June 2022

A Relational Investigation of Political Polarization on Twitter

Tyler Walton

University of Massachusetts Amherst

A Relational Investigation of Political Polarization on Twitter

A Thesis Presented

by

Tyler J. Walton

Submitted to the Graduate School of the
University of Massachusetts Amherst in partial fulfillment
of the requirements for the degree of

Master of Arts

May 2022

University of Massachusetts Department of Sociology

A Relational Investigation of Political Polarization on Twitter

A Master's Thesis

Presented By

Tyler Walton

Approved as to style and content by:

Mark Pachucki, Chair

Anthony Paik, Member

Jonathan Wynn, Member

Jonathan Wynn, Chair
Department of Sociology

AKNOWLEDGMENTS

I would like to thank my advisor, Mark Pachucki, for his years of academic and professional guidance, and his ability to always push to the next level with my work. I would also like to thank the rest of my committee, Anthony Paik, and Jonathan Wynn, for their helpful comments and suggestions throughout all stages of the current research projects. Between the three of these individuals, I have gained countless insights into the sociological research process in both methodology and theory.

I would also like to thank the university community, with a particular focus on the Computational Social Science Community. Through this community I was able to take courses across academic departments that enabled me to complete the work within this paper.

Lastly, I would like to thank the sociology department for their structure and guidance throughout this process.

Abstract

A Relational Understanding of Political Polarization on Twitter

MAY 2022

Tyler Walton, B.A., West Chester University

M.A., University of Massachusetts-Amherst

Directed by: Professor Mark Pachucki

Over the last several decades there has been a debate among social scientists on whether the United States has become, or is in the process of being, politically polarized. These conversations started with discussion of the "culture wars," moved to the discussion of selective exposure and media outrage, and currently involve concerns about online radicalization and the spread of online misinformation. Throughout these themes one characteristic has remained constant: a lack of systematic evidence despite anecdotes and feelings of animosity between the two parties. Today researchers are beginning to shift from operationalizing political polarization as growing divides in attitudes towards policy issues towards a focus on political animosity. Scholars attempting to understand the origins of affective polarization have looked at the effect of political identity, out-group perceptions, and the diffusion of moral and emotional content in social media networks. In the current study I build on this literature using a panel of longitudinal data Twitter users to examine whether there is an association between following prominent partisan Twitter accounts and the expression of emotional valence through Tweeting or Retweeting. I take a relational approach to analysis by examining how this relationship varies between networks of Twitter users and under different historical circumstances. I argue that this relational approach is necessary for understanding how political polarization is unfolding in the country and that the lack of a relational approach may explain why political polarization has been downplayed in systematic studies. This study finds that the amount of political polarization on Twitter is dependent both on cultural and historical context. It makes contributions to the literature on political polarization in the United States, research methodology, and has implications for reducing radicalization in online spaces.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

The past two elections cycles in the United States have laid bare ongoing concerns within the country. These concerns first arose in the 1990's as the country appeared to struggle over its identity and form a singular moral authority that was visible within the public spere in debates over the separation of church and state, abortion, and homosexuality (Hunter 1991; 1994). They continued to grow into the next decade as a fragmented media ecosystem made it easier for individuals to find news that they agreed with (Sunstein 2009; Stroud 2010; Pariser 2011) and these outlets produced content aimed at provoking moral out-rage towards the political out-group (Jamieson and Capella 2010; Berry and Sobieraj 2013). Today these worries have shifted from traditional media outlets to the digital sphere where algorithms aim to guide individuals down the path of most engagement, which often leads to like-minded opinions that generate a visceral response that is often misleading (Marwick & Lewis 2017; Nadler, Crain, and Donovan 2018; Lewis 2018). What these mechanisms look like in action have been relatively clear over the last several years as e-mail dumps upend political elections, political rallies result in death, and mask and vaccine policy aimed at diminishing the effects of the COVID-19 pandemic have become polarized. Despite the anecdotal evidence the question remains whether the U.S. public is politically polarized or whether news media are simply reflecting the polarized attitudes of the elites and most ardent partisans.

Research on the extent to which political polarization is a social fact in the U.S. has taken, with very few exceptions, several general tracks of analysis, and the results depend on how polarization is operationalized. The most historical operationalization of political polarization is the growth of extreme attitudes towards policy issues (DiMaggio et al. 1996; Fiorina 2008), which has demonstrated little evidence of polarization even today (Kiley and Vaisey 2020). The only segment of the U.S. where attitude polarization has been demonstrated to exist is within political elites (Theriault 2008). A second operationalization is the extent to which partisans with similar political identities align on policy issues (Baldassari and Gelman 2008; Levendusky 2009; Kozlowski & Murphy 2020). This research has shown that Republicans and Democrats are more likely to have policy identities that align with their party identity: it is easier to predict one's political identity by knowing their policy stances today than in the past. Scholars have also demonstrated that political identity is correlated with seemingly non-political characteristics (DellaPosta, Shi, & Macy 2015; DellaPosta 2020) and that political identity is central to an individual's political belief system (Boutyline & Vaisey 2017). The final operationalization of political polarization that exists measures affect towards the political out-group. These studies have found that the amount of affect between partisan individuals is much higher than it was in the past (Iyengar, Sood, & Lelkes 2012) and through a natural field experiment have demonstrated that access to broadband internet increases partisan hostility (Lelkes, Sood, & Iyengar 2017). Recent reviews of the literature on affective polarization demonstrate that little is still known about its causes (Iyengar et al. 2019; Finkel et al. 2020) but political identity, perceptions of the outgroup (van Loon et al. 2020), and exposure to partisan content on the internet are among the leading theories.

While research on political polarization stretches back decades, the field has lacked a relational approach to understanding of the phenomena and is in the process of transitioning into a new framework. The current literature tends to assume that the amount of political polarization that one possesses, however it is operationalized, can be measured regardless the state of social or historical relations that the individual is embedded in. These assumptions ignore a rich sociological literature that indicates that the relationships one is interacting with shapes their identity and that historical ruptures can make individuals more susceptible to framing effects. To demonstrate the importance of these assumptions I utilize a comparative panel of Twitter users collected at weekly intervals stretching almost 6 months during the lead-up and aftermath of the U.S. 2020 Presidential election that contain both their social ties and expressive content that occurred within the platform. Using methods from Natural Language Processing and Computational Social Science I document how these users' ego networks, emotional language, and the relationship between the two, change as major historical events unfold. In addition, I utilize 59 semi-structured interviews to demonstrate that these mechanisms depend on the set of relationships that one is situated in online. I proceed by reviewing the literature on social networks and cognitive sociology while highlighting the implications for major studies in the field of political polarization and reviewing the literature on the use of computational methods to measure culture.

CHAPTER 2

RELATIONAL SOCIOLOGY, NETWORKS, AND CULTURE

The social world is a dynamic and complex phenomenon that social scientists have set out to understand and explain the processes that drive action and social change. To do this we have developed research practices that enables us to capture the derivative of a multivariate polynomial and examine a single point in space and time. While these research practices have greatly contributed to our understanding of the social world, they lack the ability to communicate the complexity that comes with a social world defined by an infinite number of overlapping systems that all effect each other simultaneously. To move past these shortfalls Emirbayer (1998) called for research that moves beyond the assumption that individuals possess a single essence that is durable over both time and space by focusing on research that examines the relationship between entities. One example of this is White’s (1992) theory of identity and control, which posits that a single individual possesses multiple identities that are formed as they switch between different Network Domains (NETDOMS). As these individuals move throughout the social world norms change and their actions change as they determine what is acceptable and unacceptable in the current social situation (Horne et al. 2018). This general tendency of a relationality between culture and networks has been highlighted in recent years by multiple scholars (Mische 2011; Pachucki and Breiger 2010).

The implications of these theories are particularly relevant to thinking on political polarization as it relates to both the physical and online world. In the physical world researchers (Cowan & Baldassari 2018) have found that individual’s propensity to discuss politics and reveal their political identity depends on their relationship with the individual and whether the conversation will bring about conflict. Therefore, it is possible that individuals appear polarized in one context, say while venting about politics to their like-minded friends, and not others, like co-workers at the workplace. In the digital world the implications are even larger where one can divide their self into many identities within specific forums (White 2008) or where many identities may be collapsed into one when interacting with friends, family, and co-workers in the same space (Marwick & boyd 2011). Empirical research indicates that context matters in terms an individual’s willingness to share misinformation (Marwick 2018) and partisan news in general (Cinelli et al. 2021). In other words, one could have two accounts: one that is apolitical and another that represents the political echo chamber that we imagine at the peak of political polarization.

White’s theory and the findings above are important for the literature on political polarization in multiple ways. First, the systematic analyses that have found no evidence of political polarization (DiMaggio et al. 1996; Fiorina 2008; Kiley and Vaisey 2020) assume that a survey at a single point in time can capture whether the individual is politically polarized. At that moment the respondents’ relationships are those of the researcher and the academic community at large. While it is possible that the anonymity enables the respondent to give their true response it is also possible that the individual takes a safe route as they do not yet know what is acceptable (Horne et al. 2018), or that a lack of partisan relationships does not yield the same response as a discussion with partisan friends. This critique also can be laid against studies that attempt to determine changes in attitude after being introduced to stimuli on Twitter (Bail et al. 2018; Bail et al. 2019). It is possible that the knowledge the individual obtained from the Internet Research Agency and its affect are reactivated once that individual enters back into their Twitter NETDOM. In this study I aim to address these short comings in two ways. First, my dependent variable is an action in the form of a Tweet and my key independent variable is an action in the form of following a political account. This enables me to capture the outcome in the context of interest without sole reliance upon what respondents say (Mohr et al. 2020), a point I will expand upon at length in what follows. Second, the research takes a comparative approach by examining the relationship between emotion and following a partisan account across multiple contexts. Based on the above theory I hypothesize that:

> H1: A relationship between negative emotion in Tweets and following partisan accounts will only exist in highly polarized and partisan contexts.

While the current study is not experimental, I seek to create homogeneity across groups by defining each group as a set of Twitter accounts that follow a college political organization's Twitter account and have at least one mutual tie with another user that follows the same account. These accounts are niche enough, as demonstrated by their small number of followers, that I expected to find a homogenous group of individuals interested in politics. In contrast, consider taking a random sample of individuals that followed a high-profile account such as that of Donald Trump's, which would be expected to draw a wide variety of individuals including both Republicans and Democrats. This assumption was confirmed in 59 semi-structured interviews that I conducted, which found that individuals were most likely to follow the account because they were active in the political scene on their college campus or because they were interested in local politics and finding other partisans to discuss politics with. Meanwhile, I selected cases from both Republican and Democratic dominant states all with their own unique histories whose heterogeneity I demonstrate using semi-structured interviews and Principal Components Analysis.

CHAPTER 3

UNCERTAINTY AND RELATIONALITY

As individuals move through the world, they find patterns in information that allow them make sense of the social world and determine future lines of action. They reflect on their surroundings to come to an understanding of who they are (Mead 1922) and eventually develop primary frames through which to understand reality (Goffman 1974) that results in a commonsense flow of reality (Garfinkel 1967). These commonsense flows ultimately become institutionalized (Berger and Luckmann 1966), which generates a positive feedback loop that reproduces actions through time. At once, in a perpetual motion, the micro builds the macro, and the macro guides the micro that through the flow of time. Like all entities that travel through time stability should not be considered the norm as the physical laws of entropy degrade all structures. At the individual level entropy comes in the form of switching into new NETDOMs (White 1992; 2008) or the experience of sudden change such as the unexpected loss of a loved one. At a larger level disruption can come in the form of a recession, attack on the country, or a high-profile scandal. It is during these periods that uncertainty is high and that individuals latch onto ideology as they seek to find new lines of action through reality (Swidler 1986). These periods of unsettled culture are more susceptible to partisan framing and therefore more likely to adapt the politically polarized frame that the elites in the United States currently hold (Theriault 2008). To understand why these periods, open the individual to partisan framing we must explore what occurs at the micro level during these changes.

As discussed above individual actions are shaped by the social institutions that individuals operate within. During periods of settled culture individuals receive stable flows of information that generate stable cycles of positive feedback (Mead 1922; Shibutani 1968). Individuals have learned that they can act as they always have and that the future outcomes will remain the same. In unsettled times this information changes and individuals must develop knew frames of understanding about the current set of causal relations and future outcomes. Wagner-Pacifici (2017) demonstrates what these processes look like using the period during and after the 9/11 attacks on the World Trade Center. In the opening of her book Wagner-Pacifici defines an event as a “rupturing moment” that may lead us to “pause in our daily activities, consult communications media of various kinds, confer with each other, and feel somewhat dislocated and disoriented.” (pg. 1). One example from the book demonstrates how the uncertainty leads to the switching between multiple frames. Using the narrative of a high school student located within ground zero she demonstrated the uncertainty the student faced as they continued to reshape their understanding of the event; how the principal attempts to guide the students frames to help them remain calm; and how the student challenges these attempts based on their own experiences in the moment. It is not hard to imagine how everyone all around the world at this moment needed to make sense and turned to other to discuss, bounce new frames off each other, wait for new information, and eventually amalgamate into an institutional frame (McPhail 2006). During this conversation the possibility of memetic “mutations” increase both because of the scale of conversation and because the uncertainty of future outcomes increases the possibility of current understandings. This makes it possible for fringe attitudes, such as anti-Islam attitudes (Bail 2012), to find their way into the mainstream discussion and ultimately become a primary framework for many. A more modern example would be the disruption of the COVID-19 pandemic allowing the anti-vax community to find their way into new households and refusing to get the COVID-19 vaccine as polarized elites seek to politicize the event.

The theoretical discussion above leads to my second hypothesis:

H2: Individuals will be more susceptible to following a political elite during major political events and decrease during periods of relative calm.

During the early development of this project the theory was that these effects would increase as time approached the 2020 U.S. presidential election using the 2016 Presidential Election as model of what would happen. The basis for failing to reject hypothesis 2 would have been seeing the effect of following a partisan elite on negative emotion increase the closer the election approached and then decreased following the election. As we know the COVID-19 pandemic completely turned the country on its head in the middle of March 2020, and then the death of George Floyd at the end of May led to mass protests, counter-protests, and political violence across the country. It is generally accepted that the period following the election was highly contentious while Donald Trump challenged the results of the election and theories of election fraud spread online. Data collection for the current project did not start until the middle of June 202 when the Capital Hill Occupied Protest in Oregon was still ongoing and roughly a month from the Kenosha protest and shootings by Kyle Rittenhouse. After these events the political circuit was relatively quiet in comparison until just a few days after the election and then the January 6^{th}, 2021 capital protests. It is likely that the effect of following a partisan elite on negative emotions in Tweets will decrease from August until the election and then increase after.

CHAPTER 4

MEASURING CULTURE WITH WHAT PEOPLE SAY AND DO

There has been an increasing interest within the sociological literature regarding the analytical measurement of culture (Mohr 1998, Mohr et al. 2020) that takes a relational approach to meaning systems. Increases in the abilities of the computational analysis of text has driven the field of analytical text analysis using LDA topic models (Blei 2012, DiMaggio, Nag, and Blei 2013) semantic network analysis (Rule, Cointet, and Bearman 2015, Bail 2016, Hoffman et al. 2018), tools in Natural Language Processing (Mohr et al. 2013, Mische 2014, Goldenstein and Poschmann 2019), and the recent introduction of word embeddings (Kozlowski et al. 2019, Stoltz and Taylor 2020). These approaches tend to adopt a network approach by mapping (Lee and Martin 2015) the relationships between different cultural objects. For example, Fligstein and colleagues (2017) used topic models to connect topics to actors, Bail (2016) used semantic network analysis to identify cultural bridges, Mohr and colleagues (2013) used NLP and topic models to generate relationships between actor, act, and context, and Kozlowski and colleagues (2019) used word embeddings to map relationships between social class and social categories (e.g., gender, employment, education).

Recently sociological scholars interested in measuring culture in text have utilized word embeddings. Word embeddings are trained on text data and used to represent the cultural space and have been shown to be great at synonym completion. One of the more common examples is that king – man + woman = queen (Pennington et al. 2014). In more concrete terms, if one were to take the vector associated "king," subtract the vector associated with "man," and had the vector associated with "woman," one would be left with a vector that is close to the vector "queen." Recent sociological inquiries build on research that uncovers biases and stereotypes within word embedding models (Caliskan et al. 2017) to map changes along cultural dimensions (Kozlowski et al. 2019; Boutyline et al. 2020; Stoltz and Taylor 2020). This method involves finding word antonym pairs, averaging out their differences, and then finding the cosine similarity between this vector and other word vectors of interest. The present study builds on past work that uses word embeddings and longitudinal data sets of text to understand how cultural space changes over time in relation to changes in an individual's network. I do this through the creation of a Twitter data set that represents Tweets and networks collected at the level of the individual over a five-month period.

For the current study I paired these analytical approaches to measuring culture with semi-structured interviews conducted with samples of individuals whose digital trace data was collected. There are several reasons why this is complementary and beneficial. First, collecting digital trace data on these individuals' actions as a member of the public without being seen allowed me to capture what these individuals would do without the eyes of the researcher. Jerolmack and Kahn (2014) point to numerous pieces of evidence that point to the fact that what people say and do are often contradictory to each other in their argument for ethnographic observation. Similarly, sociologists pointing to findings from the cognitive sciences highlight that the amount of culture one can store is quite small, with the implication that they cannot recall exactly why they carried out the action (DiMaggio 1997; Martin 2010). While this may be the case, I argue that semi-structured interviews paired with an analysis of Twitter data are beneficial to understanding the above hypotheses regarding the relationship between following political elites and sharing emotionally charged material. First, Pugh (2013) argues that interviews enable the researcher to capture an individual’s emotions, which play a role in the schema an individual activates during times of action. To capture these emotions in the moment I asked interviewees to refer to their Twitter account during the interview and asked them to reflect on what they had recently Tweeted as well as what others had recently Tweeted. Second, interviews have been shown to be advantageous for capturing cultural narratives that guide action (Mohr et al. 2020). I use the interviews to capture not only shared understandings about what is currently happening in U.S. politics but also their own personal narratives that aid their understanding of what is happening in the country. I argue that differences in these shared narratives aid in the interpretation of why the relationship between following a political elite and emotionally charged Tweets varies.

CHAPTER 5

DATA

I collected data from all public Twitter accounts that followed the Republican and Democratic political organizations associated with 7 higher education institutions across the United States from Republican and Democratic states that are located on both the Eastern and Western coasts of the United States. I started data collection on June 23rd, 2020 and ended data collection on January 26th, 2021. The Twitter platform, unlike other popular platforms such as Facebook and Instagram, do not require a mutual acceptance of friendship for two individuals to see each other's content. When talking about Twitter network tie data I refer to a "follow" as an incoming tie and a "friend" as an outgoing tie. Each week within this period I collected a list of the accounts that follow these political organizations, each account's friendship list, each accounts follower list, and then I collected every Tweet, Retweet and Reply that they produced during that given week. Twitter data are paired with semi-structured interviews with a sample of Twitter users from 3 schools to assess how and why individuals make decisions to share information with others in their networks. This period and demographic of users of was chosen because cognitive theories of culture predict cultural change during periods of immense instability (Swidler 1986) and that younger individuals are in a period of finding their narrative before their views and beliefs solidify at older ages (Kiley and Vaisey 2020).

Throughout the course of data collection there were ~18,000 unique users that followed at least 1 of the 14 accounts. To find active users in this college political media ecosystem the sample was further refined to include only users that possessed a mutual tie with another user that follows one of the political organizations at their school, and they had to exist within the sample for all 34 weeks of data collection. Of the ~18,000 users ~7,000 users were removed from analysis either because their account was set to private, either from the beginning or at any point during data collection, or because they did not contain a mutual and local tie. Of these ~11,000 accounts ~2,000 were not in the entire data collection and of these ~9,000 accounts ~4,000 did not Tweet throughout the whole period. To ensure that I am working with accounts that are active at least one time over the 7 months of data collection, accounts that did not Tweet were removed, which resulted in an analytical sample of 5,723 individuals and 15,669,561 Tweets.

The data collection workflow for this project was generated from a pilot study that was conducted in the Fall of 2019. I used the pilot project as an opportunity to find and automate key processes of the collection workflow to ensure that the data collected, deidentified, and stored was accurate. The final product was a package that I built in R that allowed me to begin the collection process by entering the Republican and Democratic organization for a school on their day of data collection. Both the collection of the Twitter data and the interviewing of members of my sample were approved by the University of Massachusetts' Amherst Institutional Review Board (Kuali Protocol #1344).

CHAPTER 6

ANALYTICAL PLAN

To explore the relationship between following a partisan elite and the level of emotions in an individual's Tweets I first had to create several variables using the above data: 1) the average weekly emotional valence for a user, 2) a count variable of topics discussed by the user, and 3) a count variable of the amount of new Republican and Democratic partisan accounts followed each week. I will begin by describing the process that I undertook to create these three variables and demonstrate the meaning behind the outcomes that these processes produced. Next, to test Hypothesis 1 I estimated a regression model for each school and political party, which contained an entity and time effect. To explain the heterogeneity between schools I conducted a Principal Components

Analysis on the proportion of topics discussed over the 31 periods to understand how these groups differed in their discussions paired with the discussions I collected in the semi-structured interviews. Last, to test Hypothesis 2 I estimated the same models as above, absent the time effect, but this time used a Time Varying Effects Model (Tan et al. 2012), which allowed me to understand how the beta coefficient between my dependent and independent variables changed over time. Coupled with the historical events that were happening at the time I seek to demonstrate how these relationships vary as political contention waxes and wanes.

CHAPTER 7

VARIABLE CREATION

Word Embeddings and Sentence Embeddings

Word embeddings were created for both Republicans and Democrats as a device for capturing meaning from the text they produced in the form of Tweets. The process of creating the word embedding was the same for both the Republican and Democratic groups. First, I preprocessed the text, which is a form of standardization that aims to reduce redundant or unnecessary information in the text to increase the interpretability of the results. I converted all text to lowercase, removed punctuation (except hashtags), and stemmed words so that similar roots were combined (e.g., reported to report). It is also important to consider how external events, which drove the production of text, may bias the results of a word embedding. To account for these biases, I collapsed Retweets so that a single Tweet produced by Donald Trump that spread throughout the network did not bias the results of the embedding. I also accounted for the salience of discussion over time by taking a random sample of 30,000 Tweets (Demszky et al. 2019) for each month, keeping all words that occurred at least 10 times, and using these lists to generate a vocabulary, which determined what words remained in the corpus (Demszky et al. 2019). This ensured discussion that occurred in months where disproportionate amounts of text were created did sway the meaning of the embedding. Once pre-processing was complete the text was fed into the Word2Vec (Mikolov et al. 2013) algorithm using the Gensim library and Python. The Word2Vec model uses a rolling window approach to train the model to be able to predict the current word based on its context where the output is a vector space *vocabulary * 100*. In the current study I set the window to 5, which means that the model uses the previous 5 and next 5 words to train the embedding for the current word. This vector space can then be used to explore the relationship between words using cosine similarity. Using these word vectors, I created sentence embeddings using an algorithm (Arora et al. 2017) that takes a weighted average of all vectors in a single Tweet, which have been shown to be the dominant method for measuring the relationship between documents (Arora et al. 2017). I can then use these sentence embeddings to understand how the meaning expressed in an individual’s Tweets changes over time in relation to the meaning that exists in the word embedding.

Average Weekly Emotion per User

As discussed above, word embeddings are excellent tools for analogy and this characteristic has been utilized to create meaningful dimensions that can then be used to measure single entities, whether single words or entire documents (Stoltz and Taylor 2020). To get a measure of emotional valence in each Tweet I created a negative dimension using an emotional valence dictionary that was generated using Mechanical Turk (Mohammad 2018). I used the 100 most positive and 100 most negative words according to their valence score, subtracted the positive from the negative, and averaged out the differences. Alternate models that used a range of dimensions were also created using the top 50, 150, and 200 words as well, with no meaningful changes to the results found. This created a negative dimension that I could then use to assign each Tweet a continuous value representing the amount of negative emotion in a Tweet. This generated a score that ranged from 1 to -1 where 1 would be the most negative and -1 would be the most positive emotional valence. The average was then taken for all the Tweets that a user produced in each week.

Figure 1: Measurement of Emotions

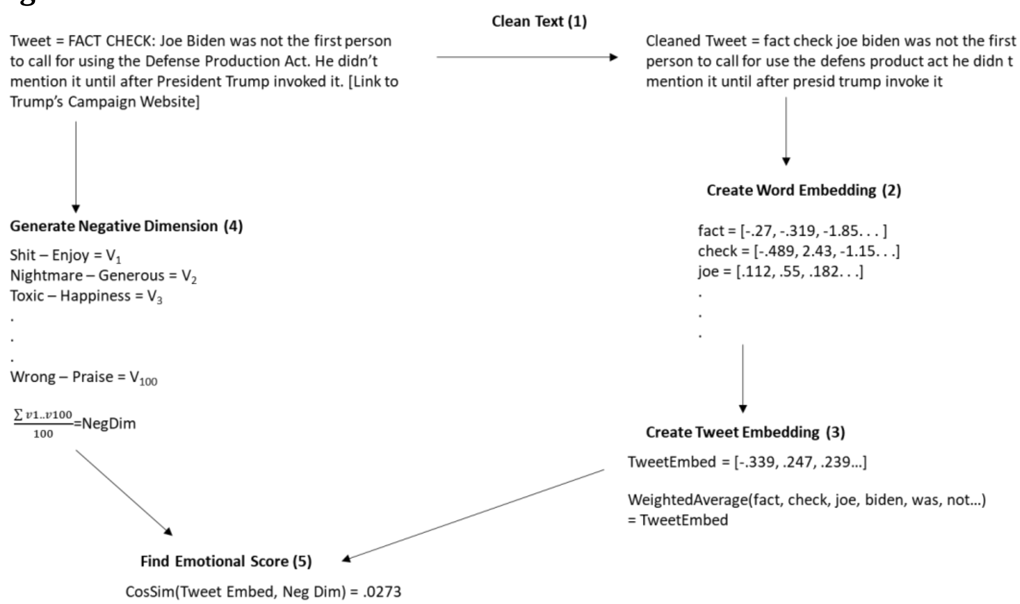


Figure 1 Caption: The above example comes from actual data and represents the path that each individual Tweet took in the process to emotional tagging. Each Tweet was cleaned (1), its tokens were converted to vectors using the Word2Vec model (2), a Tweet embedding was created by taking a weighted average of these vectors (3), and a cosine similarity score was generated (5) using a negative dimension created by averaging the difference between the word vectors associated with the most positive and negative words according to an emotional valence dictionary (5).

Weekly Topics Discussed by User

To account for any correlation between the dominant political discussion at the time and the use of emotional language I used a k-means clustering algorithm, with cosine as the distance metric, to generate topic means that can then be used to classify Tweets (Demszky et al. 2019). When conducting a k-means clustering algorithm the researcher selects *k* clusters that are randomly initialized at the beginning of the analysis. The random initialization is conducted by dividing the sentence embeddings randomly between the *k* clusters, which then are used to calculate the initial means. This is followed by an iterative process where each sentence embedding moves to its closest mean, which continues until no sentence embeddings leave their cluster. Following Demszky and colleagues (2019) I removed Tweets that were difficult to place within a single topic, which were identified by finding the ratio between the cosine similarity for a Tweets 2 closest topics and removing those in the lowest 75^{th} percentile. Determining the number of cluster means is arbitrary for the research but I used a combination of ensuring that the topics were meaningful and analyzing the Within-Cluster-Sum of Squared Errors (WSS). Analyses were conducted for *k* ranging from 15 to 55 at intervals of 5 and 45 was found to be the optimal number of clusters. This number of topics both produced the most interpretable topics and was the point at which the WSS leveled out. When WSS levels out it indicates there is no more information to gained by increasing the number of topics and the return becomes negative. On one hand we could have 1 topic mean, which would generate the maximum measure of WSS possible and would provide no additional information because all text would be assigned to that single topic. On the other, we could have a topic mean for each Tweet, which would be the lowest measure of WSS possible, but would be the same as reading each Tweet individually.

Following of Political Elites

I identified whether a user followed a Republican or Democratic elite by constructing a list of Republican and Democratic accounts using local knowledge obtained from the Twitter data. To do this I found the top 1000 followed accounts for the 7 Republican accounts and the 7 Democratic accounts and keep those that feel in all 7 groups for their respective party. This helped limit a potential research bias in determining political party and identified national level political figures. I then confirmed the results and hand coded those that appeared in the Republican and Democratic lists and identified accounts that occurred but were not political. To confirm the results, I used my own knowledge of the U.S. political system and in cases where I was unaware of the account or the individual, I would spend time reading their timeline and researching the individual's political history. When an account appeared in both lists, I considered whether either party would consider that account a member of the out-group base on my knowledge from studying the U.S. political media ecosystem. For example, while Democrats would argue that National Public Radio is a neutral source of information Republicans would most likely argue that it is a liberal source of information. It was also found that late-night show hosts were found in the liberal list only and military organizations were found in the Republican list only. These accounts were considered apolitical and not included in the analysis. If an account was no longer in existence, I could not investigate whether it was truly a Republican or Democratic account. My assumption is that these are accounts that were removed from Twitter for hateful rhetoric or misinformation and decided to include them in the count if they were followed only by Republicans or Democrats. Below is a random sample of 10 accounts from each list:

Republicans: theblaze, RepDanCrenshaw, HouseGOP, MELANIATRUMP, SenateGOP, CarlyFiorina, SarahHuckabee, JohnCornyn, RepGoodlatte, SteveKingIA

Democrats: JoeBiden, TIME, SenatorReid, DavidCornDC, TheAtlantic, DFAction, timkaine, AFLCIO, davidplouffe, ChalresMBlow

CHAPTER 8

INTERVIEW METHODS – SEMI-STRUCTURED INTERVIEWS

To understand who the individuals are in the groups and the meanings they apply to information on Twitter and the political sphere at large I conducted 57 semi-structured interviews with individuals that followed three of the schools. Interviews were conducted over the videoconferencing platform Zoom and lasted 45-60 minutes. Audio from the interviews was recorded and transcribed using Otter.io. Interviewees had to be over the age of 18 and reside in the United States.

I recruited users using the Direct Message feature on Twitter. The recruitment message was sent to the Twitter users that followed either the Republican or Democratic organization at one of these three schools. In my recruitment message I identified myself as a PhD student studying political polarization and the internet at the University of Massachusetts and that I was hoping they would be willing to elaborate on their practices regarding Twitter. A portion of users had their privacy settings set to not receive message from users they did not follow, and others simply did not respond to my message, resulting in a response rate of about 2%. The constraints of recruitment through Twitter most likely biased the interview participants towards those to be less concerned about privacy and the most active in politics. Researchers have found that social media research tends to be overrepresented by privileged groups (Hargittai 2020) and demographics from my respondents tend to indicate this happened the most regarding gender (See Appendix A, Table 7).

The interview schedule (See Appendix B) was designed with three main goals in mind: 1) to understand the interviewees overall understanding of where the country's political system is situated in history, 2) the interviewees views on current political events, and 3) the interviewees habits on Twitter and explanations for these habits. I used these conversations, particularly the first two, to understand their views of the out-group by asking them who they thought would oppose their views and how they thought this out-group would respond.

CHAPTER 9

VARIABLE CREATION – RESULTS

Word Embeddings

To demonstrate the validity of the Republican and Democratic word embedding I explored the relationship between words while also exploring some of the synonyms. While no rigorous test of the word embedding was conducted my initial exploration, along with the results following this section, indicate that the word embeddings were trained sufficiently. For example, I created vectors that equate to a "liberal politician" and "conservative politician" in both the Republican and Democratic vector spaces and then found the closest stems to those vectors using cosine similarity (see Appendix, Table 2). The word vector associated with a Republican Politicians was created by subtracting the conservative vector from the liberal vector and adding the politician vector. The same process occurred for the Democratic politician vector, but the Conservative vector was subtracted from the Liberal vector. The results indicate both the usefulness of the word embedding and indicate what type of Democrat and Republican I captured with the word embedding. We see that both dislike their out-group associating them with words like "elitist," "snob," "Lobbyist," and "corporate." At the same time, we also see some animosity for their own party such as using the acronym RINO, used to identify traditional Republicans that stand counter to Trump's more radical policy stances, and the words "centrist" and "corporatist" used to identify liberals that do not support more liberal policies.

Emotional Valence Score

Each Tweet in the corpus was assigned a value ranging between 1 (positive valence) and -1 (negative valence) using the negative emotional valence and sentence embeddings discussed above. To understand what qualitative characteristics this scale captured I took a random sample of tweets at intervals of .1 on the valence scale (See Appendix, Table 3 & Table 4). Starting with the Republican Tweets and inspecting those tagged as the most negative we can clearly see a trend starting with negativity at the highest values and positivity at the lowest values. Analyzing the first three positive bins we frequently see words such as "murder," "violence," "hate," and "war." The tone slightly changes as these words drop out of the next three bins and when they do occur, to reference COVID-19, it appears to accurately pick up on the user trying to undermine the seriousness of the deaths. Once we get to the middle of the chart, the tone begins to lighten, though it is important to note that positive words appear to cancel negative words as indicated by the Tweet discussing “BLM cheering for the death of a Patriot Prayers Member.” This example highlights some of the nuance that is lost within the model. When we move past the middle of the chart, we begin to see gratitude for “Trump”, “Happy Birthdays”, and “congratulations.”

The distribution of Democratic valence tags mirror that of Republicans, though the mean is slightly more negative in valence terms (See Appendix, Figure 3). Looking at the most negative bins we can see that most of the Tweets discuss Donald Trump and his acts being homicidal, inciting violence, being a failure, or destroying the country. Moving down the bins these Tweets begin to disappear and the tone tends to level out, though more serious topics are still being discussed such as Portland arrests of protesters or injuries of service members in Russia. Crossing the middle of the table and moving to the positive emotion side we begin to see the tone change as the discussion revolves around “getting out and voting”, “making a difference in November”, “thank you”, and “congratulations.” Overall, the analysis demonstrates that the model is overall, capturing negative emotional valence.

Topic Counts

To understand the composition of the 45 Republican and Democratic topics created using the k-means clustering algorithm I analyzed both the closest words to each cluster mean (See Appendix, Table 5 & Table 6) as well as a qualitative analysis of random Tweets from each topic to confirm their meaning and dig deeper into those without a clear meaning. For topics such as COVID-19 or the election it was clear what was captured but there were others that were unclear or that ended up being surprising in their meaning. For example, for both Republicans and Democrats there was a cluster mean involving words related to family. A closer analysis of the Tweets assigned to the family cluster are not so much about family but rather using a family frame to discuss political events. Another example is that the use of numbers indicated that the user was citing a statistic as evidence when making their political claim. Topics that appear to be more in line with frames than topics are indicated in the tables in the Appendix. There were also topics that were captured that were either not political, had no real trend, or captured other aspects of language. For example, it was clear the "outdoors" topic discussed the outdoors in non-political ways, the "random objects" topic had no trend when reading the random sample, and the "contractions" topic captured all Tweets that contained a contraction but with no real trend.

For further analysis I selected 12 topics, spread over the categories above, to understand how the discussion varied over time and whether we see up-ticks at key moments in time (See Appendix, Figure 4 & Figure 5). Looking at the figures we see that topics do capture discussion of major events that occurred during the week. The topic "riot" and "police violence" capture the death of Jacob Blake and the ensuing unrest in Kenosha along with the January 6th capital riots. Other spikes exist in the data such as the death of Ruth Bader Ginsburg in the "SCOTUS" topic or discussions of the second stimulus bill in the "economics" topics. The results can also be used to gain insights into what topics in the category of “political frame” are truly capturing. Despite a slight uptick in use during the confirmation of Amy Coney Barrett, perhaps due to abortion discussions, use of the family frame remains relatively flat. Meanwhile we see that the use of the location framing experiences a spike during the week of the election as people discussed results and locations suspected of housing voter fraud. Looking at the discussion of topics over time for Democrats we see similar trends to those in the Republican discussions. The figure shows that discussions about protests and racism spiked around the death of Jacob Blake and the capital riots, that discussion about the Supreme Court was captured between the death of Ruth Bader Ginsburg and the nomination of Amy Coney Barrett, and that topics like health care are not associated with any of the major events. These trends indicate that the topics are capturing real time discussion of political events and real time salience.

CHAPTER 10

TESTING HYPOTHESIS 1 – NEGATIVE EMOTIONS AND PARTISANSHIP

Longitudinal Modeling

A fixed effects model including time effects was used to test whether increases in out-group exposure was associated with the productions of Tweets containing more negative sentiment. Confidence intervals were calculated using clustered standard errors to account for heteroskedasticity that occurred at the level of the user. This model was trained on Republicans and Democrats separately. This model is an ideal choice of analysis because the fixed effect controls for time constant differences that occur between individuals (e.g., race) and the time effect controls for time varying effects that occur at the same rate between individuals (e.g., the emergence of highly contentious political events) (Allison, 2009). To aid in interpretability of the model I transformed the Democratic and Republican count variable by taking a plus-1 smoothing log transformation. The plus-1 smoothing is necessary because log(0) = infinity and does not change the results because it is a linear transformation.

Principal Components Analysis

Principal Components Analysis (PCA) is a form of dimension reduction that finds the dimensions that best explain the data set by searching for a solution that explains the most variance in the data (Friedman et al. 2009). Sociologists have used this method on survey data to, among other things, to identify cultural groups and shared understandings (Goldberg 2011). In this study I conducted a PCA on the proportion of topics discussed by each school for Republicans and Democrats to understand how these groups differed in what they discussed within the corpus. This analysis will aid in the understanding of how these groups differ by identifying what differentiates them in terms of topics discussed. PCA has two outputs: 1) a location for each group indicating where they are located on the dimension, and 2) loadings that indicate what variables best explain the dimension. For both Republicans and Democrats, I calculated the first three dimensions, which explained at least 80% of the variance in the data, plotted each group on these dimensions, and reported the 5 most positive and 5 most negative dimensions. I then used semi-structured interviews conducted with members of three of the groups to confirm the findings from the PCA.

CHAPTER 11

TESTING HYPOTHESIS 1 – RESULTS

Fixed Effects Models

I estimated separate fixed effects models for both Republicans and Democrats to understand the relationship between following political elites on Twitter and negative emotional valence in Tweets. Below (Tables 1 & 2) are the summary statistics of the final datasets that are modeled for both Republicans and Democrats. Looking at these tables we see that Republicans tended to Tweet more, have more negativity in their Tweets, and follow more of the political out-group compared to the Democrats. What is important for this analysis is that Democrats follow very few Republicans by choice, indicating that there may not be enough variance in the independent variable to capture an effect in the fixed effects model.

Table 1: Republican Summary Statistics

Characteristic	**s1**, N = 4,763[1]	**s2**, N = 3,005[1]	**s3**, N = 14,487[1]	**s4**, N = 2,697[1]	**s5**, N = 24,837[1]	**s6**, N = 4,700[1]	**s8**, N = 19,931[1]
Emotional Valence	-0.10 (0.14)	-0.08 (0.12)	-0.01 (0.10)	-0.07 (0.12)	-0.03 (0.10)	-0.09 (0.13)	-0.05 (0.12)
Democrats Followed	17.04 (28.21)	32.86 (39.50)	15.32 (28.76)	27.69 (33.98)	20.90 (33.20)	20.92 (29.51)	14.12 (26.99)
Republicans Followed	82.68 (63.53)	91.90 (69.84)	81.42 (62.13)	96.87 (69.58)	103.80 (62.92)	76.96 (63.63)	98.45 (63.40)
Tweets	58.68 (208.57)	86.77 (217.88)	193.08 (410.40)	213.43 (477.47)	171.76 (370.68)	54.12 (184.04)	202.09 (432.95)

Characteristic	s1, N = 4,763[1]	s2, N = 3,005[1]	s3, N = 14,487[1]	s4, N = 2,697[1]	s5, N = 24,837[1]	s6, N = 4,700[1]	s8, N = 19,931[1]
Retweets	43.14 (199.41)	63.96 (202.03)	141.01 (357.77)	146.98 (404.63)	127.30 (320.82)	36.43 (161.50)	168.25 (398.54)

[1] Mean (SD)

Table 2: Democratic Summary Statistics

Characteristic	s1, N = 9,481[1]	s2, N = 1,266[1]	s3, N = 9,250[1]	s4, N = 5,697[1]	s5, N = 14,401[1]	s6, N = 3,921[1]	s8, N = 10,919[1]
Emotional Valence	-0.11 (0.12)	-0.14 (0.11)	-0.12 (0.13)	-0.12 (0.12)	-0.11 (0.12)	-0.13 (0.13)	-0.10 (0.12)
Democrats Followed	58.91 (51.61)	67.33 (46.46)	75.38 (56.81)	86.18 (63.13)	87.32 (59.84)	69.66 (52.16)	71.07 (58.76)
Republicans Followed	5.39 (12.85)	7.50 (13.15)	8.44 (19.29)	8.98 (19.65)	11.19 (25.45)	8.64 (20.03)	8.73 (20.70)
Tweets	37.35 (112.74)	21.19 (34.05)	48.17 (146.40)	34.92 (77.44)	87.96 (270.86)	39.62 (99.83)	69.67 (219.17)
Retweets	22.48 (85.83)	8.89 (19.52)	29.15 (112.27)	19.36 (58.05)	66.29 (248.94)	21.57 (70.44)	48.92 (201.43)

[1] Mean (SD)

The first two models that I estimated regressed the count variable for Republican and Democratic elites on the negative emotional valence variable. I took the log of each of the count variables using add-one smoothing to account for the skew in the count variables.

Table 3: Republican Base Fixed Effects Model

	Dependent variable:						
	Emotional Valence						
	School 1	School 2	School 3	School 4	School 5	School 6	School 8
Democrats Followed	0.009	-0.017	**0.012*****	0.032	**0.013***	0.007	0.009
	(0.013)	(0.027)	(0.005)	(0.021)	(0.007)	(0.015)	(0.007)
Republicans Followed	**0.027***	0.026	-0.011	-0.018	-0.012	**0.028****	**0.010***
	(0.014)	(0.029)	(0.008)	(0.029)	(0.011)	(0.012)	(0.006)
Note:	*p<0.1; **p<0.05; ***p<0.01						

Looking at the Republican base model we can see that following Democrats was associated with an increase in negative valence in Tweets for School 3 and that the same association existed for School 6 but when following Republican elites. The coefficients indicate the magnitude that the negative emotion scale will increase for every 100 percent increase in the count variable. While the magnitudes are quite small, they would still be of significance for individuals that started out following a small amount of the out-group. For example, an individual that started following one Democrat and went on to follow 9 in a single week would be an 800% increase that would result in an increase of about .1 on the emotional valence scale.

Table 4: Democratic Base Fixed Effects Models

	Dependent variable:						
	Emotional Valence						
	school 1	school 2	school 3	school 4	school 5	school 6	school 8
Democrats Followed	**-0.023****	-0.024	-0.016	0.029	-0.012	0.002	0.016
	(0.011)	(0.022)	(0.018)	(0.054)	(0.014)	(0.026)	(0.011)
Republicans Followed	0.015	0.052	**0.025***	-0.018	-0.005	0.009	0.006
	(0.011)	(0.086)	(0.015)	(0.033)	(0.011)	(0.032)	(0.009)
Note:	*p<0.1; **p<0.05						

Looking at the Democratic model there is only one significant coefficient that indicates that there was an association between following Democrats and increases in positive valence for School 1. This was one of two schools located within a Republican state and could indicate that there is an effect from being an outsider in a state or that individuals were transitioning to following Democratic accounts. School 8 was the other school located in a Republican state. There coefficient is in the same direction though it is not significant.

After training both the base models I included the topic counts for all topics except for those coded as random topics in the tables above. I included the topics because it is likely certain topics are correlated with the negative dimensions and what drives these discussions is not likely to be homogenous for all individuals over time. For example, it might be likely that a core group of Republicans are so interested in talking about the Portland protests that they follow Democrats to learn their perspective and Tweet about it at the same time. The negativity associated with the protests would make it appear as though following the Democrats is associated with the increase in negativity. The topic variables are logged count variables using add-one smoothing.

Table 5: Republican Fixed Effects Model with Controls

	Dependent variable:						
	Emotional Valence						
	School 1	School 2	School 3	School 4	School 5	School 6	School 8
Democrats Followed	0.012	-0.015	**0.007***	**0.026***	**0.012***	0.007	0.010
	(0.012)	(0.024)	(0.004)	(0.014)	(0.007)	(0.013)	(0.007)
Republicans Followed	0.021	0.024	-0.007	-0.025	-0.011	**0.027****	0.010
	(0.014)	(0.027)	(0.007)	(0.023)	(0.011)	(0.011)	(0.006)
Covid Restrictions	**0.004***	**0.009*****	**0.003*****	**0.004***	**0.003*****	**0.007*****	**0.002****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
COVID-19	**0.007*****	**0.006****	**0.003*****	**0.013*****	**0.007*****	**0.016*****	**0.005*****
	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)

Police Violence	0.002	**0.007***	**0.008*****	**0.008*****	**0.009*****	**0.011*****	**0.007*****
	(0.003)	(0.004)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Riot	**0.012*****	**0.007*****	**0.008*****	**0.006****	**0.007*****	**0.011*****	**0.008*****
	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Racism	0.003	0.002	**0.004*****	**0.005***	**0.003*****	-0.002	**0.003*****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)
Ideology	**0.008*****	**0.014*****	**0.005*****	0.003	**0.007*****	**0.005***	**0.007*****
	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Law Constitution	**0.013*****	**0.007*****	**0.004*****	**0.005****	**0.004*****	**0.012*****	**0.005*****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
SCOTUS	**-0.008*****	**-0.005****	**-0.003*****	-0.002	**-0.003*****	**-0.007****	**-0.004*****
	(0.003)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Federal Investigation	-0.004	0.0002	0.001	0.002	0.0002	**-0.005***	0.001
	(0.004)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Republicans	**-0.009*****	**-0.006****	**-0.007*****	**-0.005****	**-0.005*****	**-0.011*****	**-0.005*****
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Innovate	-0.0001	-0.0003	**-0.002***	-0.004	**-0.002*****	0.0001	**-0.002***
	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Economics	0.002	**0.006***	**-0.002***	-0.001	**-0.001***	0.003	0.001
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Foreign Enemies	0.004	0.001	-0.0004	0.002	0.001	**0.005***	**0.003*****
	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Globalism	**0.020*****	**0.019*****	**0.013*****	**0.013*****	**0.014*****	**0.022*****	**0.015*****
	(0.003)	(0.004)	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)
Election	**-0.005****	-0.003	**-0.007*****	**-0.008*****	**-0.007*****	**-0.014*****	**-0.007*****
	(0.002)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Democracy Future	0.003	0.0001	**-0.005*****	0.001	**-0.003*****	-0.004	**-0.002***
	(0.002)	(0.003)	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)
Voting	-0.0004	-0.003	0.001	0.002	**0.002****	0.001	**0.004*****
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Biden Campaign	-0.001	-0.003	**-0.002****	-0.001	**-0.002*****	**-0.007****	**-0.002****
	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Social Media Derogatory	**-0.007*****	**-0.008*****	**-0.003*****	**-0.010*****	**-0.004*****	-0.006	**-0.005*****
	(0.002)	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)
News Media	**-0.007****	-0.004	**-0.003*****	**-0.007*****	**-0.005*****	**-0.006****	**-0.005*****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Derogatory Media	**0.005***	0.002	**0.004*****	**0.006****	**0.006*****	**0.008*****	**0.006*****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)

Social Media	**-0.013*****	**-0.011*****	**-0.009*****	**-0.005****	**-0.011*****	**-0.011*****	**-0.009*****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Numbers	0.004	-0.002	-0.0005	-0.002	**-0.001****	**-0.004***	-0.0005
	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Names	**-0.012*****	**-0.016*****	**-0.008*****	**-0.008*****	**-0.007*****	**-0.006****	**-0.009*****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Location	**-0.006****	**-0.013*****	**-0.005*****	**-0.009*****	**-0.007*****	**-0.012*****	**-0.010*****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Family	**-0.008*****	-0.001	**-0.007*****	**-0.004****	**-0.004*****	**-0.006****	**-0.003*****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Argument	**0.016*****	**0.014*****	**0.009*****	**0.010*****	**0.009*****	**0.019*****	**0.012*****
	(0.003)	(0.003)	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)
Awesome	**-0.029*****	**-0.026*****	**-0.016*****	**-0.018*****	**-0.019*****	**-0.030*****	**-0.019*****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Sexual Violence	**0.008****	**0.007****	**0.007*****	**0.010*****	**0.009*****	**0.016*****	**0.008*****
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)
Note:					*p<0.1; **p<0.05; ***p<0.01		

Including the controls for the Republican model move the out-group effect for School 3 outside of the .05 significance level but there are three out-group effects within the .1 significance level. The in-group effect is still significant at the .05 significance level indicating that as Republicans at School 6 follow Republican elites their Tweets increase in negative valence. Including the controls for the Democratic model also take the coefficient for School 1 outside of the .05 significant level though it remains significant at the 0.1 significance level. Further exploration of the model found that significance was lost after including the “celebrate” topic indicating that users were likely to be celebrating Democratic success and following Democrats at the same time.

Table 6: Democratic Fixed Effects Model with Controls

	Dependent variable:						
	Emotional Valence						
	School 1	School 2	School 3	School 4	School 5	School 6	School 8

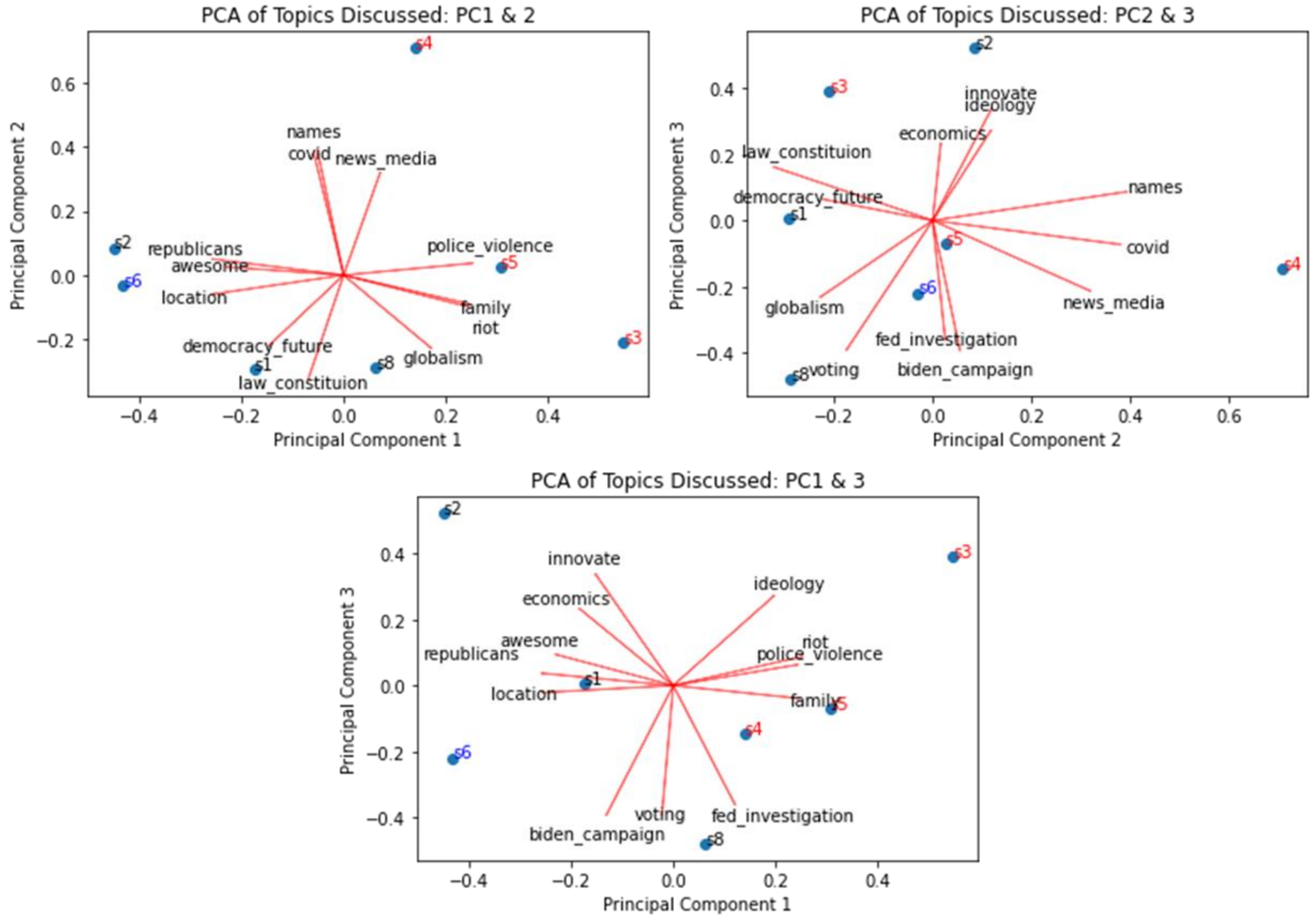
Democrats Followed	**-0.018***	-0.031	-0.007	0.025	0.001	0.006	0.010
	(0.010)	(0.022)	(0.016)	(0.050)	(0.014)	(0.024)	(0.011)
Republicans Followed	0.011	0.072	0.013	-0.011	-0.001	0.009	0.002
	(0.009)	(0.096)	(0.014)	(0.028)	(0.010)	(0.028)	(0.009)
COVID-19	**0.014*****	**0.009**	**0.010*****	**0.013*****	**0.007*****	**0.007****	**0.011*****
	(0.002)	(0.006)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
Covid Restrictions	-0.002	0.0002	-0.002	-0.003	-0.002	-0.005	-0.001
	(0.002)	(0.005)	(0.002)	(0.002)	(0.001)	(0.004)	(0.001)
Protest	**0.015*****	**0.017****	**0.017*****	**0.011*****	**0.012*****	**0.016*****	**0.015*****
	(0.002)	(0.007)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)
Racism	**0.017*****	**0.025*****	**0.013*****	**0.013*****	**0.017*****	**0.018*****	**0.012*****
	(0.002)	(0.008)	(0.002)	(0.003)	(0.002)	(0.006)	(0.001)
Trump	**0.011*****	**0.026*****	**0.010*****	**0.016*****	**0.010*****	0.005	**0.008*****
	(0.002)	(0.008)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)
Outrage	**0.018*****	**0.021***	**0.012*****	**0.016*****	**0.012*****	**0.018*****	**0.018*****
	(0.003)	(0.012)	(0.003)	(0.004)	(0.002)	(0.004)	(0.002)
Trump 2	**0.009*****	**0.029***	**0.018*****	**0.013*****	**0.014*****	**0.011****	**0.007*****
	(0.003)	(0.016)	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)
Russia	0.003	-0.006	-0.003	-0.002	0.001	0.005	0.002
	(0.003)	(0.016)	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)
Federal Investigation	**0.014*****	**0.018*****	**0.010*****	**0.009*****	**0.007*****	**0.010*****	**0.008*****
	(0.002)	(0.007)	(0.002)	(0.002)	(0.001)	(0.004)	(0.002)
SCOTUS	-0.001	0.003	**-0.004****	0.002	**-0.007*****	**-0.006***	**-0.004****
	(0.002)	(0.009)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
Punish Law	**0.019*****	**0.035*****	**0.011*****	**0.014*****	**0.009*****	**0.009****	**0.013*****
	(0.003)	(0.013)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)
Institutions	**0.010*****	-0.002	**0.011*****	**0.011*****	**0.007*****	**0.006***	**0.006*****
	(0.002)	(0.005)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
Primaries	-0.002	-0.008	-0.001	-0.001	-0.001	-0.005	-0.001
	(0.002)	(0.007)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
VP Nomination	**-0.005****	-0.012	**-0.007*****	**-0.008*****	**-0.008*****	**-0.011*****	**-0.009*****
	(0.002)	(0.007)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Senate Election	-0.003	**-0.020*****	**-0.011*****	**-0.007*****	**-0.005*****	**-0.009*****	**-0.008*****
	(0.002)	(0.006)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Vote Tomorrow	-0.**006*****	0.006	**-0.007*****	**-0.006*****	**-0.009*****	**-0.010*****	**-0.010*****
	(0.002)	(0.006)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Voting Methods	0.002	0.002	**0.004****	0.002	0.002	**0.006***	0.002
	(0.002)	(0.008)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)

Fight For Progress	-0.003	-0.001	-0.001	**-0.005****	**-0.003****	**-0.006***	**-0.003***
	(0.002)	(0.006)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
Congress Legislation	0.004	0.004	**0.005****	**0.006****	**-0.003***	0.003	-0.002
	(0.002)	(0.008)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
Healthcare	**0.008*****	**0.015*****	**0.012*****	**0.010*****	**0.010*****	**0.007****	**0.006*****
	(0.002)	(0.006)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
Climate	**0.004****	0.003	**0.008*****	**0.005****	**0.010*****	-0.001	**0.005*****
	(0.002)	(0.006)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Economy	0.002	0.005	**0.003***	**0.004***	**0.005*****	0.004	**0.003***
	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Education	**-0.019*****	**-0.032*****	**-0.014*****	**-0.021*****	**-0.017*****	**-0.017*****	**-0.014*****
	(0.002)	(0.008)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
News Media	-0.001	0.009	0.001	0.004	0.0005	0.005	-0.001
	(0.002)	(0.009)	(0.002)	(0.003)	(0.001)	(0.004)	(0.002)
Political Heros	**-0.009*****	-0.005	**-0.010*****	**-0.008*****	**-0.009*****	-0.004	**-0.008*****
	(0.002)	(0.005)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)
Numbers	**0.013*****	**0.022*****	**0.011*****	**0.017*****	**0.012*****	**0.011*****	**0.014*****
	(0.002)	(0.008)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)
Family	0.0002	0.005	-0.001	0.003	**0.003****	-0.002	0.002
	(0.002)	(0.007)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)
Events	**-0.016*****	**-0.013****	**-0.013*****	**-0.011*****	**-0.016*****	**-0.014*****	**-0.018*****
	(0.002)	(0.007)	(0.002)	(0.002)	(0.001)	(0.004)	(0.002)
Arguments	**0.008*****	0.007	**0.006*****	**0.006****	**0.008*****	0.006	**0.007*****
	(0.002)	(0.008)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)
Celebrate	**-0.031*****	**-0.029*****	**-0.033*****	**-0.035*****	**-0.028*****	**-0.036*****	**-0.025*****
	(0.002)	(0.007)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
Nouns	**-0.006*****	0.004	**-0.008*****	-0.002	**-0.007*****	**-0.006****	**-0.006*****
	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Note:							*p<0.1; **p<0.05; ***p<0.001

Principal Components Analysis

The below figures include the results from the PCA modeled using the proportions of topics discussed for each school with the purpose of understanding the heterogeneity that exists between the cultures. Three dimensions for each were calculated that explained over 80% of the variance. These dimensions are visualized using three subplots that contain the top 10 topics that explain each dimension.

Figure 2: Principal Components Analysis Republican Topic Proportions

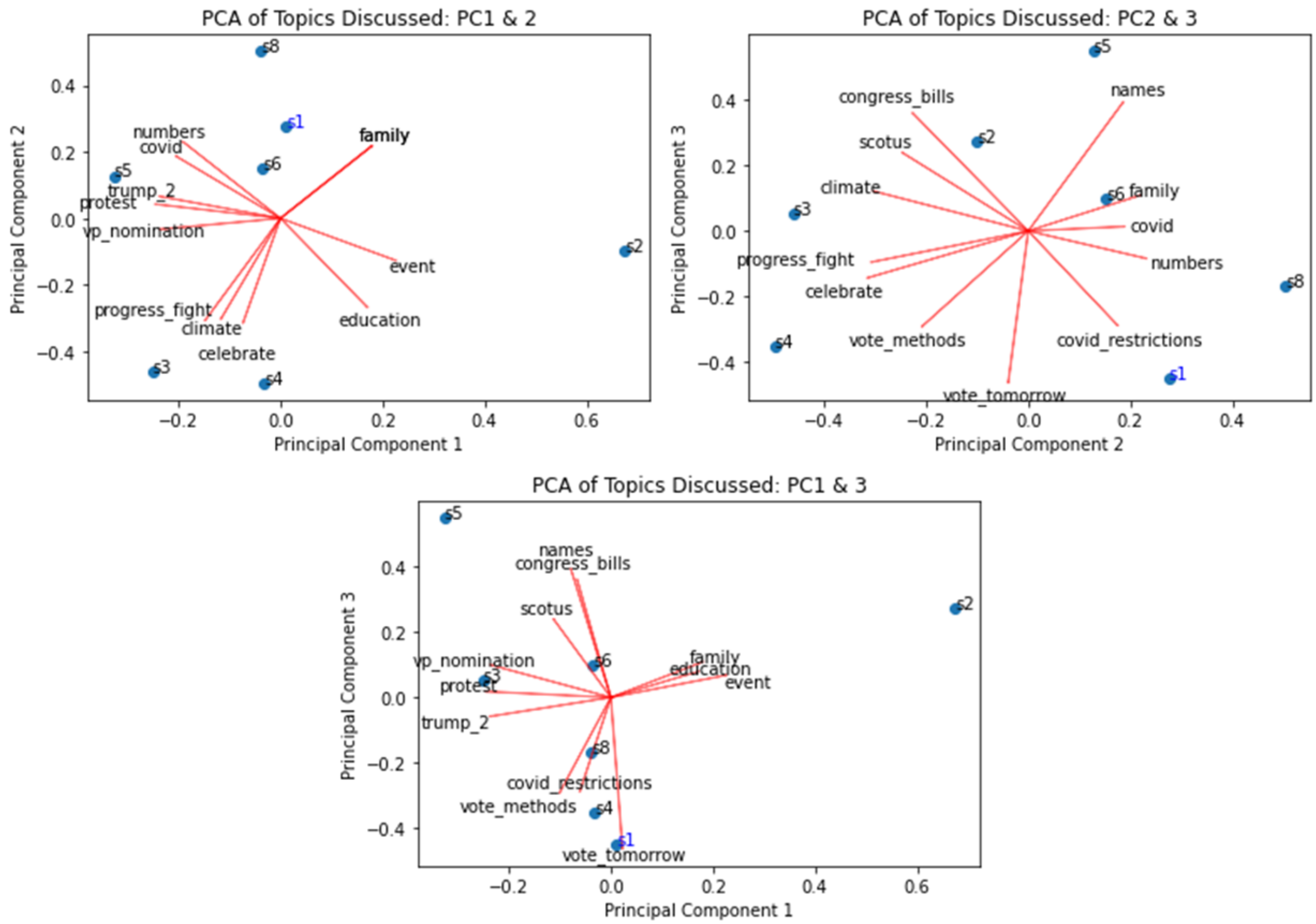


In the figure above schools that had significant coefficients for out-group effects are colored in red and those that had a significant in-group effect are colored in blue. The figures that plot the first and second component and the first and third components demonstrate that Schools 4, 5, and 6 are defined by discussion involving riots, police violence, and use the family to frame their discussions. School 4 is the standalone in this group as in two of the figures they align with the names, covid, and news media topic while school 3 and 5 never do and tend to focus more on riots, police violence and family twice. What my readings of the riot, police violence, and family frames suggest that these conversations are some of the more extreme on the Republican spectrum and include negative views of many of the prominent actions in the country associated with Democrats like the protests following the murder of George Floyd and attempts to bring racial awareness to the country. The findings indicate that those who will have negative out-group effects are those likely to have negative view of the out-group and their values.

A more in-depth qualitative analysis of some random samples of Tweets from these topics demonstrate a clearer picture of the discussions that define these schools. Example of Tweets from the "riot" topic include *"I wish someone would bash that Marxist," "not all Democrats are rioters and looters, but all rioters and looters are Democrats," "An Antifa militant in Oregon is responsible for the fire. He livestreams his own arrest. Holy crap,"* and *"the people literally burning down and destroying America keep trying to blame the guy that's actually saving it."* Example Tweets from the "police violence" topic include "12-year-old white kid sucker punched by some black thug," "please share 100k reward offer for the suspect who cowardly ambushed two LA county sheriff's deputies," and "Kyle Rittenhouse is a patriot who defended himself from the crazy Democrat lynch mob terrorist. Michael Reinoehl is a democrat lynch mob terrorist who killed a patriot in cold blood. Any questions leftard?" Lastly, Tweets from the "family" topic include "black mob viscous attack father and daughter in Manhattan," "Maybe the almost 1 million dollars in GoFundMe donations for Jacob Blake should be given to the 14-year-old girl he raped instead. Faint sound of mic hit the floor," "this woman is a Jewish law student encouraging rioter to bring weapon to white neighborhood and attack a white home," and "Satan Disney World refused entry to autistic 7-year-old girl who can't wear a mask." These are by no means the only type of

Tweet in these topics, such "How's your brother by the way," "you're in charge right now," and "fucking lunatic," but they do define the overall trend.

Figure 3: Principal Components Analysis of Democratic Topic Proportions



In the figures for the Democratic topic proportions the school that saw a significant positive in-group effect was highlighted in blue. What stands School 1 apart from the other schools is its location in the second and third figure that is defined by COVID-19 restrictions. The Tweets that fall into this category can be represented by "Look at my new face mask," It's an easy ask to wear a mask," "I believe if everyone wear a cloth face cover for the next 4 to 6 weeks, we can get the #covid19 epidemic under control," and "One is a mask the other is a chin guard. No one told you to wear a chin guard. Wear a mask." It is important to note that School 1 is in a Republican state, and while it is likely all Democrats were concerned about COVID-19 restrictions, given the narrative at the time it is likely Democrats in a Republican state were more concerned because restrictions were not as large of a concern. It is possible that this is what created the positive reaction to democratic Tweets from these individuals.

Semi-Structured Interviews: Completing Insights

I conducted 57 semi-structured interviews with individuals that follow either the Republican or Democratic political Twitter account associated with School 1, School 3, and School 5. All three of these schools had significant results in the above models though they are not the only to have significant results. These groups were not chosen after the models were estimated but were instead chosen due to their uniqueness within the overall sample. School 1 is one of two schools located in a Republican state and is the only to be in a state capital, where political careers and internships are likely to be sought by students. School 3 and School 5 are in two of the more Democratic regions of the United States and their Republican organization has undergone local media scrutiny for the views the have espoused as of lately. The purpose that the interviews serve for this study is to understand the overall perspective that the users in these groups must aid the understanding of the above modeling results. I use the semi-structured interview to demonstrate the heterogeneity that exists within the Republican models.

Heterogeneity within Republican Modeling Results

School 3 – Blue Region Filled with Strife and Protest – Significant Relationship

The Republican organization associated with School 3 has a history with alt-right politics, clashes over white supremacism under the guise of "free speech," and had garnered media attention for its clashes with other Republican and Democratic organizations. In addition, the school is in a region of the area that experienced both peaceful protests and violent interactions between these protesters and counter-protesters. The extent to how far right these individuals were was first understood during the interview process when it was discovered that the researcher's recruitment message was being spread to other users who were being warned to watch out for the "feds" along with other derogatory responses. These accounts tended to have some form of symbolism that associated themselves as a Groyper, an organization lead by Nick Fuentes as an attempt hide the white nationalist supremacist of their politics (Anti-Defamation League, 2021). While many of these individuals did not respond to my messages one self-identified Groyper did but this still indicates that my respondents most likely were the least extreme of the individuals that follow this account.

Of the three interviews from this group that I reference for this analysis they can be best described as an Info Wars warrior, a Groyper, and a Proud Boy sympathizer who spends time photo documenting their rallies. What ties all three of these individuals together is their disdain for liberal ideals of equality and multi-culturalism, though these all stem from slightly different locations. The Info War warrior's largest concern was the left's agenda, in cooperation with the UN and other globalists, to "depopulate and create a technocratic panopticon of surveillance and control over humanity." They viewed the lefts actions of promoting multi-culturalism, equality, and humility towards America's past atrocities (e.g., the Native American genocide) as attempts to "destroy the last sovereign nation" so that globalists could take control. The Groyper found their way to Nick Fuentes after a journey through Discord chat rooms and subreddits and expressed disdain for what they considered "indoctrination" throughout their high school experience. They claimed that they had to "write essays on how white people are evil or you'll get a C in the class", and did not understand why they had to learn about non-white male scientists in Chemistry class as if they had not already learned about a bunch. The Proud Sympathizer was the most subtle and least about multi-culturalism but was still a disdain towards movements of equality and "political correctness." Her biggest issue with the country was an inability to talk with neighbors who have differing viewpoints and said that she can barely recognize her hometown that has been flooded with "intolerance." She told two stories that demonstrate this. The first was when her neighbors put up a sign that US soldiers are responsible for the death of children in Iraq the day before her husband return. The second was when she attended a child's birthday party with her daughter and told the birthday girl that she looked pretty in her dress, to which the mom responded "you're more than just pretty" in what was perceived as a condescending tone.

When discussing current events with these respondents, it is clear how their overall perceptions help them make sense of new events that unfold. For example, the Info Wars warrior recalls being present at some of the earlier BLM and ANTIFA protests where the only flag flying was that of the United Nations and that through talking with the local ANTIFA he learned that "rioters" were not being charged. Through his own research he drew the connections that the mayors of these cities have an incentive to act in the UN's best interest because these cities are UN ambassador cities. He believes that the UN and globalists such as Bill Gates are also behind the COVID-19 pandemic and cites Event 201, a tabletop exercise that simulates a global pandemic outbreak to prepare for future outbreaks, as evidence that the pandemic was planned. He says that the exercise helped uncover media messages that would send people into a panic and worry about a virus that was not that big of a deal. When talking with these individuals about how their out-group views their perceptions of current events, they have had some contact and do not believe the out-group has a positive image of them. For example, when asked what others would think they think about the pandemic one responded:

> "They think there's some frickin Trump virus and people are gonna die and it's hella contagious and the masks are saving people and and all this other stuff. He's a US fascist Nazi, anyone that supports Trump's a fascist, he's a Nazi super spreader."

Above we can see that the interviewee does not assume that a member of the out-group would have logical counterarguments but would instead simply attack their identity.

School 5 – A Historically Blue Region (Positive Results)

Republicans from this group of Twitter were mixed in terms of their similarity to the group above and those that had issue with Trump and his supporters. To discuss this group, I look at three interviewees: a college student active in their College Republican organization, an individual that is highly involved in local politics and the Republican party, a member of the Proud Boys, and an extremely conservative individual attempting to build an online media presence. While the members interviewed for this group were not all as extreme in their views as those interviewed for school three, their similarities are still there and are reflected in the PCA above.

All four of these individuals did not believe that the country was headed in the right direction. The local activist believed that this was a result of how the U.S. political system was structured and argued that congressional redistricting and single member plurality has led to the divisiveness that we see in the country. When asked to present evidence of the division they cited Donald Trump and argued that this was all “because a bunch of people on the right were pissed off and they essentially just wanted someone who would own the libs.” The college student believed that the country was headed in the right direction economically, but that the COVID-19 pandemic and the Trump administration’s inability to handle it had undone all of that. The Proud Boy believed that the country was heading in the wrong direction because of multi-culturalism, a decline in nationalism, and a decline in civil society, specifically religion. They believed that the human mind is naturally wired to create “tribes” and that without nationalism or religion “the experiment” that is multi-culturalism would and has failed. Lastly, the climbing political commentator said that the “decline in American values,” such as freedom of speech, are taking the country in the wrong direction.

Two of these interviewees showed some form of disdain for Donald Trump or the Republican party in general throughout the interview. The local activist believed that Trump was taking the country in the wrong direction, and it was clear that their identity as a “brown, gay, non-religious” individual played a role in this. He believed that the Republican Party was losing the youth movement and that this could potentially be the demise of the party. The biggest issue that he saw from the administration in terms of recent events was the handling of the COVID-19 pandemic, which he thinks failed because Trump did not put people with government experience in charge of handling the pandemic. Even though the local activist identifies as a Republican they believe that it is the hardcore MAGA Republicans that would disagree with his interpretation of the pandemic because they are the 35%, according to polling numbers, that backed Trump's handling. The college student referred to himself as "pro-science" and believed that Trump's failing to enact a mask mandate and lack of testing held back our ability to handle the pandemic. At the same time, he does mention that it is hard for anyone to say exactly what they would have done in Trump's shoes and that they supported Trump closing the borders early on. When asked who would disagree with them, he believed that both Democrats and hardcore Trump fans would disagree with their positions. He felt that both groups would criticize him for his ability to both commend and criticize Trump for how he handled the pandemic. When talking about the Democrats he referenced them criticizing Trump for closing the border "because it's xenophobic…and they're too sensitive about everything." When talking about hardcore Trump fans he said "We have some [college Republican] member who are incapable of their own thoughts. So yeah, they'll agree with everything that Trump will say." The college student also went on to criticize Trump, Mitch McConnell, and Lindsey Graham for their handling of the Merick Garland nomination and their ensuing push of Amy Coney-Barrett into the supreme court following the death of Ruth Bader Ginsburg. While the Proud Boy never outright criticized Trump, he did question the evidence that Trump had regarding election fraud and said that "I think most serious people don't believe anything Trump says or take it at face value." Meanwhile, two of the individuals took a racial lens towards understanding the current political landscape.

Of these two individuals the Proud boy openly acknowledged that his vote was a backlash to racial politics and even went as far to question is political orientation. When talking about the interviewees' political orientation he said:

> "the older I get, the more I agree with Nietzsche, that everyone's philosophies as much as we like to believe that we're being rational, and we're choosing like, the most rational and correct, but the truth is, we're all kind of motivated by emotion, and white and some kind of deep psychology."

He went on to say that while he would like to think that his adoption of both left-wing anarchism and now right-wing libertarianism were objective decision, he knows it's likely a result of his disdain for authoritarianism, either because of "daddy issues" or fighting with high school teachers. When talking with the political commentator about the election, he claimed that what gave the media and Democrats the ability to claim Joe Biden the winner before the electoral process was completed was their ideology of "racial identity." He went on to say that "when you can get people to make a simple decision about race, then you can get people to make all sorts of decisions by infusing race into an issue." This individual was also one of the livider speakers of COVID-19 policies:

> "I don't think that the press or Democrats have the right to come along and tell me this is the new fucking normal. . .And it isn't normal for me to have a mask on my fucking mask. . .And the arrogance with which they say these things, you know, particularly Cuomo, who has the worse record on COVID of any governor. He has more deaths. And then he writes the book about it. Now he's, I see him yesterday on a video talking to Dr. Fauci about, you know, in this like back

> slapping conversation that’s obviously intended to humanize that skeletal Fauci mother fucker.”

School 1 – Southern Red State (No Clear Association)

The three interviewees analyzed from this group of Republicans were all college students. One was a Trump supporter and the other two were struggling with their identity as a Republican but still insisted that they held conservative and Republican ideals at their core. While the Trump supporter did not struggle with their identity what sets them apart from the groups discussed previously was his ability to see the whole situation while not simply chastising one group or the other.

Of the two individuals struggling with their identity, one grew up in staunch Republican household with an evangelical pastor for a father. This individual started to see their views shift more towards the middle when the entered college in 2018 as a political science major. While they would still consider themselves a fiscal conservative, they believe that the Republican party has done a bad job coming up with policy to deal with climate change or the healthcare system in the U.S. They also believe that Trump is doing no good for the country through his hateful rhetoric that sows doubt within the country’s institutions, which he believes leads to events such as the potential kidnapping of Governor Whitmer of Michigan. The other individual struggled with the tension between their identity as a person of color and a Republican after the election of Trump. This individual registered as a Democrat following Trump’s election but plans to re-register as a Republican because they see themselves as holding Republican ideals more than Democratic ideals. One area that they recently struggled with these identities was the BLM protests where on one side as a Black individual they understood the importance of the protests, but on the other they did not side with liberal that called for defunding the police because their father is a police officer, and they think that defunding the police would lower the morale in those departments. When both individuals discussed the COVID-19 pandemic they recognized that their own party would disagree with them and that they would say that they are being too hard on Trump's response.

While the aspiring politician does not fit into this group because Trump and other aspects of the party did not lead them to question their identity, they were unique in that they were able to recognize and criticize why things are the way they are. For example, when talking about the coronavirus he mentioned that individuals were not so much interested in the facts but rather how the event would play out in politics. The example that he gave that people were interested in what Fauci had to say but rather what team Fauci was one:

> "So if Fauci says something, well, he's in Trump's cabinet, but he was appointed by this person, and it's like, everything is politicized."

This individual believed that the pandemic should be taken seriously but that masks or lockdowns should not be nationally mandated because every local municipality is different. He used the fact that his local hometown had experienced a recent natural disaster that they were still recovering from and that they did not feel as though they could undo all that progress.

CHAPTER 12

TESTING HYPOTHESIS 2 – TEMPORALITY AND PARTISNASHIP

Time Varying Effects Model

To understand how the relationship between emotional valence and following partisan elites varies over time I estimated a Time Varying Fixed Effects (TVEM). A TVEM model is a Generalized Additive Model (GAM) that contains a smoothing function on the interaction between the variable indicating time and the independent variables of interest (Tan et al. 2012). The TVEM framework allows the researchers using intensive longitudinal data to understand the relationship between environmental changes and behavioral process (Tan et al. 2012). For example, Tan and colleagues (2012) used the model to show how the relationship between positive affect and belief that one can quit smoking increases and then decreases over time and Kang and colleagues used the model to demonstrate the effect that oil market shocks have on the stock market. When using this method, the researcher must select the number of splines to use in the smoothing function. It is suggested that the researcher run a model for each of the possible number of splines (the number of time periods) and choose the model with the lowest AIC (Tan et al. 2012). For Republican models this resorted in choosing 31 splines for schools 1, 2, 3, and 8 and 30 splines for schools 4, 5, and 6. For Democratic models this results in choosing 31 splines for all models except school 4. This model includes an entity effect to control for heterogeneity between the Twitters users.

CHAPTER 13

TESTING HYPOTHESIS 2 – RESULTS

Time Varying Effects Model

Below I present the results of the TVEM models by plotting the coefficients over time along with the 95% confidence interval. The first takeaway from these figures is that the 95% percent confidence interval suggests that the trends seen are not statistically significant. This is likely due to a lack a variance in the independent variables for the fixed effects models. When the fixed effect is removed the confidence interval tightens but the coefficients are in the opposite direction indicating that the actual effect of these variables is opposite at the aggregated level from the individual level. While the coefficients are not significant, we do see trends that we would expect, especially the spike in the relationship for 4 out of the 7 Republican groups during the January 6th storming of the capital. At the same time, we see that the effect of following a Democratic account on Republicans experiences an opposite trend as negativity continues to slowly increase over time. Looking at the Democratic figures though there tends to be no apparent trend with many of the lines remaining relatively static over time.

Figure 4: Time Varying Fixed Effects Model for Republican Organizations

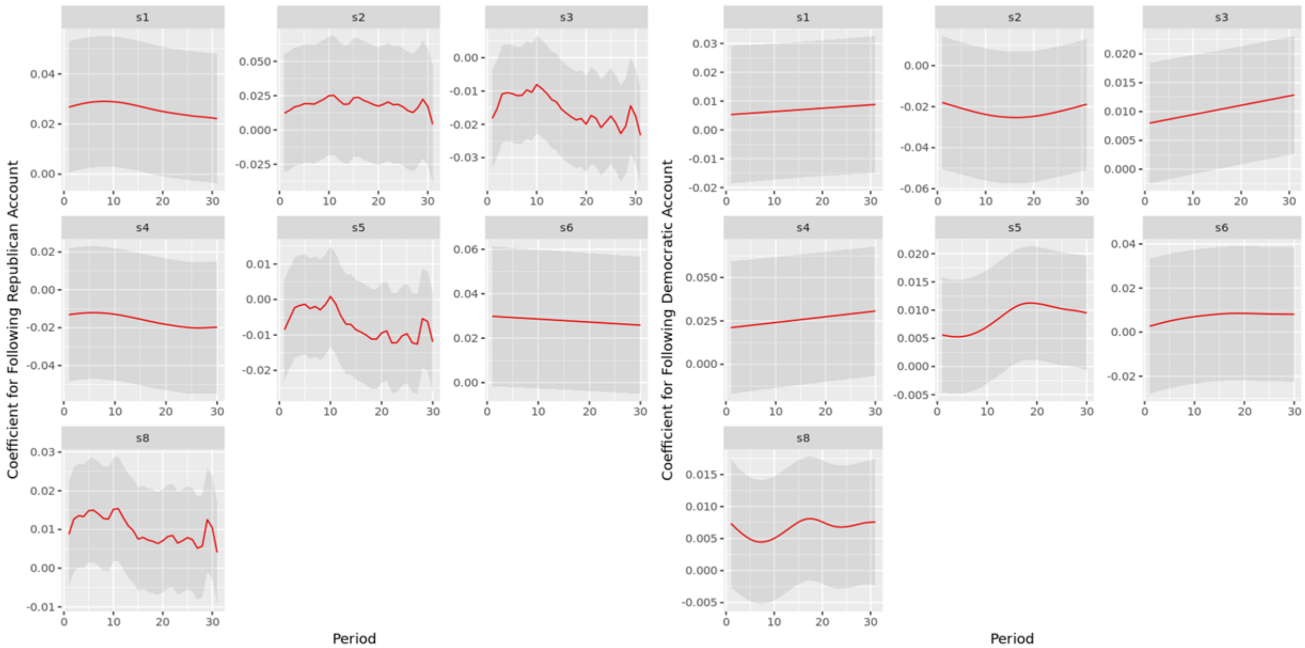
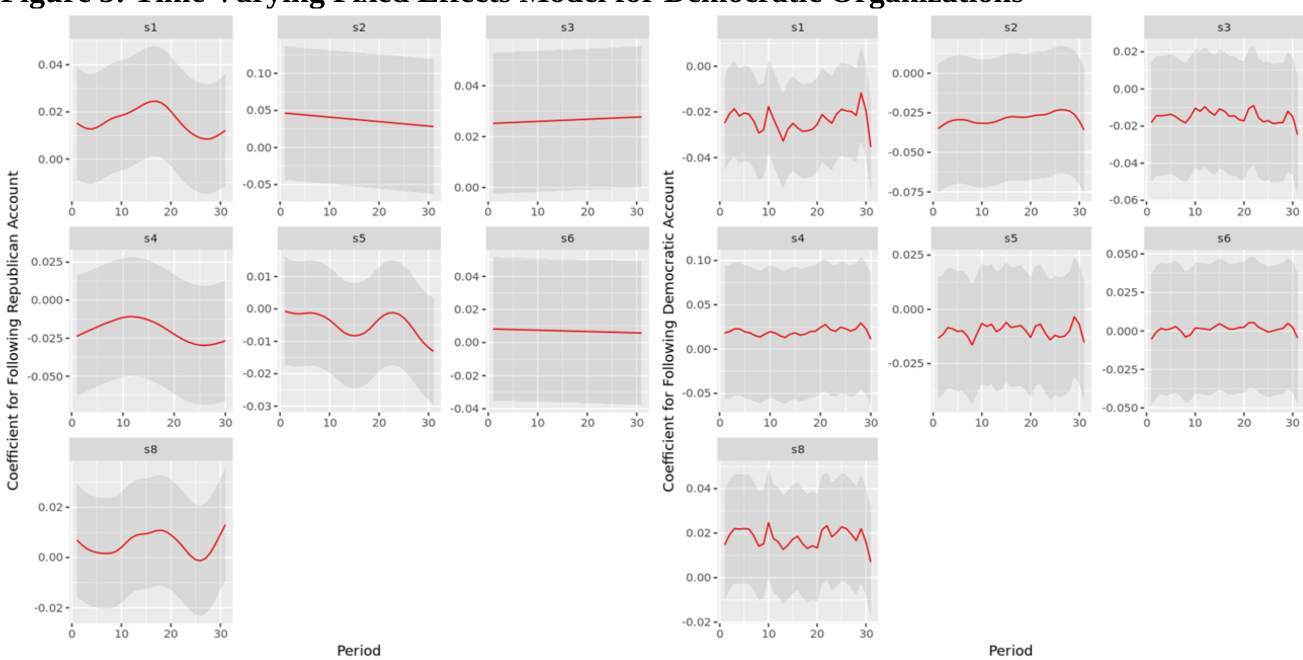


Figure 5: Time Varying Fixed Effects Model for Democratic Organizations



CHAPTER 14

CONCLUSION

Political polarization in the United States is a complex and fluid phenomenon that needs to be studied as such, which the internet and computational methods makes possible. This paper began by reviewing the literature on political polarization, which tends to either find anecdotal evidence of the phenomena or a lack of systematic evidence albeit when using some different operationalizations. Sociological literature indicates why these paradoxes may exist when looking at the relationships between social networks and culture (White 2008) and when considering the different cultural models that can be in play during different historical periods (Swidler 1986). In other words, who an individual interacts with and the period under which they interact with a stimulus may affect their response. To understand whether these effects exist I collected an intensive longitudinal set of data from Twitter with groups selected for theoretical comparative theory building (Small 2009) paired with semi-structured interviewing to understand who these groups are. Through this analysis I was able to confirm Hypothesis 1, which stated that reactions to the following of political elites would vary based on the group level schemas. Using the semi-structured interviews and Principal Components analysis I was able to demonstrate why some Republican groups had negative interactions when they followed Democratic elites. Evidence for Hypothesis 2 was directional but without the statistical significance to confirm as the confidence intervals were too large and straddled the possibility of no effect.

Overall, the current study has important implications for literature on political polarization, sociological methodology, and efforts to fight online radicalization that occurs on social media platforms. First, the paper demonstrates a need for taking a relational approach for understanding political polarization and the ongoing processes that are driving the phenomenon. The current study has demonstrated how both social and historical contexts can vary the effect of mechanisms that drive political polarization. Studies that fail to take these into account may under or overestimate the effect of political polarization. Second, while a vast literature uses computational analysis of text to understand how culture changes over time, they rarely involve semi-structured interviews with the creators of the text. The semi-structured interviews that I conducted allowed me to capture the narratives where these Tweets were derived from. It should also be noted that shortly after the conclusion of the study Twitter changed their terms of service so that it is extremely difficult to DM people that you do not personally know on Twitter making the research design one of the few that will be able to happen. Third, while using text for causal inference as predictors, predictions, and confounders has been a growing interest in NLP (Feder et al. 2021) these techniques have not yet found their way into sociology. These techniques could greatly benefit the field by connecting historical text archives, such as national news, to our major surveys, such as the General Social Survey. These studies could aid our understanding in changes in survey responses over time. Last, the study has implications for combatting online radicalization on social media platforms. The relational analysis indicates that backfire effects are most likely not constant across time and historical context. While experimental evidence (Bail et al. 2018) indicates that breaking the “filter bubble” may be a doubled-edged sword, the current study indicates that it is a matter of understanding when to intervene. For example, a contentious election cycle may not be the time to expose Twitter users to their political out-group, but periods of relative calm may be.

While the current study makes great strides it does not come without its short-falls and areas for improvement. First, because the study is observational it requires that the individual opts into the independent variable of interest: following a political elite. There are two main reasons that this variable may not experience much variability: 1) they do not wish to follow their political out-group, and 2) their following political elites is already saturated. Variance in the independent is importance for developing statistical significance in fixed effects models and may explain the lack of significance in the models ran, especially the TVEM. In addition, it is possible that the propensity to Tweet a particular emotion is related to the propensity to follow or unfollow a political elite. In other words, the model does not tell us whether someone began to Tweet negatively because they followed the Republican or whether they followed the Republican because they were angry at the current political atmosphere. Second, at the outset there was an attempt to use the interview data to aid in the interpretation of Hypothesis 2. The research design was to have the interviewees analyze their timeline during the interview with the intention of capturing differences in their interpretations depending on the news cycle at the time of the interview. While the interviews were carried it out it was discovered that it was quite rare to time an interview perfectly with the release of breaking news creating only a few comparative cases.

The ability for researchers to understand the complexity of political polarization as it unfolds and operates within disparate locations in the social world is of importance for solving many of the social issues that we face today. The current state of the political environment in the U.S. takes an approach that creates right and wrong with no room for grey in the middle that makes it difficult to have important discussions during difficult times by diminishing the complexity of the situation. This forces individuals to focus on the most extreme arguments coming from their out-group to protect their position. For example, rather than finding the optimal solution to the COVID-19 pandemic that allowed the economy to continue as smooth as possible while also diminishing the number of deaths we argued over masks and whether one should get a vaccine. Once these debates became attached to a political party one could no longer succeed defeat to their out-group, even if it was the right choice. To understand these phenomenon sociologists, need to utilize the ability to collect and analyze finely grained data, with the additional of traditional methods, to solve the problems we face.

APPENDIX A – SUPPLEMENTARY TABLES AND FIGURES

Table 1: Interview Participant Breakdown

Variable	Percent
School	
S1 (Red State)	35.09%
S3 (Disgruntled Blue)	26.32%
S5 (Blue)	38.59%
Race	
White	57.39%
Multi-Race	16.39%
Hispanic	14.75%
Asian/Pacific Islander	6.55%
Black	3.28%
Gender	
Male	64.91%
Female	17.54%
Non-conforming	1.75%
N/A	15.79%
Ideology	
Right	43.86%
Left	43.86%
Libertarian	12.28%
College Student	
Yes	45.61%
No	54.39%
Age	Mean = 30

Word Embedding Results

Table 2: Liberal and Conservative Politicians from a Republican Perspective

LIBERAL POLITICIAN		CONSERVATIVE POLITICIAN	
Word	**Cosine Similarity**	**Word**	**Cosine Similarity**
Bureaucrat	.679	Leader	.525
Elitist	.673	Republican	.502
Commi	.618	RINO	.479
Leftist	.598	Journalist	.473
Snob	.577	Businessman	.463

Table 3: Liberal and Conservative Politicians from a Democratic Perspective

LIBERAL POLITICIAN		CONSERVATIVE POLITICIAN	
Word	**Cosine Similarity**	**Word**	**Cosine Similarity**
Leftist	.611	Corporate	.555
People	.573	GOPer	.554
Corporatist	.556	Republican	.532
Lefty	.551	Lobbyist	.529
Centrist	.546	Trumpist	.513

Emotional Valence Score Results

Figure 2: Republican Emotional Valence Distribution

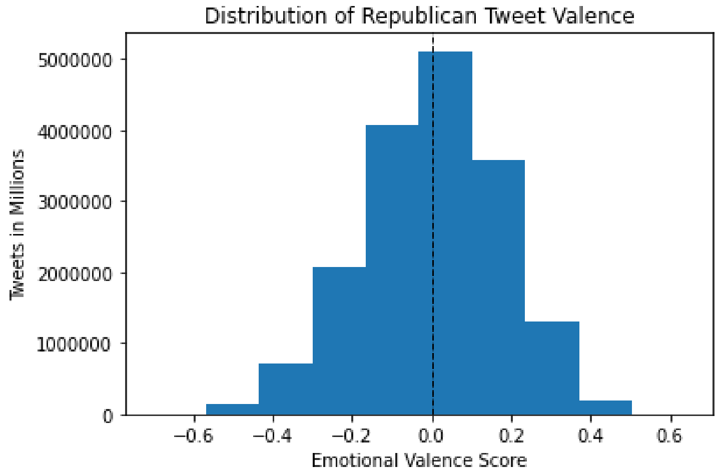


Table 4: Random Samples of Republican Tweets by Emotional Valence Score

Emotional Valence Score (Counts)	**Sample Tweets**
1 to .6 (42)	• And near all these murder are relat to drug prostitut or domest troubl there is no epidem of anti tran hate crime murder it's total fabric but don't let that stop you • Nygovcuomo hahaha histori repeat itself like kill thousand of elder peopl at nurs home by send infect peopl there you're a crimin fraud and should be prosecut for crim against human and neglig homicid • And then there's this we the people are the victim of their filithi murder psyop • You mean the civil unrest that has gone on for month or the continu threat from the left scream systemat racism burn it down kill cop defund polic yeah caus that seem fair • Polic use of dead force is not about racism
.6 to .5 (6,337)	• An anarchist is just a libtard that commit crime • The tear are of rage toward killer like Cuomo who tortur senior like these in nurs home mani were separ needless for month or forc to be imprison with activ infect stranger and left to die alon meanwhile actual prison like avenatti were freed • Liter violenc • Virtu signal caus more suicide drug overdos death abus women children and domest violenc victim than ani virus but they like to claim without evid their mask save live elsewher • The democrat are dead
.5 to .4 (103,015)	• Left wing report fals accus murder Portland trump support of back terror • More giddi racist hate monger from the • If you leftist provoke a civil war you won't get a say in when it stop • Nah it's realli not it's actual pretti fuck simple savag are kill peopl • Trump is go to jail after this for elder abus #debates2020
.4 to .3 (549,163)	• I'm sure he was will to risk his life to show the world what a group of unhing loon that are vote for biden look like whi we alreadi know you guy have been spew in the street for month • Democrat ego would rather have Chicago burn to the ground instead of admit that republican were right

	• Trump just destroy • If presid how long will stay in offic befor he has a tragic accid or the leftist have him remov #joebiden #electoralcolleg #potus #stopthest #maga #nwo #2020elect • Can't beliv how bad is do in the rate they play right into the hand of the radic left democrat and now are float in hire fire and far wors allow endless negat and unedit commerci is dead realli sad
.3 to .2 (1,556,221)	• This pandem is over covid death profil is extrem signfic yet total ignore by the media focus on case death count is vast more import and onli a small of case now end in death case may linger but become increas manag • Tom Patterson #blm is a Marxist racist fraud • This is one under note but bizarr aspect of the assang prosecut so often you'll hear American accus him of treason or espionag he's not American he's been to the us onc for a few day commit no crime in the us how doe the us assert author to grab him • Establish media have utter themselv for four year with Russian collus nonsens trump as respons for covid propaganda and trump as fascist garbag now they'll morph into biden American are tune out and they should • This video is one of the most aboslut brutal thing I've ever watch from the parti that is constant lectur about retor I doubt they will have a word to say about this
.2 to .1 (2,918,319)	• This has been proven fals which is whi the dem don't ever talk about it anymore but good luck live in fantasi • See these face they are the face of mom and dad wive and husband son and daughter face form everi race color and creed taken from the people who love them these are the face of polic office who have been kill in the line of duti in 2020 #bluelivesmatt • Biden want to pack the court with radic left crazi he doesn't even want to make a list to explain who they are can't let this happen • But but the pandem • Divis in this countri start under the administer and continu today becaus of the swamp which consist of #fakenew #bigtech #fbi #cia #doj otherwis the #bidencrimefamili would have been expos #trump2020tosaveamerica #draintheswamp
.1 to 0 (3,817,207)	• Republican legislatur propos to impeach a republican governor over the lockdown • Anoth fire has been start on feder courthous property #portland • When you log off twitter • Is he realli suppose to be everi citi • Cover them with a hand emoji is a nice touch
0 to -.1 (3,518,494)	• One nation under god • Portland black live matter monster cheer and celebr murder of patriot prayer member video via • Abc protect these monument they are live memori to democrat treacher • California now generat a third of it electr from renew larg solar and wind it is also experienc it first electr blackout for two decad the proglem it is prematur close gas and nuke plant that plug the gap for wind and solar • Mile high mad should be shame daili the marin and me have your six brother anyon with a private jet out there poni up #semperfi
-.1 to -.2 (2,460,682)	• Break los angel mayor say he will order water and power util to be shut off at home host parti • Free speech from conserv hate speech hate speech from radic leftist free speech gotta love equal • Big upgrad from • Break news a panel of the court of appeal affirm by a 2 1 vote a feder district court's rule that so call larg capc are protect by the

	• The latest the tea parti cheer daili
-.2 to -.3 (604,359)	• Yes final prais the lord let's go no more promis speech think tank paper and tweet do it • Read this veri sincer and uplift thread from the great journalist traci you speak for million of American and patriot around the world pray for America to remain the beacon of hope for the rest of the world • Realdonaldtrump presid trump is work for peac great news mr presid well done • Uncl ted a mini today veri cool • I am now in touch with team thank you all for the help
-.4 to -.5 (210,506)	• Valuabl insight I learn much as will some veri interest parti thank you ron stay tune • This was so beauti that I had to share visit • Realdonaldtrump happi birthday to the woman who will never be presid • My good gracious • Watch voic his support for visit to st john's church after his address from the rose garden I like when our presid lift up religi liberti
-.5 to -.6 (37,243)	• To keep strengthen the president's team I announc the follow at our all staff meet this morn justin clark dep campaign manag matt morgan campign counsel nick trainer dir of battleground strategi all are long tim #maga and will help djt win in 105 day • Beauty even in Henderson Nevada with great American patriot thank you #maga • Happi birthday • Huge victori tonight I'm truli humbl and honor big thank you to my famili and our hard work volunt that knock door wave sign and made call to ensur southwest florida had a proven conserve I look forward to serv you in Washington • Happi 7th birthday to my favorit companion lov ya buddi
-.6 to -1 (1,508)	• Thank great pitcher • Left California for Arizona leav Arizona after a great meet with our incred hispan communiti heard fantast and inspir success stori will be land in Washington dc soon big white hous ceremony tomorrow morn with Israel uae and Bahrain • Congratul to the amaz patriot • Thank great pitcher • Have an extra special bless and happi birthday

Figure 3: Democratic Emotional Valence Distribution

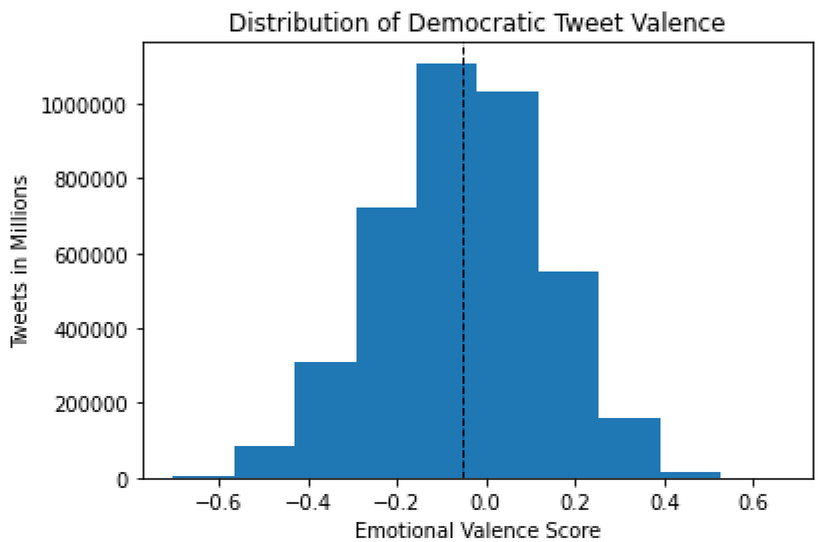


Table 5: Random Samples of Democratic Tweets by Emotional Valence Score

Emotional Valence Score (Count)	**Sample Tweets**
1 to .6 (12)	• He's a lie homicide maniac. He's kill his support. • Dem use dead people all the time use dead to exagger number of covid 19 and use the dead to vote and use brain dead to push for gov office and vote and riot and hide corrupt and lie • How about mass murder and crimin neglig • Presid Donald trump could be charge with crimin neglig homicid over his inact and intent obstruct of govern function concern the dead coronavirus pandem • Whi isn't Trudeau thrown out of office or arrest for treason or genocide for what he cause to happen to our elder
.6 to .5 (967)	• Yet they went fuck nut over 4 death in Benghazi • Given the context of the pro trump murder plot against whitmer there's realli no way to see this as anyth but incit to violenc and murder atlas is sore because his time in the white hous is end in disgrace and this is how he act out • Republican kill • How can people ration Donald trump's behavior incit violenc and death to a governor and a doctor becaus they disagre with him and how the hell is he still in our white hous and not arrest and put in jail for incit terror sombodi explain • The president of the unit state has now admit on tap that he blatant repeat lie to the American peopl about a dead virus rampag through the countri kill hund of thousand of citizen and that is the highest of crim disqualifi him from offic
.5 to .4 (13,546)	• There is noth trump has done which isn't either a miser failure or destroy with intent • This is terror • Recent declassifi white hous tape reveal how presid nixon's racism and misogyni led him to ignore the genocid violence of the militari in what is today Bangladesh • The epa illeg destroy record deiv the about that destruct and fals blame the coronavirus pandem to escap account we couldn't paint a cleare pictur of corrupt if we tri • Crazi how I did this exact thing at a protest of polic brutal in Vallejo but got arrest press with two feloni charg two midsdemeanor and a bail yet these peopl just got to do their thing and go home in peac where are the offic in riot gear
.4 to .3 (78,202)	• Crow is to murder is to pack economist is to rage • Unidentifi militar agent are polic Portland arrest peopl and put them in unmark vehicl just becaus it left the timelin doesn't mean the fight is over • Crimin act done from the insid are still cimin arrest dejoy now • Whi do we always have to explain walk away from office turn your back on offic even resist arrest is not a death penalti crime • Stephen hawk dead tho
.3 to .2 (242,097	• Donald trump hasn't grown into the job becaus he can't • Not one blm or antifa has been arrest for destroy busi or blog instead it's been white supremaci dude arrest and blm is alreadi work in those communiti where are your assumpt come from • Ask to defend bogus fraud claim meadow logic 101 #smartnew • Do cathol priest believ in karma priest who blast congreg for not come to mass over coronavirus fear get covid • Break trump has pardon four former us servic member who wer convict of kill Iraqi civilian while work as blackwat contractor in 2007

.2 to .1 (504,199)	• Citizen must remov state and the fedr govern abil to unilater shutdown econom commerc over 150000 small busi have perman close their door these small busi owner who've lost everyth will have their vengeance • Politico us service member were injur after an with Russian forc in northeast Syria this week accord to a draft militari statement and a person familiar with the matter • How the 99 can forc the 1 to defeat covid 19 • When will republican have stimulus go big or go home as trump said or was it all just a lie and mcconel is block everyth as he think wall street is all that matter and peopl don't need stimulus check despit what fed reserve chief powel say • Republican can never figur out whi black people hat them huh realli work overtim for that 4 black vote again
.1 to 0 (759,032)	• A depart of homeland secur plane is circl over protest in downtown Portland tonight this is the second time an aircraft link to feder law enforce has flown over demonstr in Portland • Brain are not a for serv in public offic in a texa • Break you will not believ what's happen on fox news in addit to gringrichs comment sen lindsey graham agre with top trump domest polici advis sean hanniti that throw out the elct result should be on the tabl if trump doesn't win his lawsuit in pa • Let me look into that also a subset of affect custom may have experienc flood custom can get inform about how to file a claim for properti damage by call 866 40 • Donald jr will get the best care possible and access to midicin and therapeut are not avail to ani of us I worri that an averag of 1000 american are die everyday and that near have been infect by the # coronavirus and now have a preexist condit
0 to -.1 (849,894)	• Will never forgiv the republican parti for not even give us one singl night to griev over gbg before they turn into it was the least they could do but they are a rogu galleri of cartoon villain so can't say that I'm shock • I'm afraid so • What a season so far let's keep it go • What presid say matter never thought that would be a groundbreak statement but today after the last four year it realli is • Maryland's eastern shore east of the
-.1 to -.2 (708,580)	• It is in everyone's best interest to make progress against the nation's legacy of racial injustic marc dure a talk at • If you are one of the 6.5 million American live abroad go to to request your ballot get faq and ask vote question even though you're live abroad you're still American you can still #vote and we can make a differ #novemberisnow • Are and betsi your if so that's so ador • A ground level perspect • Take your time
-.3 to -.4 (240,776)	• Yesterday even sen was announc as the vice presidenti run mate by joe biden for the democrat ticket for the 2020 elect applaud this histori make vp select • Folk upset about clovi unifi open up school here's some import info four differ seat on the school board are up for elect this year and there is no file fee or collect signatur you can run for school board if you file by august 7 • Good night my friend what ever happen tomorrow rememb you are love • Monday's scotus rule was a landmark victori for lgbtq right but there's still work to do to make sure all American regardless of sexual orient or gender ident enjoy the same protect under the law add your name and support the equal act • Kathi not sure what you mean by believe poll can off campaign a great deal of insight which is whi larg campaign across the aisl conduct them and place valu in the data the problem often come down to people what they mean

-.4 to -.5 (100,608)	• It is truli an honor I was stun when I saw this self invest is a critic compon to build a better communiti you must push forward even dure turbul moment in life a better you bring a better societi faith and work are everyth • So proud of my futur presid speech love you joe • Icymi support for is of great import when it come to win the florida latino vote • Great start to the 26th annual harris Truman award • We're immens grate
-.5 to -.6 (25,825)	• I appreci that • Today we celbr the start of a new chapter for our country thank you parti and campaign staff thank you phone banker thank you text banker thank you door thank you advoc thank you letter writer thank you mail carrier thank you voter • Thank you • Congrat anna great choic • This make me incred happi
< -.6 (1,353)	• I'm incred late to the game here but have to give a shoutout and huge welcom to of for join the ambassador program can't wait to work with and fight for a sport communiti that's equal and inclus for the #lgbtq communiti • Congrat amaz even • Congratul to look forward to work with you • Thank you gal this make me so happi • That's great thank so much

Topic Counts

Table 6: Republican Topics

COVID-19	**Covid Restrictions**	Mask, Restaurant, Quarantine, Indoor, Lockdown, Dine, Mandate, Shutdown, Gym, Compliance
	COVID-19	COVID-19, Infection, CV19, C19, Pneumonia, #SARSCOV2, Symptom, Virus, Influenza, Antibody
Race	**Police Violence**	Shot, Shoot, Cop, Carjack, Ambush, Beaten, Murder, Handcuff, Knife, Assailant
	Riot	Rioter, Anarchist, Riot, Thug, Antifa, Looter, BLM, Protest, Violent, Protestor
	Racism	Racist, LGBT, POC, Oppress, Jew, Bigot, Imperialist, LGBTQ, Hindu, Anti-Semite
	Ideology	Ideology, Concept, Characteristic, Hierarchy, Inherent, Collective, Philosophy, Framework, Orthodoxy, Progressive
Law	**Law & Constitution**	Constitution, Unconstitutional, Usurp, Punish, Government, Law, Rule, Coercion, Citizenry, Punitive
	SCOTUS	SCOTUS, Judge, #SCOTUS, ACB, Court, #SupremeCourt, Barret, Appeal, Supreme, Appellate
	Federal Investigation	FBI, Leaker, DOJ, Wiretap, Mueller, Comey, Spygate, Halper, Leak, Entrapment
	Republicans	Senate, GOP, McConnel, RINO, Schumer, Rep, Republican, McCarthy, Sen, Congressman
Policy	**Innovate**	Innovate, Environment, Resource, Literacy, Employ, Equity, Rand, Technology, Output, Healthcare
	Economics	Subsidy, Money, Taxpayer, Money, Pension, Handout, Pay, Bailout, Tax, Reimburse
	Foreign Enemies	PRC, Iran, Regime, China, Hegemony, Imperialist, Diplomacy, Yemen, Tibet, USSR
	Globalism	Globalist, Subversive, Leftist, Establish, Marxist, Despot, Corrupt, Lawless, Neoliberalism, Deceit
Election	**Election**	Win, Reelect, Landslide, Victory, 2024, Winner, Concede, Defeat, Primary, November
	Democracy Future	Freedom, Republic, Democracy, Sovereignty, America, Fight, County, Tyranny, USA, Prosper
	Voting	Ballot, Vote, Count, Duplicate, VBM, Mail, Cheat, Absentee, Signature, #MailInBallot
	Biden Campaign	VP, Joe, Kamal, Obama, Biden, Hillary, Harry, BHO, Jill, #JoeBiden
Media	**Social Media Derogatory**	Twitter, Facebook, Fakebook, FB, Blacklist, Snapchat, Parler, Twatter, Google, Censor
	News Media	CNN, MSNBC, NBC, FoxNews, Newsmax, ABC, OANN, CSPAN, CBS, CNBC
	Derogatory Media	MSM, #FakeNews, Misinformation, Disinformation, FakeNews, Falsehood, Propaganda, Lie, Unfound, Baseless

	Social Media	Article, Thread, Screenshot, Tweet, Blog, Edit, Archive, PDF, Timeline, Website
Political Frames	**Numbers**	85, 83, 65, 62, 61, 113, 55, 86, 66, 115
	Names	Carl, Shawn, Fred, Smith, Evan, Coleman, Campbel, Jenkin, Harold, Lloyd
	Location	NC, California, Florida, Wyoming, FL, OHIO, AZ, Texas, Arizona, Minnesota
	Family	Daughter, Mother, Mom, Girlfriend, Dad, Wife, Girl, Teenage, Cousin, GF
	Argument	Valid, actual, Anything, Proof, Obvious, Logic, Legitimate, Simplify, Inconsistent, Malfeasant
	Awesome	Fantastic, great, Terrific, Phenomenal, Awesome, Excellent, Amaze, Incredible, superb, Fabulous
	Sexual Violence	Rape, Child, Rapist, Sodomy, Victim, Adultery, Cruelty, Molest, Mutilate, Abuse
Random Topics	**Contractions**	Didn’t, Won’t, Wouldn’t, Shouldn’t, Doesn’t, Wasn’t, Isn’t, Don’t, Weren’t, Couldn’t
	Religion	Christ, Lord, Spirit, Jesus, Salvation, God, Divine, Heaven, Yeshua, Messiah
	Date & Time	Saturday, Tonight, Tomorrow, Sunday, Kickoff, Noon, 5PM, 6PM, 3PM, Friday
	Spam	Retweet, Follow, RT, DM, Pleasant, Click, Reply, Venmo, Pls, Tag
	Miscellaneous	Pull, Put, Turn, Throw, Kick, Lock, Blow, Come, Bring, Roll
	Outdoors	Sunset, Ocean, Desert, Snow, Breeze, Pine, Surf, Splash, Dock, River
	Sports	MLS, Playoff, Yankees, Dodgers, Bucs, Tournament, Game, NHL, #Yankee, Lakers
	Movement	Go, Ready, Back, Start, Tomorrow, 2022, Soon, Wait, Stop, #HoldTheLIne
	Holiday	Birthday, Happy, BDay, #MerryChristmas, Greet, Christmas, #Christmas, Shoutout, #VeteransDay, Thanksgiving
	Possibility	Accurate, Odd, Strange, Obvious, Implausible, Somewhat, Unusual, Certain, Complicated, Legit
	Prayer	Thank, Pray, Bless, Prayer, Godspeed, Grateful, #ThankYou, TY, Generosity, Commend
	Small Talk	Said, Knew, Say, Know, Told, Mention, Realize, Guess, Assume, Conclude
	Calendar Day	Day, Month, Week, Hour, Minute, Year, Time, Consecutive, Season, Rough
	Food	Soda, Veggies, Snack, Fridge, Burrito, Steak, Beverage, Booze, Appliance, Cheese
	Random Objects	Strap, Bag, Pant, Grease, Belly, Hose, Bottle, Broom, Poop, Head
	Yeah	Yeah, Uh, Um, Oh, Yea, WTF, LOL, Ummm, Umm, Yep

Figure 4: Republican Topic Discussion Overtime

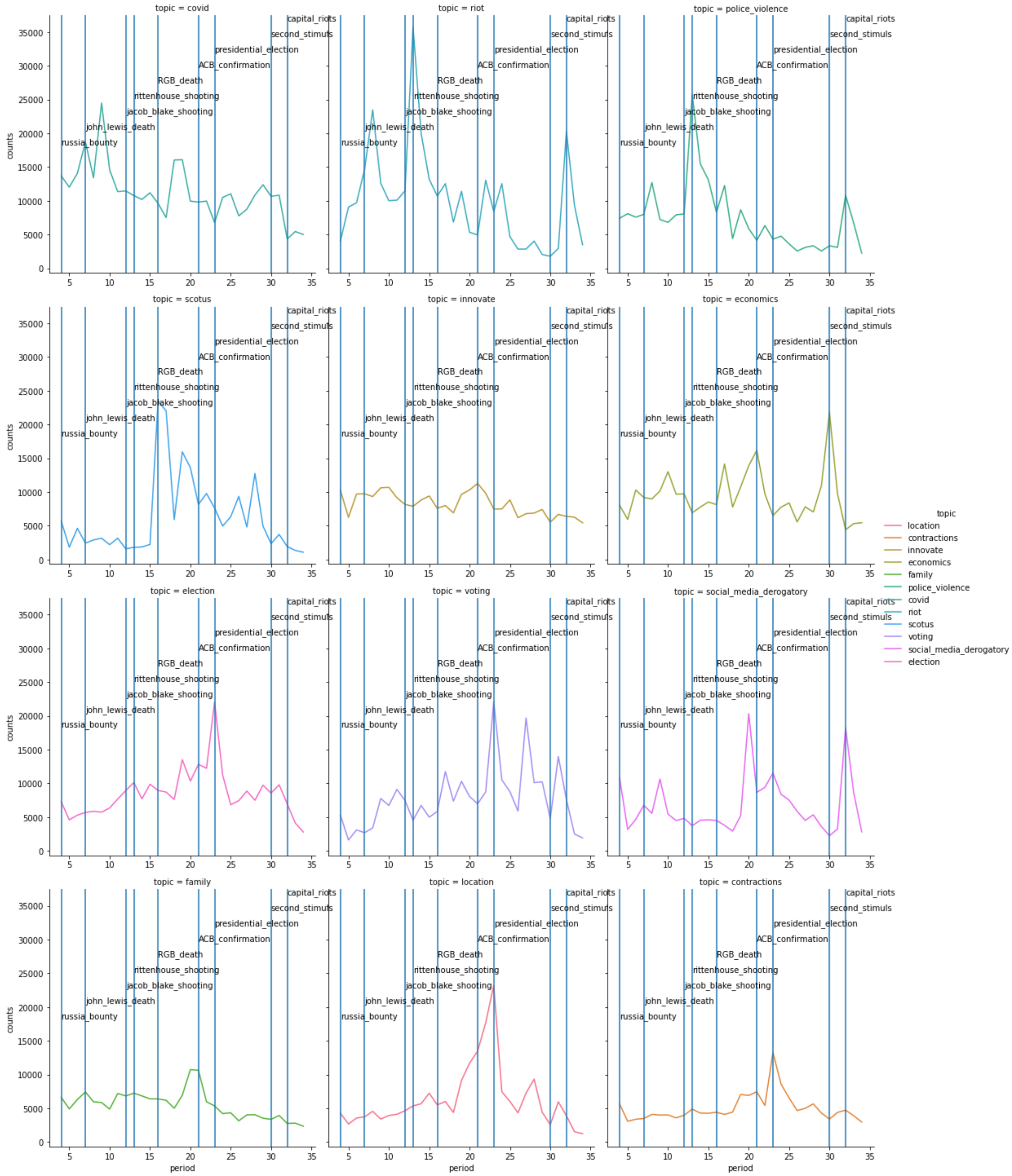
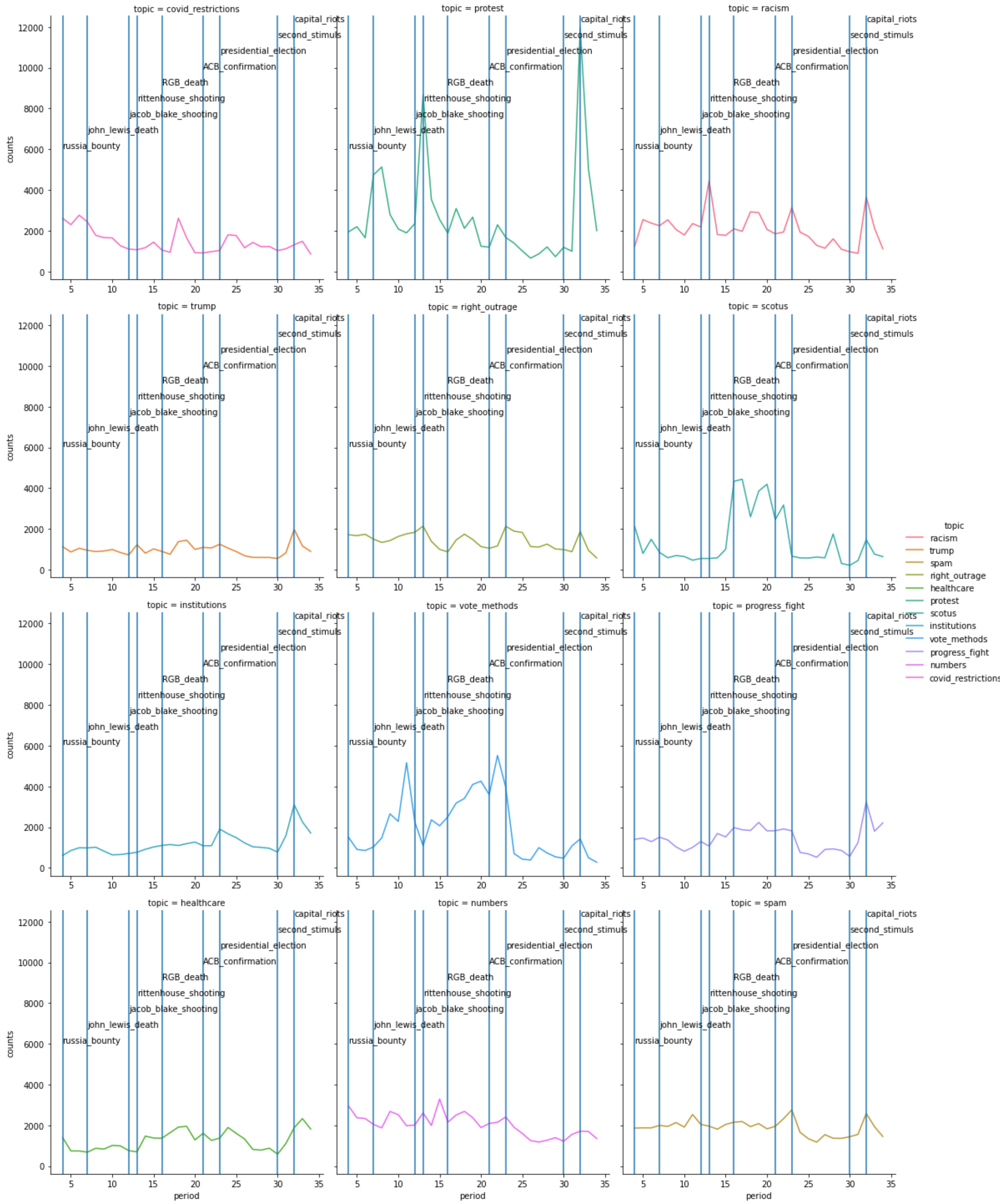


Table 7: Democratic Topics

COVID-19	**COVID-19**	Infect, Vaccine, #Sarscov2, COVID-19, #Coronavirus, Symptomatic, Asymptomatic, Test, Outbreak, #COVID-19
	Covid Restrictions	Mask, Indoor, Dine, Visitor, Takeout, Safe, Restaurant, #SocialDistance, Quarantine, #Mask
Police Brutality	**Protest**	Abduct, Indiscriminate, Protestor, Protest, Arrest, Riot, Arson, Teargass, Gunman, Ambush
	Racism	Patriarch, Zionist, Oppress, Subjugate, Reactionary, Islamophobia, POC, Anti-Semite, Islam, Imperialist
Trump	**Trump**	Calamity, Catastrophe, Turmoil, Instable, Downturn, Unsustainable, Crisis, Worsen, Collapse, Dysfunctional
	Outrage	Sycophant, Traitor, Scumbag, Conman, Craven, Buffon, Lowlife, Shameless, Unamerican, Vindictive
	Trump 2	Undermine, Legitimacy, Malfeasance, Enable, Subvert, Capitulate, Thwart, Sabotage, Undemocratic, Lawless
	Russia	Russia, #Russia, Ukraine, Kremlin, Ukrainian, #Putin, Cyberattack, KGB, CCP
Law	**Federal Investigation**	DOJ, Investigate, Indict, Probe, SDNI, Subpoena, Lawyer, Prosecutor, Prosecute, #DOJ
	SCOTUS	SCOTUS, #SCOTUS, Judge, Court, Appeal, Injunction, Appellate, Nominee, Rule, Judicial
	Punish & Law	Coercion, Punish, Prosecute, Criminal, Unlawful, Unaccountable, Pretext, Retaliate, Retribution, Repress
	Institutions	Framework, Society, Perception, Institution, Pervasive, Inherent, Characteristic, Hierarchy, Conception, Imbalance
Elections	**Primaries**	EC, 232, Primary, Wisconsin, Pennsylvania, 2016, Win, PA, Margin, Arizona
	VP Nomination	VP, Nominee, President, Nominate, Joe, Biden, Shortlist, Pres, Presumption, Vice
	Senate Election	#KSSEN, Flip, Senate, Georgia, Primary, Win, GA, #TXSEN, Governorship, #MTSEN
	Vote Tomorrow	Ready, Go, Tomorrow, #Vote, #FlipTheSen, #FlipFLBlue, Momentum, #VoteReady, #RetireRubio, #GOTV
	Voting Methods	Ballot, VBM, Absentee, Mail, Vote, Count, #VoteByMail, Request, Register, #AbsenteeBallot
	Fight for Progress	Fight, Strengthen, Future, Resilience, Ensure, Safeguard, Community, Transform, Equal, Inclusion
Legislation	**Congress & Legislation**	Stimulus, McConnel, #COVIDRelief, Relief, #HeroesAct, NDAA, Bill, Stall, Pass, Congress
	Healthcare	Healthcare, benefit, Employ, Compensate, Childcare, Stabile, Workforce, Necessity, Lifesaving, Wellbeing
	Climate	Atmosphere, Contaminate, Debris, Moisture, Sewage, Reservoir, Vegetation, Footprint, Cloud, Emit
	Economy	Subsidy, Deduction, Pension, Dollar, Bailout, Money, Tax, Cash, Subsidize, Taxpayer
	Education	Resource, Curriculum, #Higher, Tutor, Stakeholder, Experience, Nonprofit, Telehealth, #Stem, Student

Random Politics	**News Media**	CNN, OANN, OAN, NYT, Newsmax, Breitbart, Unsubstantiate, Report, Unverified, Fox News
	Political Heros	Spirit, Bravery, Heroism, Honor, Honour, Cherish, Persevere, Strength, Beloved, Soul
	Numbers	145, 184, 142, 000, 185, 213, 120k, 177, 128, 129
	Family	Daughter, Mother, Newborn, Grandmother, Son, Mom, Husband, Wife, Dad, Nephew
	Events	Tomorrow, Livestream, 6PM, 3PM, 4PM, Kickoff, 8AM, Tonight, 9AM, 12PM
	Arguments	Substantiate, Suffice, Valid, Indict, Preclude, Remedy, Feasible, Compromise, Assumption, Therefore
	Celebrate	Powerhouse, Congratulate, Alumni, Honor, Congrats, Proud, Thrill, Champion, Grateful, Alumna
	Nouns	Patrick, Wright, Corey, Cynthia, Wesley, Perkin, Watkin, Peterson, Smith, Cox
Random Topics	**Verbs**	Jump, Walk, Stomp, Pull, Head, Crawl, Pedal, Scrape, Strap, Chew
	Spam	DM, Text, Donate, RT, Venmo, Please, Retweet, Click, Download, E-Mail
	Social Media	Blog, Edit, Thread, Wikipedia, Video, Vid, Graphic, Artwork, Article, Excerpt
	Contractions	Didn’t, Wouldn’t, Won’t, Shouldn’t, Doesn’t, Don’t, Isn’t, Aren’t, Wasn’t, Couldn’t
	Mixture	Straightforward, Worthwhile, Tricky, Fascinate, Strange, Bleak, Worrisome, Scary, Fantastic, Great
	Knew Had	Knew, Had, Said, Saw, Thought, Met, Found, Seen, Notice, Realize
	Date & Time	Day, Hour, Week, Month, HRs, Rough, 10, Minute, Consecutive, 107
	Grateful	Thank, TY, Grateful, Appreciate, THX, Shoutout, #ThankYou, Bless, Gratitude, Generosity
	Slang	LOL, Haha, Cus, OMG, Really, Bro, Ugh, Dang, LMAO, Bruh
	Location	Venice, Downtown, Harlem, Kayak, Oak, Chinatown, Boulevard, Creek, Highland, Pine
	Food	Strawberry, Shrimp, Crab, Chili, Coconut, Spaghetti, Tomato, Fridge, Noodle, Burrito
	Slang 2	Oh, Uh, Yea, Um, Yeah, Nevermind, Haha, Ummm, Uhh, Bruh
	Holiday	Happy, Birthday, BDay, Chanukah, Joyous, #MerryChristmas, Celebrate, Hanukkah, 80th, #FathersDay
	Sports	Postseason, Playoff, Game, Quarterback, MLS, QB, Buccaneers, Colts, Bengals, Yankees

Figure 5: Democrat Discussion Over Time



APPENDIX B – SEMI-STRUCTURED INTERVIEW SCHEDULE

Introduction / Consent

- Hi, my name is Tyler. I am a graduate student at UMass Amherst conducting research on political polarization and the internet. I would like to ask you some questions about your political beliefs, the events leading up to the 2020 U.S. Presidential election, and your use of Twitter during this time. I hope to use this interview to get a better understanding of the political divide in the U.S. and how people interact with politics online. This interview will take approximately 60 minutes. Do you have time to answer my questions now?

Transition

- Okay, I would now like to ask you some questions about your political views and beliefs.

Political Views/Country Narrative

- Do you think the country is headed in the right direction?
- What do you think has caused the country to go in this direction?
- Could you give some examples? What has/will ______ done/do to put the country in that direction?
- How do you describe yourself politically?
- Have you always had these same political views?
    - Do you remember a particular moment that really influence your political views??

Transition

- This is all very interesting. I would like to hear your opinion on the events that have unfolded over the past couple months.

Interpretations of Recent Events

- (If after the election) – What do you think is currently happening/has happened regarding the election?
    - Is there a particular event or individual that you would place the blame on?
- What would you say are the top 3 most important events to occur leading up to the U.S. 2020 Presidential Election during the past couple months?
- Do you think (the event) helped or hurt the country? Could you give a few examples?
    - (If an actor/group of actors are mentioned) What do you think ______'s intentions
- Who do you imagine would oppose this understanding of the event?
    - Why do you think they would oppose your understanding of the event?
    - How would they interpret the event?
- Do you think the consensus within the country about this situation is the truth?
- Have any recent events made you question your political orientation?

Transition

- Okay, I would like to hear about your use of Twitter for following/taking part in politics. Would you mind if we looked at your Twitter account together?

Twitter use

- Are you a current student at [Sample University]? If not, why do you follow their political organizations' Twitter account?
- Has Twitter played any role in keeping you informed regarding these recent events?
    - How do you use Twitter?
    - Do you see post by people you don't agree with? Do you ever look at the reply threads?
- Are there any accounts that you find more reliable than others?
    - What makes an account reliable? What makes an account unreliable?
- Now I would like you to take out your Twitter account. Could you scroll through your Twitter stream and point out any Tweets that stand out to you?
    - What make these Tweets stand out?
    - Would you retweet these Tweets? Why or why not?
- What do you take into consideration when you compose a political Tweet?
    - Who is your audience when you compose a Tweet?
- (If conducted after the election) How have the results of the election changed your approach to Twitter?

Transition

- This has been a great conversation, and everything has been extremely useful. I would just like to wrap the interview up with a few demographic questions.

Background Questions

- If college student, how long have you attended [Your Current University]?
- How old are you?
- Where do you call home?
- What would you consider to be your race?
- What would you consider to be your ethnicity?
- What would you consider to be your gender?
- What would you consider to be your class?

Conclusion

Thank you for your participation. As promised, I will send you a link to the Amazon gift card right now while we are still having this interview, so you can confirm that you received it in your email before we sign off.

APPENDIX C – INTERVIEW RECRUITMENT MESSAGE

Hello, my name is Tyler Walton. I am a graduate student at the University of Massachusetts Amherst conducting research on political polarization and the internet. I have been analyzing the Tweets produced by the Twitter accounts that follow your organizations' Twitter account and my assumption is that most of you follow it. I was hoping that some of you would be willing to elaborate on these opinions during an interview. My hope is that through this project I can develop an understanding of the division that currently exists between our two parties to find common ground. I would really enjoy hearing your opinions on this issue as well as the events that have occurred leading up to the current presidential election. If you are interested in taking place in this study, feel free to respond with any questions by phone (717 669-1769) or e-mail (twalton@umass.edu). This interview will take approximately 60 minutes and you will be eligible to receive a $10 Amazon gift card at the conclusion of the interview. We can conduct this interview either by Zoom/Skype voice or video at a time that works for you.

WORK CITED

Allison, Paul D. 2009. *Fixed Effects Regression Models*. Sage Publication Inc, Thousand Oaks, CA.

Arora, Sanjeev, Yingyu Liang, and Tengyu Ma. 2017. "A Simple but Tough-to-Beat Baseline for Sentence Embeddings." *ICLR 2017*.

Bail, Christopher A. 2012. "The Fringe Effect: Civil Society Organizations and the Evolution of Media Discourse about Islam since the September 11th Attacks." *American Sociological Review* 77(6):855-79.

Bail, Christopher A. 2016. "Combining natural language processing and network analysis to examine how advocacy organizations stimulate conversation on social media." *PNAS* 113(42):11823-28.

Bail, Christopher A., Lisa P. Argyle, Taylor W. Brown, John P. Bumpus, Haohan Chen, M. B. Fallin Hunzaker, Jaemin Lee, Marcus Mann, Friedolin Merhout, and Alexander Volfovsky. 2018. "Exposure to opposing views on social media can increase political polarization." *Proceedings of the National Academy of Sciences* 115(37):9216-21.

Bail, Christoper A., Brian Guay, Emily Maloney, Aidan Combs, D. Sunshine Hillygus, Friedolin Merhout, Deen Freelon, and Alexander Volfovsky. 2019. "Assessing the Russian Internet Research Agency's impact on the political attitudes and behaviors of American Twitter users in late 2017." *Proceedings of the National Academy of Sciences* 117(1):243-50.

Baldassarri, Delia, and Andrew Gelman. 2008. "Partisans without Constraint: Political Polarization and Trends in American Public Opinion." *American Journal of Sociology* 114(2):408-46.

Berger, Peter L., and Thomas Luckmann. *The Social Construction of Reality*. New York, NY: Anchor Books.

Berry, Jeffrey M. and Sarah Sobieraj. 2014. *The Outrage Industry: Political Opinion Media and the New Incivility*. New York, NY: *Oxford University Press*.

Blei, David M. "Probabilistic topic models." *Communications of the ACM*.

Boutyline, Andrei and Stephen Vaisey. 2017. "Belief Network Analysis: A Relational Approach to Understanding the Structure of Attitudes." *American Journal of Sociology* 122(5):1371-1447.

Boutyline, Andrei., Alina Arseniev-Koehler, and Devin Cornell. 2020. "School, Studying, and Smarts: Gender Stereotypes and Education across 80 Years of

American Print Media, 1930-2009. Retrieved (https://files.osf.io/v1/resources/bukdg/providers/osfstorage/5eefd45976ebd8017ecd65e2?action=download&direct&version=1).

Caliskan, Aylin, Joanna J. Bryson, and Arviind Narayanan. 2017. "Semantics derived automatically from language corpora contain human-like biases." *Science* 356(6334):183-6.

Cinelli, Matteo., Gianmarco De Francisci Morales, Alessandro Galeazzi, Walter Quattrociocchi, and Michel Starnini. 2021. "The echo chamber effect on social media." *Proceedings of the National Academy of Sciences* 118(9):1-8.

Cowan, Sarah K. and Delia Baldassarri. 2018. "'It could turn ugly': Selective disclosure of attitudes in political discussion networks." *Social Networks* 52:1-17.

DellaPosta, Daniel., Yongren Shi, and Michael Macy. 2015. "Why Do Liberals Drink Lattes?" *American Journal of Sociology* 120(5):1473-1511.

DellaPosta, Daniel. 2020. "Pluralistic Collapse: The 'Oil Spill' Model of Mass Opinion Polarization." *American Sociological Review* 85(3):507-36.

Demszky, Dorottya., Nikhil Garg, Rob Voigt, James Zou, Matthew Gentzkow, Jesse Shapiro, and Dan Jurafsky. 2019. "Analyzing Polarization in Social Media: Method and Application to Tweets on 21 Mass Shootings." Retrieved (https://arxiv.org/abs/1904.01596).

DiMaggio, Paul. 1997. "Culture and Cognition." *Annual Review of Sociology* 23:263-87.

DiMaggio, Paul., John Evans, and Bethany Bryson. 1996. "Have American's Social Attitudes Become More Polarized?" *American Journal of Sociology* 102(3):690-750.

DiMaggio, Paul, Manish Nag, and David Blei. 2013. "Exploiting affinities between topic modeling and the sociological perspective on culture: Application to newspaper coverage of U.S. government arts funding." *Poetics* 41:570-606.

Emirbayer, Mustafa. 1998. "Manifestor for a Relational Sociology." *American Journal of Sociology* 103(2):281-317.

Finkel, Eli J., Christophe A. Bail, Mina Cikara, Peter H. Ditto, Shanto Iyengar, Samara Klar, Lilliana Mason, Mary C. McGrath, Brendan Nyhan, David G. Rand, Linda J. Skitka, Joshua A. Tucker, Jay J. Van Bavel, Cynthia S. Wang, and James N. Druckman. 2020. "Political Sectarianism in America." *Science* 370(6516):533-6.

Fiorina, Morris P., and Samuel J. Abrams. 2008. "Political Polarization in the American Public." *Annual Review of Political Science* 11:563-88.

Fligstein, Neil, Jonah Stuart Brundage, and Michael Schultz. 2017 "Seeing Like the Fed: Culture, Cognition, and Framing in the Failure to Anticipate the Financial Crisis of 2008." *American Sociological Review* 82(5):879-909.

Friedman, Jerome., Trevor Hastie, and Robert Tibshirani. 2009. *The Elements of Statistical Learning: Data Mining, Inference and Prediction*. New York, NY: *Springer Publishing*.

Garfinkel, Harold. 1967. *Studies in Ethnomethodology*. Englewood, NJ: Prentice-Hall.

Goffman, Erving. 1974. *Frame Analysis*. Cambridge, MA: Harvard University Press.

Goldberg, Amir. 2011. "Mapping Shared Understandings Using Relational Class Analysis: The Case of the Cultural Omnivore Reexamined." *American Journal of Sociology* 116(5):1387-436.

Goldenstein, Jan and Philipp Poschmann. 2019. "Analyzing Meaning in Big Data: Performing a Map Analysis Using Grammatical Parsing and Topic Modeling." *Sociological Methodology* 49(1):83-131.

Hargittai, Eszter. 2020. "Potential Biases in Big Data: Omitted Voices on Social Media." *Social Science Computer Review* 38(1):10-24.

Hoffman, Mark Anthony, Jean-Philippe Cointet, Philipp Brandt, Newton Key, and Peter Bearman. 2018. "The (Protestant) Bible, the (printed) sermon, and the word(s): The semantic structure of the Conformist and Dissenting Bibble, 1660-1780." *Poetics* 68:89-103.

Horne, Christine., Justine Tinkler, and Wojtek Przepiorka. 2018. "Behavioral Regularities and Norm Stickiness: The Cases of Transracial Adoption and Online Privacy." *Social Research: An International Quarterly* 85(1):93-113.

Hunter, James Davison. 1991. *Culture Wars: The Struggle to Define America.* New York, NY: *Basic Books*.

Hunter, James Davison. 1994. *Before the Shooting Begins: Searching for Democracy in America's Culture War*. New York, NY: *Free Press*.

Iyengar, Shanto, Yphtach Lelkes, Matthew Levendusky, Neil Malhotra, and Sean J. Westwood. 2019. "The Origins and Consequences of Affective Polarization in the United States." *Annual Review of Political Science* 22:129-46.

Iyengar, Shanto., Gaurav Sood, and Yphtach Lelkes. 2012. "Affect, Not Ideology: A Social Identity Perspective on Polarization." *Public Opinion Quarterly* 76(3):405-31.

Jamieson, Kathleen Hall and Joseph N. Capella. 2010 *Echo Chamber: Rush Limbaugh and the Conservative Media Establishment*. New York, NY: *Oxford University Press*.

Jerolmack, Collin and Shamus Kahn. 2014. "Talk is Cheap: Ethongraphy and Attitudinal Fallacy." *Sociological Methods and Research* 43(2):178-209.

Kiley, Kevin, and Stephen Vaisey. 2020. "Measuring Stability and Change in Personal Culture Using Panel Data. *American Sociological Review* 85(4):477-506.

Kozlowski, Austin C., Matt Taddy, and James A. Evans. 2019. "The Geometry of Culture: Analyzing the Meanings of Class through Word Embeddings." *American Sociological Review* 84(5):905-49.

Kozlowski, Austin C., and James P. Murphy. 2020. "Issue Alignment and Partisanship in the American Public: Revisiting the 'Partisans Without Constraint' Thesis." Retrieved (osf.io/preprints/socarxiv/jex9k).

Lee, Monica and John Levi Martin. 2015. "Coding, Counting and Cultural Cartography." *American Journal of Cultural Sociology* 3(1):1-33.

Lelkes, Yphtach., Gaurav Sood, and Shanto Iyengar. 2017. "The Hostile Audience: The Effect of Access to Broadband Internet on Partisan Affect." *American Journal of Political Science* 61(1):5-20.

Levendusky, Matthew. 2009. *The Partisan Sort*. Chicago, IL: *University of Chicago Press*.

Lewis, Rebecca. 2018. "Alternative Influence: Broadcasting the Reactionary Right on YouTube." *Data & Society*.

Martin, John Levi. 2010. "Life's a ceach but you're an ant, and other unwelcome news for the sociology of culture." *Poetics* 38:228-43.

Marwick, Alice, and danah boyd. 2011. "I Tweet Honestly, I Tweet Passionately: Twitter Users, Context Collapse, and the Imagined Audience." *New Media & Society* 13(1):1-20.

Marwick, Alice, and Rebecca Lewis. 2017. "Media Manipulation and Disinformation Online." *Data & Society*.

Marwick, Alice. 2018. "Why do People Share Fake News? A Sociotechnical Model on Media Effects." *Georgia Law Technology Review* 2(2):474-512.

McPhail, Clark. 2006. "The Crowd and Collective Behavior: Bring Symbolic Interaction Back In." *Symbolic Interaction* 29(4):433-64.

Mead, George H. 1922. “A Behavioristic Account of the Significant Symbol.” *The Journal of Philosophy*. 19(6):157-63.

Mikolov, Tomas, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. “Efficient Estimation of Word Representations in Vector Space.” Retrieved (https://arxiv.org/abs/1301.3781).

Mische, Ann. 2011. “Relational Sociology, Culture, and Agency.” *The Sage Handbook of Social Network Analysis*.

Mische, Ann. 2014. “Measuring futures in action: projective grammars in the Rio+20 debates.” *Sociological Theory* 43:437-64.

Mohammad, Saif M. 2018. “Obtaining Reliable Human Ratings of Valence, Arousal, and Dominance for 20,000 English Words.” *ACL 2018*
.

Mohr, John W. 1998. “Measuring Meaning Structures.” *Annual Review of Sociology* 24:345-70.

Mohr, John W, Robin Wagner-Pacific, Ronald L. Breiger, and Petko Bogdanov. 2013. “Graphing the grammar of motives in National Security Strategies: Cultural interpretation, automated text analysis and the drama of global politics.” *Poetics* 41:670-700.

Mohr, John W and Petko Bogdanov. 2013. “Introduction—Topic Models: What they are and why they matter.” *Poetics* 41:545-69.

Mohr, John., Christopher A. Bail., Margaret Frye., Jennifer C. Lena., Omar Lizardo., Terence E. McDonnell., Ann Mische., Iddo Tavory., Fredrick F. Wherry. *Measuring Culture*. New York, NY: *Columbia University Press.*

Nadler, Anthony, Matthew Crain, and Joan Donovan. Weaponizing the Digital Influence Machine: The Political Perils of Online Ad Tech.” *Data & Society*.

Pachucki, Mark A., and Ronald L. Breiger. “Cultural holes: Beyond relationality in social networks and culture.” *Annual Review of Sociology* 36:205-244.

Pariser, Eli. 2011. *The Filter Bubble: What the Internet is Hiding from You*. New York, NY: *Penguin Books*.

Pennington, Jeffrey, Richard Socher, Christopher D. Manning. “GloVe: Global Vectors for Word Representation.” *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing* 1532-43.

Prior, Markus. 2013. “Media and Political Polarization.” *Annual Review of Political Science* 16:101-27.

Pugh, Allison J. 2013. "What good are interviews for thinking about culture? Demystifying interpretive analysis." *American Journal of Cultural Sociology* 1(1):42-68.

Rule, Alix, Jean-Philippe Cointet, and Peter S. Bearman. "Lexical shifts, substantive changes, and continuity in State of the Union discourse, 1790-2014." *PNAS* 112(35):10837-44.

Shibutani, Tamotsu. 1968. "A Cybernetic Approach to Motivation." In *Modern Systems Research for the Behavioral Scientist*.

Small, Mario Luis. 2009. "'How many cases do I need?': On science and the logic of case selection in field-based research." *Ethnography* 10(1):5-38.

Stoltz, Dustin S., and Marshall A. Taylor. 2020. "Cultural Cartography with Word Embeddings." Retrieved (https://arxiv.org/abs/2007.04508).

Stroud, Natalie Jomini. 2010. "Polarization and Partisan Selective Exposure." *Journal of Communication* 60(3):556-76.

Sunstein, Cass R. 2009. *Going to Extremes: How Like Minds Unite and Divide*. New York, NY: *Oxford University Press*.

Swidler, Ann. 1986. "Culture in Action: Symbols and Strategies." *American Sociological Review* 51(2):273-86.

Tan, Xianming, Mariya P. Shiyko, Runze Li, Yuelin Li, and Lisa Dierker. 2012. "A Time-Varying Effect Model for Intensive Longitudinal Data." *Psychological Methods* 17(1):61-77.

Teriault, Sean M. 2008. *Party Polarization in Congress*. New York, NY: *Cambridge University Press*.

van Loon, Austin A., Amir Goldberg, and Sameer B. Srivastava. 2020. "Differences Beyond Identity: Perceived Construal Distance and Interparty Animosity in the United States." Retrieved (osf.io/preprints/socarxiv/j2f6u).

Wagner-Pacific, Robin. 2017. *What is an Event?* Chicago, IL: The University of Chicago Press.

White, Harrison. 1992. *Identity and Control: A Structural Theory of Social Action*. Princeton, NJ: *Princeton University Press.*

White, Harrison. 2008. *Identity and Control: A Structural Theory of Social Action – Second Edition*. Princeton, NJ: *Princeton University Press.*