims and radical distrust of political leaders and institutions which are represented either complicit with Islamists or their dupes—beliefs that inspired Anders Breivik's massacre of left-wing youth in Oslo" (Douglas et al. 14). While this sentence relates specifically to anti-Muslim conspiracy theories, the principle holds true for those theorizing about the 'deep state', or about Hillary Clinton's blood-drinking.

Travis Brisini discusses Mrs. Clinton's role in conspiracy theories as it parallels the witch-hunts

of European history. He writes in comparison between the accusations of cannibalism and the hunts, "It was not necessarily a prefigured set of specific crimes that motivated witch hunting—the 'crimes' themselves were loosely defined, largely unprovable, and often so fantastical as to be impossible to commit—but rather the need for a structure that would permit the application of punishment with ex post facto justifications and evidence" (Brisini 214). In essence, the point of painting the enemy as violent is to justify violence, whether vigilante as in the cases of the so-called 'MAGABomber', or systemic, as in the calls for the U.S. military to try and execute high-profile Democrats. Even if a tweet does not contain the call to violence, it still contains the justification for said violence.

The first step in determining the relative violence of the community, like for Paranoia, was to run a difference of means test, to determine whether the two samples differed enough for further analysis. The results of the test are laid out in Fig. 8. As the reader can see, there is an even stronger difference between the two means than in the paranoia sample. The p-value is .011, which causes me to reject the null hypothesis that the two populations display no differences in their degree of violence.

```
Null hypothesis: Difference of means = 0

Sample 1:
 n = 250, mean = 0.984, s.d. = 1.61561
 standard error of mean = 0.10218
 95% confidence interval for mean: 0.782753 to 1.18525

Sample 2:
 n = 248, mean = 0.657258, s.d. = 1.24989
 standard error of mean = 0.0793678
 95% confidence interval for mean: 0.500934 to 0.813582

Test statistic: t(496) = (0.984 - 0.657258)/0.129514 = 2.52283
Two-tailed p-value = 0.01195
(one-tailed = 0.005977)
```

**Figure 8. Difference of means, Degree of Violence.**

Like in the Paranoia sample, there ought to be a consideration as to whether a QAnon tweet is more likely than a conservative tweet to display violent tendencies. This helps to establish that QAnon is not only more violent in individually highly violent tweets, but also more likely to be violent just by nature of being part of the community. Once again like the Paranoia tests, I conducted a Logit test on the sample as a whole, using the dummy variable determining whether a tweet was part of the QAnon sample and the dummy variable which measured whether there was any violent ideation present in the tweet whatsoever. The results are presented in Fig. 9. In this case, the QAnon sample demonstrates a high correlation between a given tweet being part of their community and demonstrating violent behavior. The results of this test provide evidence that the QAnon community has cultivated a community of violent ideation.

```
Model 5: Logit, using observations 1-498
Dependent variable: Pres_Violence
Standard errors based on Hessian

             coefficient   std. error      z      p-value
  ---------------------------------------------------------
  const      -0.816761     0.137738     -5.930   3.03e-09 ***
  Qanon       0.394601     0.188932      2.089   0.0367   **
```

**Figure 9. Binary logistic regression, QAnon dummy variable and Presence of Violence.**

It behooves us to examine the types of violence that the QAnon sample demonstrates. Principally, the tweets demonstrate the justifications for violence earlier discussed. Take, for instance, Figs. 10 and 11, which demonstrate the two tweets which scored the highest on the Degree of Violence scale of all of the QAnon samples, at 10 each. The first, Fig. 10, links to a Madonna performance for the song competition Eurovision 2019, but alleges that it is an example of a cultish ceremony. The nature of the collected tweet's reply is intensely othering. It is designed to identify perfectly normal celebrities and politicians as beyond human reasoning or mercy, as psychopathic. This othering is the first step towards violence. The specificity of the accusations is common among this type of tweet, outlining vague connections between specific public figures, such as former President Obama, and their supposed true, cultish motives.

The second tweet, Figure 11, is slightly dif-

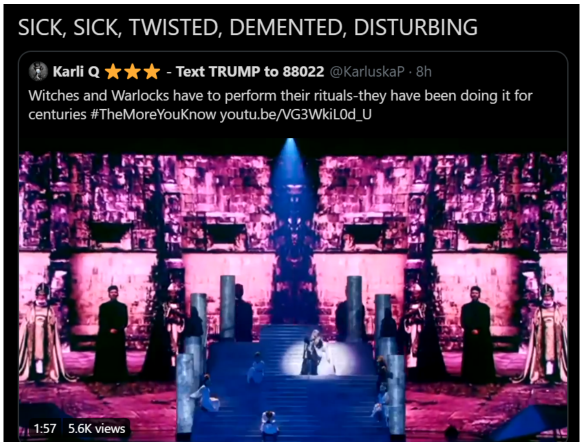


**Figure 10. Othering of public figures through baseless claims.**

ferent in mindset than the tweet in Figure 10. When compared to its counterpart, it demonstrates something of a cleavage in the more radical side of the QAnon community, namely the difference between the religious/supernaturalist side of the community, and the more materially grounded, economic side. The tweet makes no reference to spirituality, to magic, or to rituals. Rather, it is almost McCarthyism for the modern day, focusing on rooting out the enemies within who are at war with the United States, and on punishing those enemies through state violence, based off of no evidence. The enemies are hidden, and by their very nature of being hidden, could be anywhere. However, rather than warlocks or Satanists, the enemies are economic in nature, seeking socialism or communism, or to control the media. By portraying the current political situation as a war, a world war at that, the account is calling for identification as part of an army, protecting the United States from those who wish to do it harm. It is a form of preparation for vigilantism.

The final form of violent tweet characterizes the vast majority of the QAnon movement's violent rhetoric, rating around a 3 or 4 on the Degree of Violence scale. It does not principally focus on painting the enemy as evil witches, nor on McCarthyite tactics of more materially grounded crimes, but rather expresses a unique sentiment. It


**Figure 11. McCarthyite tactics of claiming the existence of hidden enemies.**

shares the distrust of the 'deep state' that the other two share, but prefers to take a more backseat approach. These accounts are more observers than anything else. They do not seek to call others to arms, as in Figure 11, "Get ready to fight the hidden enemies", and they do not focus on accusations of specific individuals, such as is displayed in Figure 10. These tweets will, like in the example, often use biblical imagery, but the crimes alleged are not necessarily supernatural in nature, which excludes them from inclusion in the first type of violent tweet.

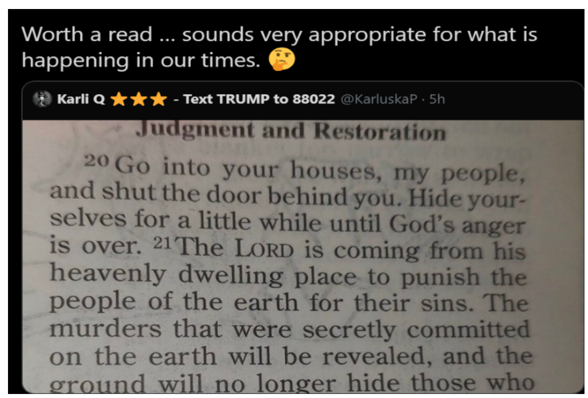


**Figure 12. Discipline and punishment through higher authorities.**

These tweets are the background noise of the movement, the average. They reflect a contentment to abdicate responsibility for the actual work of identifying and rooting out such hidden enemies, trusting the President and those close to him to leverage the violence of the state on their behalf.

Violent conservative rhetoric takes a much different tack from that of the QAnon movement. Where the conspiracy theorists discuss present-

day violence, and glorify the prospect of engaging in that violence, conservatives focus on the violence of the past, mythologizing it and viewing it as a potential future guide, but not one that is likely to be actualized. Consider Figure 13, displaying a tweet which rated above average on Degree of Violence. The tweet discussed a foundational moment in American history, the War of Independence, and holds up the violence by which independence was achieved as a positive. It then reminds its audience to be prepared for the potential of future violence, although it is not immediately at hand.

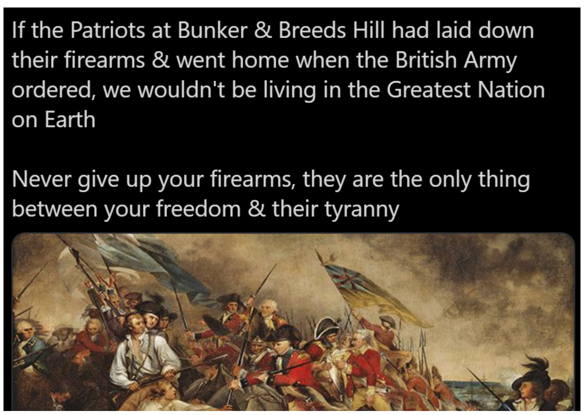


**Figure 13. Mythologizing of past violence as justification for unlikely future violence.**

This is the primary difference between the conservative sample and the QAnon sample. The QAnon sample believes that the moment for violence is either here or close at hand. The conservative sample believes that violence is a potential for the future, but that the conditions have not yet been met for that violence to be necessary.

## 9. Religiosity and Economy

The other gathered variables, Religiosity and Economy, returned data which suggests another cleavage between the QAnon and mainstream Conservative sample. Where the former sample is primarily concerned with religion, the latter sample takes far more time to discuss economic issues. This parallels the split between the neoconservative and business wing of the Republican party and the Evangelical Christian wing, the "three-legged stool" that makes up their base.

The Qanon sample demonstrates a much higher degree of religiosity on average than their Conservative counterparts. This presents another interesting avenue for further research, into whether evangelicals are more likely to support this theory than neoconservatives are. In order to determine the statistical extent of the difference, the test used was a difference of means two tailed t-test, applied to both variables. First, to discuss religiosity. The results of the Religiosity test are detailed in Figure 14. With a p-value of .029, the data does suggest that there may be a correlation between membership in the Evangelical Christianity and QAnon.

```
Null hypothesis: Difference of means = 0

Sample 1:
 n = 250, mean = 0.552, s.d. = 1.62538
 standard error of mean = 0.102798
 95% confidence interval for mean: 0.349535 to 0.754465

Sample 2:
 n = 248, mean = 0.270161, s.d. = 1.23199
 standard error of mean = 0.0782317
 95% confidence interval for mean: 0.116075 to 0.424248

Test statistic: t(496) = (0.552 - 0.270161)/0.129321 = 2.17937
Two-tailed p-value = 0.02977
(one-tailed = 0.01489)
```

**Figure 14. Difference of means, Religiosity.**

The kind of religiosity that the QAnon movement demonstrates is worth examining. They generally focus on apocalyptic themes, such as quotations from or references to the Book of Revelations. They take on an eschatological figure, premillennial in nature, as though they are attempting to predict the second coming of Christ and are looking forward to the "silent war", as shown in Figure 15.

The QAnon movement views the conspiracy in the terms of apocalypse, of a final great battle to destroy all evil and achieve the victory of all that is good. Even in their religious tweets, the movement demonstrates a desire for conflict and for violence, to be part of a war, to take part in

righteous battle.

> Our deliverance is drawing near.
> Babylon is falling, falling.
> 1963-2020 AD
> Lord we thank you for delivering us. We pray for those fighting on the ground in this silent war. We know you will protect them. We love you. Forgive our sins. Bless us with wisdom and discernment.
> IJNA

**Figure 15. QAnon eschatological religiosity.**

As further evidence for the possibility of the factional split between evangelicals and neoconservatives paralleling the split between the sample of conservatives and QAnon adherents, there are the results of the same difference of means test conducted for the degree of economy variable. The results demonstrate the exact opposite of the degree of religiosity variable, namely that the QAnon sample is extremely less likely to talk about economic matters than the members of the Conservative sample. The p-value of this test was $3.97 \times 10^{-5}$, a remarkably stark difference in rhetorical topics between the two communities, as demonstrated in Figure 16.

```
Null hypothesis: Difference of means = 0

Sample 1:
 n = 250, mean = 0.46, s.d. = 1.01416
 standard error of mean = 0.0641409
 95% confidence interval for mean: 0.333672 to 0.586328

Sample 2:
 n = 248, mean = 0.927419, s.d. = 1.46303
 standard error of mean = 0.0929026
 95% confidence interval for mean: 0.744437 to 1.1104

Test statistic: t(496) = (0.46 - 0.927419)/0.112734 = -4.14621
Two-tailed p-value = 3.976e-005
(one-tailed = 1.988e-005)
```

**Figure 16. Difference of means, Economy.**

This data indicates that there may be a signif-icant relationship between evangelicalism and belief in the QAnon conspiracy theory, at least from the perspective of the ways that the QAnon theory expresses itself. Do evangelical belief systems play a contributing role in distrust of government and other institutions, in a way that neoconservative belief systems do not?

In conclusion, the QAnon sample and the Conservative sample demonstrate a key cleavage that defines their communities, outside of the belief or lack thereof in the conspiracy theory. Where one prefers to discuss religious matters, the other primarily concerns itself with economic matters.

## 10. Regressions

The full understanding of this issue requires an analysis of the relationship between the variables themselves. How do each of the variables of degree interact with each other?

First, we will discuss the relationship between violence and paranoia, examining the whole sample, the QAnon sample, and the Conservative sample respectively. These two variables correlate moderately to weakly, with a p-value of $3.67 \times 10^{-18}$ and a correlation coefficient of .258. This does imply a weak positive correlation between paranoia and violence, that as paranoia increases, violence likewise increases, although not as strongly correlated as might be supposed. The correlation between violence and paranoia is simi-

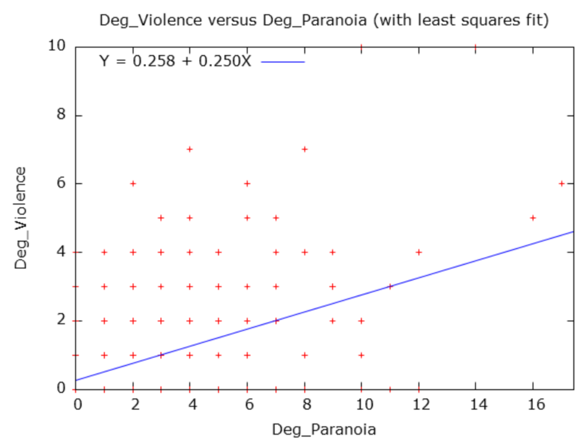


**Figure 17. OLS graph: Degree of Violence and Degree of Paranoia, whole sample.**

lar between the QAnon and conservative samples, with a Correlation Coefficient of .255 and .222 respectively. This indicates that, as either ideology becomes more paranoid, they are likely to become more violent in their rhetoric, typically invoking

the state's mechanisms for violence.

```
Model 1: OLS, using observations 1-498
Dependent variable: Deg_Violence

                 coefficient   std. error   t-ratio    p-value
  --------------------------------------------------------------
  const           0.258090     0.0736787     3.503    0.0005    ***
  Deg_Paranoia    0.249752     0.0205799    12.14     7.38e-030 ***

Mean dependent var   0.821285   S.D. dependent var   1.452878
Sum squared resid    808.9090   S.E. of regression   1.277053
R-squared            0.228945   Adjusted R-squared   0.227391
F(1, 496)            147.2748   P-value(F)           7.38e-30
Log-likelihood      -827.4179   Akaike criterion     1658.836
Schwarz criterion    1667.257   Hannan-Quinn         1662.141
```

```
Model 3: OLS, using observations 1-250
Dependent variable: Deg_Violence

                 coefficient   std. error   t-ratio    p-value
  --------------------------------------------------------------
  const           0.331902     0.109986      3.018    0.0028    ***
  Deg_Paranoia    0.255925     0.0263398     9.716    4.06e-019 ***

Mean dependent var   0.984000   S.D. dependent var   1.615607
Sum squared resid    470.7392   S.E. of regression   1.377731
R-squared            0.275715   Adjusted R-squared   0.272794
F(1, 248)            94.40643   P-value(F)           4.06e-19
Log-likelihood      -433.8400   Akaike criterion     871.6801
Schwarz criterion    878.7230   Hannan-Quinn         874.5147
```

```
Model 5: OLS, using observations 1-249
Dependent variable: Deg_Violence

                 coefficient   std. error   t-ratio   p-value
  -------------------------------------------------------------
  const           0.225155     0.101517      2.218    0.0275   **
  Deg_Paranoia    0.222774     0.0355278     6.270    1.60e-09 ***

Mean dependent var   0.662651   S.D. dependent var   1.250262
Sum squared resid    334.4278   S.E. of regression   1.163597
R-squared            0.137323   Adjusted R-squared   0.133830
F(1, 247)            39.31797   P-value(F)           1.60e-09
Log-likelihood      -390.0392   Akaike criterion     784.0784
Schwarz criterion    791.1133   Hannan-Quinn         786.9101
```

**Figure 18. OLS table: Degree of Violence against Degree of Paranoia. Top to Bottom: Whole sample, QAnon, and Conservative.**

The variable which measures Degree of Religiosity correlates much less strongly with Degree of Violence than Paranoia does, and Degree of Economy does not correlate with Degree of Violence whatsoever. The correlation coefficient for Degree of Religiosity is .136, indicating the model is not very accurate at determining the relationship between religion and violent rhetoric. Even when taking the QAnon example by itself, the correlation coefficient is only .163. However, the p-value for the overall sample when considering the two variables is .0023, which indicates that there does exist a statistically significant relationship between the two variables. The Degree of Economy variable has no relationship with the Degree of Violence variable whatsoever. The p-value for the Ordinary Least Squares regression between the two is .589. Whether a given tweet discusses economic matters has no bearing on whether it will use violent rhetoric to convey its thesis.

The final regression to examine is the relationship between the Sentiment of a given tweet and its propensity for violence. It may seem intuitive that as violence goes up, overall sentiment decreases. This is not always the case, however, as demonstrated by the coding of the example tweet in Section Four. Violence can be portrayed not as a negative thing, but as a social good, as the glorious means to the prelapsarian future. In the model, Degree of Sentiment is weakly negatively correlated with Degree of Violence, with a p-value of $1.21 \times 10^{-11}$, and $r = .297$. This demonstrates that Sentiment and Violence are related in a similar manner to Religiosity and Violence, that Sentiment is not a good predictor of Violence, but does have a relationship.

The only variable which has any predictive power of the violent rhetoric that a tweet will display is the Degree of Paranoia. Each other, besides Degree of Economy, has a relationship with Degree of Violence, but doesn't have any meaningful predictive power.

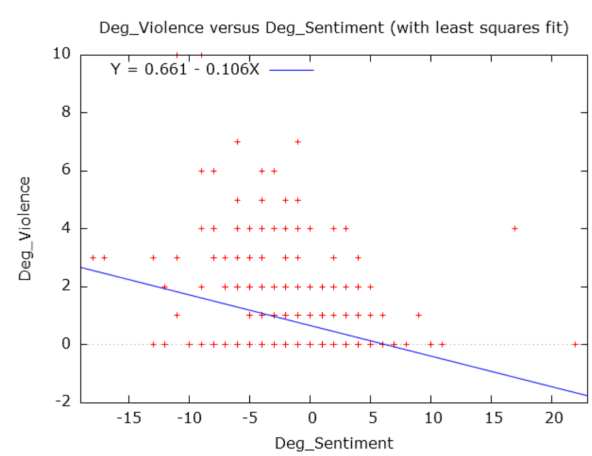


**Figure 19. OLS graph: Degree of Violence against Degree of Sentiment.**

```
Model 6: OLS, using observations 1-498
Dependent variable: Deg_Violence

                  coefficient   std. error   t-ratio    p-value
  --------------------------------------------------------------
  const            0.661015     0.0663624     9.961    1.99e-021 ***
  Deg_Sentiment   -0.105575     0.0152069    -6.943    1.21e-011 ***

Mean dependent var   0.821285   S.D. dependent var   1.452878
Sum squared resid    956.1770   S.E. of regression   1.388444
R-squared            0.088569   Adjusted R-squared   0.086732
F(1, 496)            48.19927   P-value(F)           1.21e-11
Log-likelihood      -869.0648   Akaike criterion     1742.130
Schwarz criterion    1750.551   Hannan-Quinn         1745.435
```

**Figure 20. OLS table: Degree of Violence against Degree of Sentiment.**

## 11. Limitations

This study is limited in several ways that require further research to be conducted. First, it only concerns the social network Twitter. Because social networks are each structured so uniquely, the solutions which work for one will not necessarily work for another. Further, the types of rhetoric seen on any given social network may vary dramatically based on the parameters the site allows for expression. For example, Twitter limits each Tweet to 280 characters, where posts on sites such as Reddit may be the size of an essay in length.

Secondly, this research's sample size is very small, especially when considering the volume of traffic on Twitter. In order to more fully understand the QAnon movement on Twitter, automation must be used to gather a sample in the thousands or tens of thousands of tweets, rather than utilizing a variant of chain sampling. Both the size and the method of sampling limit the validity of the paper without further research.

Third, the predictive power of the variable measuring Degree of Paranoia is not strong enough on its own using the existing model to draw definitive conclusions. Through further study of the kind of rhetoric that the QAnon movement uses, as well as the theories they promote, the hypothesis of paranoia acting as a good predictor of violent rhetoric might be more definitively confirmed.

## 12. Responses and Conclusion

The QAnon movement, thus far, has been responsible for a number of crimes, violent and non-violent alike (McIntire and Roose). Their rhetoric demonstrates a commitment to painting their enemies as supernatural foes, committing foul crimes without repercussion, a recipe for vigilantism. What, then, is the role of the government in addressing the growth and networking of this movement? In truth, the United States government has very little power to limit the ability of QAnon members to organize and discuss online, as their speech falls under the protections of free speech, as they are currently understood, outlined in Brandenburg v. Ohio, handed down in 1969.

The case establishes that, in order for the government to curtail a citizen's speech, it must intend to produce imminent lawless action. The extent to which speech over social media relates to 'imminence' is debated, generally concerning whether imminence ought to be measured as relating to the speaker/poster, or relating to the viewer, which may happen at any point in the future, as long as the post remains on the social network (Beausoleil 2134).

This lack of promoting imminent action be taken precludes the involvement of government actors on a wide scale, although more specific actions may be taken to target particularly violent individual accounts. One method of screening for these accounts may be to use a measure of paranoia, as outlined in this paper: a glossary of terms generally associated with the conspiracy specifically, giving particular weight to hashtags and capitals. Using a method akin to this, law enforcement may be able to target specifically violent actors in the community to surveil for possible criminal activity.

One group which will have a vital role to play in curbing QAnon's spread, and the spread of other conspiracy theories, are the social networks themselves. Many of the tweets in the sample clearly broke the community guidelines of Twitter,

specifically their March 2019 prohibition against the glorification of violence. By enforcing their community guidelines more strictly, Twitter can play a vital role in ensuring that these theories are not allowed to spread, at least through their own platform. The principal means of combatting the spread of hate speech or violent speech on a platform is to consider the means by which that platform allows users to connect with one another and form communities. On the social media site Reddit, the wholesale banning of two communities which practiced hate speech on their platform did not lead to a proliferation of hate speech there, even as members of the communities spread throughout the rest of the site, and in fact, their individual uses of hate speech decreased by 80%. (Chandrasekharan 11).

Where Twitter is concerned, there are no formal communities to ban; the site is structured very differently to Reddit. In this case, possible interventions might include disallowing certain hashtags to be searchable or to trend, thus limiting recruitment and keeping the movement contained to a small population. Likewise, being more aggressive with bans of members who use violent or dehumanizing rhetoric in their tweets will further decrease the existing population on the site. While this will not dismantle the theory by any means, their primary congregation occurring on the anonymous image boards 4chan and 8kun, it will at least curtail the spread of the theory to the main user base of Twitter.

The QAnon movement represents a growing trend of belief in conspiracy theories in the American public, to the extent that one study found "over 55% of respondents in 2011 agreed with at least one [theory]" (Oliver and Wood 956). Much effort will have to be expended to combat this growing distrust of institutions, both of government, of media, and of business. Twitter only represents one area where these ideas can be combatted and contained, and a positive effort to restore trust between Americans and their institutions must be made.

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