THE DIGIPOLITICAL ANIMAL: INVESTIGATING THE MEMETIC DIFFUSION OF POLITICAL MESSAGES ON TWITTER

Jonathan Carey Clark
Brian H. Spitzberg, Chair
School of Communication
&
Ming-Hsiang Tsou
Department of Geography

San Diego State University

San Diego, CA 92182-4560

Correspondence to: 23jonathan.clark@gmail.com

Paper submitted to the Western States Communication Association Conference

Santa Clara, CA, February 2018

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ABSTRACT

Social Media occupies a central role in the future of American political communication. Twitter specifically has emerged as a unique public space where digital political discourse can emerge. Past research has attempted to utilize Twitter data in order to make predictions and generalizations about political behavior. The presidential election of 2016 was used as a case study in an exploratory analysis of online political deliberation. This study seeks to understand the various ways messages can diffuse through political social networks. The Multilevel Model of Meme Diffusion (M^3D) was used as a framework for understanding memetic diffusion. Data was analyzed using a mixed-methods approach. Analysis revealed that online communities can develop around political groups online. Sentiment analysis and social network analysis provided additional support for the presence of online communities. A form-based typology of election memes was developed. This research seeks to validate and expand upon the social network and meme levels of M^3D.

Key words: politics, elections, Twitter, tweets, communities, sentiment, meme, diffusion.

Social media have revolutionized modern society. The Internet has created a world in which people are more connected than ever before (Brandwatch, 2016). Social media represent "a collection of websites and applications designed to build and enhance online communities for networking and sharing information" (Osborne-Gowey, 2014, p.55), which constitute digital interaction spaces (Himelboim, Lariscy, Tinkham, & Sweetser, 2012). Social media can vary in both the types of users they attract and the type of content that is shared. Social media technologies have dramatically compressed spatial and temporal distances in communication, and begun to dissolve the differences between one-to-one and one-to-many forms of communication. Social media and their many iterations have created an unprecedented change in how people understand and use communication. Understanding the processes by which ideas diffuse through social media is rapidly becoming an essential priority for communication research. This case study examines the role of Twitter in the presidential election of 2016.

Social Media and Politics

Social media has emerged as a platform critical to political discussion and deliberation in the United States. Online political mobilization directly affects voting behaviors offline. Political activism and engagement through digital technologies are potential bright spots in an American political system that by other indicators is often increasingly moribund (Pew Research Center, 2013). In their analysis of the "I Voted" button on Facebook, Bond et al. (2012) found that the sharing of a single message resulted in a growth of 340,000 votes. This number accounts for 24% of the growth in voter turnout seen from 2006 to 2010. Some of the most popular social media accounts on Twitter are politicians. As an example, President Barack Obama is the fifth most followed Twitter user with over 77.52 million total followers (Twitter, 2016). Trending topics on Twitter often reflect many of the issues Americans consider important. The information gathered from social media sites can serve as an important medium for generating an understanding of political communication in the United States. While many traditional forms of political engagement seem to be floundering, there has been an explosion of political engagement on social media websites (Loader, Vromen, & Xenos, 2015).

Twitter

Through Twitter, users can share their thoughts with both individuals and groups of followers. Tweets often contain a variety of other content in addition to the text of the tweet. Twitter has four primary functions (Java, Song, Finin, & Tseng, 2007). First, it is used for chat

concerning everyday experiences and thoughts. Second, Twitter can also be used for holding virtual conversations. Message strings between different individuals, or directed toward certain individuals, can be identified by the use of an @ preceding usernames. Third, Twitter has established itself as primary news media source. Tweets often link to outside websites or are used to report on breaking news as it occurs. Fourth, tweets can be used to share information through the use of shortened URLs. Fifth, given this feature, considerable research has tried to identify the effects of Twitter use by politicians. The personal nature of social media correspondence moves conversations away from party politics, and places renewed focus on the individual politician (Gunn & Skogerbo, 2013). Given these functions, Twitter has found widespread adoption as a tool in American politics (Jungherr, 2016). It is used to research, comment, and interact with public reactions to politics. It is inherently different from other social network sites in that Twitter posts can easily be viewed by all users. Twitter posts are also unique for their use of hashtags. Hashtags are topical markers used to contextualize a tweet and briefly express the core idea present in the tweet's message (Tsur & Rappoport, 2012). Hashtags are strings of characters following a hash (#) symbol. They are typically utilized at the end of Twitter messages. #MAGA is one example of a hashtag utilized during the presidential election in 2016. Messages published to Twitter are circulated in public domain.

On October 9, 2016 Donald Trump and Hillary Clinton engaged in the most tweeted debate ever. There were more than 17 million tweets over the course of a ninety-minute debate (Stelter, 2016). Extraordinary political engagement of that scale is only possible through social media. Tweeting during presidential debates has specifically been linked to increases in overall learning and engagement with the concepts discussed during debates (Houston, Hawthorne, Spialek, Greenwood, & McKinney, 2013). In addition to this, social media have created forums for live, ongoing political deliberation with other Americans and elected officials. When queried, 97% of congressional staffers reported regularly reviewing and responding to social media posts by constituents (Fitch & Goldschmidt, 2015). Elected officials are more involved with their constituents and are able to garner a greater understanding of the needs of their community based on the conversations started on social media.

@REALDONALDTRUMP @POTUS

The election of Donald Trump as the 45th president of the United States placed Twitter at a unique position within American politics. On March, 4th 2017, at 3:35 AM, Donald Trump

posted a message on Twitter that will likely go down as an infamous and egregious tale of misinformation on the part of the president. He tweeted "Terrible! Just found out that Obama had my 'wires tapped' in Trump Tower just before the victory. Nothing found. This is McCarthyism!" (Trump, 2017). The ensuing media flurry serves as an example of the power of Twitter in the current political landscape. Throughout the course of March, many political conversations were rife with stories about the President's tweet. Tweets by the President have even been the topic of several questions asked during congressional investigations. During a Congressional hearing on Russian influence on the presidential elections of 2016, James Comey, the director of the Federal Bureau of Investigation, was asked whether he could comment on the veracity of the President's tweets. Never before have tweets been in the center of American politics in such a way. Donald Trump's classification of national newspapers as proponents of "fake news" has also dominated conversation on Twitter. For many of Donald Trump's followers, Twitter is seen as a tool that can be used to bypass the biased media (Presto, Gingras, & Welch, 2017). Research into political communication must seek to understand this new form of communication.

MAPPING THE DIGITAL TERRITORY

With the widespread adoption of social media has come an influx of new research focused on understanding how social media function as a part of the political process. Twitter specifically has been the focus of several studies. For example, research has attempted to use Twitter posts as a method of predicting election outcomes (Tumasjan, Sprenger, Sandner, & Welpe, 2010; Gayo-Avello, 2013; McKelvey, DiGrazia, & Rojas, 2014). Such studies have had limited, but promising, success in attempting to predict election outcomes. Within the field of communication, research has looked at social media and how they can be analyzed in terms of agenda-setting theory (Wolfe, Jones, Baumgartner, 2012; Thesen, 2013; Neuman, Guggenheim, Jang, & Young Bae, 2014). There has also been considerable interest in Twitter's use as a platform for social movements and specifically social activism (Bond et al., 2012; Treré, 2012; Spitzberg et al., 2013).

If politics are about societal influence, and if social media are a substantial means through which such influence is wielded, then the particular ways in which social media influence become an important arena of research. One of the social media processes that receives extensive speculation, but still relatively limited theoretical attention, is the process of messages

that "go viral." The vast majority of Tweets move only one or two links past the sender (Lu, Zhang, Cao, Hu, & Guo, 2014). In contrast, some Tweets get re-tweeted millions of times. Every tweet is a potential influence message, but every re-tweet is by definition an index of social influence (Spitzberg, 2014). This phenomenon therefore rests at the very center of all other communication theory and research. There is a significant need for a theory that identifies the factors that determine the replication and success of messages in cyberspace. At the most basic level, it is important to understand how messages are able to diffuse throughout social networks in political contexts.Chapter 2

MULTILEVEL MODEL OF MEME DIFFUSION (M^3D)

Spitzberg (2014) developed a heuristic framework for beginning to understand the role of new media in the diffusion of ideas. This paper seeks to expand upon the Multilevel Model of Meme Diffusion (M^3D) and apply the proposed framework to political deliberation on Twitter. Memes are communications that are replicated by individuals. Just as genes are the mechanism of information transfer between biological organisms, memes transfer cultural information across humans. Memes can take a variety of forms but usually consist of a single internally consistent message. Analogous to species adaptation to local competitive environments, M^3D proposes that memes fill information niches in broader information ecologies. As organisms compete for survival, memes compete for attention. Information is abundant, but attention is a scarce resource. Humans are limited information processors. As such, the fitness of a meme is determined by its ability to adapt in a broader information ecosystem and sustain itself in the attention space of such ecosystems in regard to meme diffusion, duration, speciation (i.e., variation), and progression (Spitzberg, 2014).

Six levels of factors have a direct effect on the process of meme diffusion. M^3D theory uses these six levels as a method of illustrating the life span of memes: Meme level, source level, structural social network level, subjective social network level, societal level, and geotechnical level. Meme diffusion can be investigated using each of these distinct levels. This study will expand and investigate the source, structural social network, and subjective social network levels of the M^3D model. The *source level* looks at the specific characteristics of the individual in order to determine how those characteristics might affect meme diffusion. Examples of how a source level analysis might manifest include: Investigating the speaker's motivations, communication skill, perceived credibility, or relative adaption to media technologies. The

structural social network level focuses specifically on how the structure into which a meme is introduced can affect diffusion. Finally, the *subjective social network* level represents how the characteristics of a specific social network might affect diffusion processes.

The multilevel model of meme diffusion builds heavily on previous research concerning the diffusion of innovations. A key component of diffusion of innovations concerns the creation of a peer promotion model (Valente & Davis, 1999). Within social networks there are individuals who serve as role models for adopting new behaviors and ideas. These people are known as opinion leaders, or influentials. Opinion leaders have consistently been shown to have a positive effect on changing public opinion and are crucial to the diffusion of innovations. van Eck, Jager and Leeflang (2011) found that opinion leaders are crucial to the diffusion of innovations within a social network. Adoption occurred faster in populations with opinion leaders and new ideas were more widely accepted.

The political views of opinion leaders also play an important role in the diffusion of ideas. Conservative opinion leaders vary greatly in their use of social media as a means of disseminating information. Brundidge, Reid, Choi, and Muddiman (2014) found that there exists a divide between the conservative and liberal camps. Liberals are exposed to alternate points of view that are filtered through like-minded opinion leaders, while conservative users of social media are unlikely to acknowledge the presence of opposing views. While ultimately, the success of diffusion relies on the average user, opinion leaders still play a critical role in message adoption (Park, 2013; Rogers, 2003; Zhang, Jichang, Xu, 2015).

PREDICTING CANDIDATE PREFERENCE

With regard to presidential elections, opinion leaders can be used to ascertain the relative popularity of a specific candidate. Shama (1976) argues that political candidates are marketed in much the same way that new products are marketed. Using the tweets and retweets of influentials, researchers can make assumptions concerning how popular a candidate is at a given point in time. Because influentials are at critical junctures in social networks, the adoption of their opinions can serve as a measure of candidate popularity. It is not known if diffusion, awareness of, and popularity are equivalent. Thus, the first research question:

RQ_1: Do retweets of influentials predict (or reflect) candidate popularity?

Analyzing the tweets of influentials provides a novel method of tracking candidate popularity. Opinion leaders can signal the relative popularity of a given candidate based on

acceptance and subsequent diffusion or replication of those tweets. Such influence is likely to be moderated by factors such as political affiliation and homophily of social networks. For example, an opinion leader who is only followed by extremely conservative Twitter users is not likely to provide an accurate representation of candidate popularity when considered in a vacuum (Gayo-Avello, 2013). On the other hand, such opinion leaders may serve as bellwethers in a polity, serving as variably weak or strong signals of a candidate's popularity.

Political research has long been concerned with forecasting the outcomes of presidential elections. The most often used metric in predicting candidate success is scientific polling (Brooker & Schaefer, 2006). Popularity or 'horserace' polls are taken almost daily throughout the course of an election to measure public opinion and voting likelihood. During the 2016 election, both national and state election polling consistently projected Donald Trump's loss. Forecasters from different networks placed Clinton's victory chances as high as 99% (Mercer, Deane, & McGeeney, 2016). Almost without exception, polls underestimated the popularity of Donald Trump. One surprising metric that consistently pointed toward Trump's popularity was social media engagement. In the early stages of the election, social media posts by Trump reliably outperformed both Clinton and Sanders in terms of likes, favorites, and retweets (Pew Research Center, 2016).

Cha, Haddadi, Benevuto, and Gummadi (2010) developed three criteria for measuring influence on Twitter: Indegree, retweets, and mentions. These criteria were found to be the most reliable indicators of influence. For the purposes of measuring candidate preference, it is important to focus on one of these specific measures, the average number of times a user is retweeted. Indegree centrality is fairly constant across major political Twitter accounts (Hsu & Park, 2012). Accounts having more than one million followers typically link to many other influential accounts. During the 2016 presidential election, each of the presidential candidates was @mentioned frequently based on their involvement in election-relevant conversations (Pew Research Center, 2016). Therefore, the only remaining variable for measuring candidate influence is average number of retweets. This variable can be used as a metric for determining the relative popularity of each presidential candidate.

When trying to determine candidate preference, the personal popularity of presidential candidates is no longer of central importance. Recent research has actually pointed toward a steady decline in the personal popularity of American presidents. With this decline has come an

increase in the importance of candidate issues (Wattenberg, 2004). The key to understanding candidate preference is a renewed focus on candidate-centered issues. Retweets are by nature an indicator of support for certain viewpoints (Boyd, Golder, & Lotan, 2010). Users retweet posts that resonate with their personal beliefs and opinions. Retweets are used to share someone else's tweets with a personal list of followers. This means that users essentially rebrand the tweet as their own message. A retweet is generally seen as expressing support and agreement with the content of the original message. For the average Twitter user, a retweet signifies an endorsement (Metaxas et al., 2015). In their survey, Metaxes et al. found that 94% of users reported that they retweet a message based on personal interest. Further, 75% of users report that they retweet a message based on their agreement with the content of the tweet. They also found that when hashtags are included, this strengthens the likelihood of agreement. Hashtags are often illustrative of distinct social groups for this reason.

Presidential candidates are typically considered the most important opinion leaders within American politics. In order to win a nomination, and a presidency, millions of voters must align with a campaign's stated goals and agenda. Once elected, the President has substantial influence on the ideological position of their party (Rottinghaus, 2009). Additionally, presidents are often looked to as a source of personal identification for countless Americans (Jacobson, 2015). Twitter provides a unique opportunity to monitor in real time, the priorities of the president. Twitter has emerged as a strategic means of guiding political conversations both on and offline.

ESCAPING THE ECHO CHAMBER #HASHTAGCOMMUNITIES

The Twitterverse is a particularly noisy universe, and attention space may be flexible but also difficult to dominate. As such, it would also be beneficial to develop an understanding of the influence of specific Twitter accounts. It is necessary to develop a method of determining the effect of specific Twitter accounts on the overall Twitter universe. BrandWatch (2016) attempted to map out influence based on three distinct metrics. These three metrics were in turn used to generate an Influence Score to visualize the magnitude of the effect of these accounts.

Research has attempted to map the influence of Twitter users based on in-degree and eigenvector centrality (Dubois & Gaffney, 2014). In-degree centrality awards a single point for every message connection. When measuring influence in this way, each reference to the original tweet or tweeter is valued equally. Eigenvector centrality proposes that a message is important only if it is linked to by other important users or tweets. Based on eigenvector centrality, certain

accounts may be positioned in such a way that they are more influential based on their position within a social network. Cha, Haddadi, Benevenuto and Gummadi (2010) instead operationalized influence as, "an individual's potential to lead others to engage in a certain act" (p. 11). They identified following, retweeting and mentioning as indicators of influence.

M^3D anticipates that homophily of sources and social networks facilitate meme diffusion. As such, it is still unclear whether there exists a general public sphere, or a grouping of segmented homophilous social network clusters or echo chambers (Barberá, Jost, Nagler, Tucker, & Bonneau, 2015). An echo chamber is a social network structure characterized by the absence of alternative viewpoints. Within an echo chamber, existing beliefs are reinforced due to a lack of engagement with differing ideas (Vergeer & Vaccari, 2013). Recent research has analyzed social networks as echo chambers (Bakshy, Messing, & Adamic, 2015). Research needs to consider whether or not political Twitter is an echo chamber, or the degree to which it fosters an environment that forms tight-knit echo chambers.

Hashtags have emerged as one of the integral components of modern Twitter use. Hashtags are often used to connect a tweet with specific online communities of users (Moore, 2014; Sharma, 2013; Small, 2011; Weber, Garimella, & Teka, 2013). Online communities have group-specific hashtags that are widely accepted and utilized by members. They are typically constrained by thematic and linguistic communities (Bastos, & Mercea, 2015). Thus, hashtags are searchable linguistic markers that serve as a means of affiliation (Zappavigna, 2011). Hashtags invite other users to align with a community or belief. This would suggest that politically motivated Twitter users utilize hashtags to align themselves with people of similar views. By adopting a specific hashtag, people and groups can express their support for, or opposition to, an organization, social movement, or individual (O'Hallarn & Shapiro, 2014; Smith & Smith, 2012). Users who tweet concerning presidential elections seem likely to utilize hashtags in similar ways.

Internet memes are used to facilitate the construction of shared identity (e.g., Gal, Shifman, & Kampf, 2016). A community can be defined as groups of nodes that are closely connected with each other, while having only weak connections with other nodes outside the community (Radicchi et al., 2004). Community structures often emerge within social networks. Social network analysis has attempted to map these communities in a variety of ways. Darmon, Omodei, and Garland (2015) detail the various methods used in automatic community detection.

They argue that it is not only important to consider how communities are grouped within social networks, but the communities need to be identified through their underlying attributes or motivations. Gubanov, Mikulich, and Naumkina (2014) found that language use and linguistic style could accurately distinguish online communities. Members of the same online communities often structure their messages in similar ways.

The multilevel model of meme diffusion posits that frames must compete for survival. In order to answer this question, research must first ascertain whether or not messages interact in the first place. If there is no interaction among ideas and different frames across social networks in the Twitterverse, then it would suggest relatively little between social networks. As evolutionary biologists E. O. Wilson and D. S. Wilson (2007, p. 345) propose: "selfishness beats altruism within groups. Altruistic groups beat selfish groups. Everything else is commentary." Echo chambers would represent competition for status within echo chambers, thereby revealing strong opinion leaders within echo chambers, but strong within group sentiment homophily whenever there are competing echo chambers in the broader information ecology. This line of conjecture suggests the following research questions.

RQ2: Do political conversations on Twitter reflect structures interpretable as online communities?

RQ2a: Is there evidence that political conversations in a Twitter information ecosystem reflect competing communities?

A key concept across theories of communication is homophily (Choi, Sang, & Woo Park, 2014; Colleoni, Rozza, & Arvidsson, 2014). People have a tendency to identify and associate with individuals who have similar belief systems and worldviews (McPherson., Smith-Lovin, & Cook, 2001). When applied to politics, homophily can result in the political polarization of specific groups. In this regard, online social networks might have the unintended consequence of shielding users from contrasting values and information. Twitter has evolved into a primary source of news for many of its users (Chen, 2011). Twitter as a news medium can be distinguished from Twitter as a means of social networking. Twitter as a news medium functions much like a public sphere. It exhibits low amounts of homophily. This means that news seekers are exposed to perspectives that may run counter to their personal beliefs. The presence of an echo chamber effect is negligible in these situations (Colleoni, Rozza, & Arvidsson, 2014). Twitter users who seek out news through Twitter are usually exposed to a

variety of different perspectives. It is important to consider the role of influentials in connecting different social network groups. While some accounts might be heavily skewed toward liberal or conservative users, this does not necessarily mean that they exist in distinct social networks.

Social media have created a unique situation through which news media organizations directly interact with individuals as a singular entity. News outlets, while composed of many different individuals, do not have numerous disparate identities. These organizations must unify under a single shared identity on social media. The social media accounts of news sources function as human actors during their interactions with other users. News organizations are influenced by the ideologies held by owners and executives (Al-Rawi, 2016). Many news organizations implement guidelines on social media use by employees, and hire social media specialists in order to maintain a certain identity and public image. Hofstetter (1976) found that in general, news outlets give more coverage to the issues they feel are most important. It is important to include such organizations in research pertaining to political events and the diffusion of memes through social networks.

Social media sites have changed the way people stay abreast of politics. Anderson and Caumont (2014) estimate that more than half of social media users have shared a news story, image, or post. More so than ever before, people look to social media as a primary source of news information (Pew Research Center, 2016). News outlets will respond to user comments and interact with other users posts in order to increase the likelihood that their own content is viewed by as many users as possible. Holcomb and Gross (2011) found that the agenda promoted by news outlets on Twitter closely follows the agenda of legacy platforms. Twitter allows news media to promote their agenda with greater reach.

Memes are naturally constructed to be selfish and seek replication (Coker, 2008). Yet, as in nature, the vast majority end up contributing little to the larger information genepool. In nature, as with memes, there often exist scenarios where the existence and replication of a meme is dependent on the presence of competing counter-memes. Counter-memes are ideas or messages in direct opposition to the original meme. Godwin (1994) argues that researchers have an obligation to improve informational environments by creating counter-memes. The presence of these counter-memes often force original memes to evolve and adapt in order to survive. The fitness of a meme is directly affected by the presence of such competition. In these instances, it is entirely possible for memes to become dependent on their competition. That is, memes may

be directly competing *against* one another, or they may exist in a more symbiotic relationship. For example, from one perspective, the conservative Fox media empire might be viewed as competing with the liberal MSNBC empire. From another perspective, however, they only exist because the other enables their ongoing relationship. If Fox did not exist, would MSNBC? The survival of one is directly influenced by the survival of the other. Rogers (2017) claims that the creation of MSNBC played an important role in the creation of Fox News. Price (2017) writes that the Trump's rise has resulted in millions of dollars for the major news networks. Political opposites exist in a position of interdependence. This state of symbiosis is characteristic of political meme diffusion. In order for a meme to replicate, it often needs, or at least may elicit, a countermeme to aid in its growth. Such a dynamic process would manifest a thrust-parry cycle in political social media discourse. Political opposites use opposing viewpoints to garner further support from their respective bases. A *thrust-parry cycle* can be defined as an exchange of memes during which a user levies an attack against their opponent, followed quickly by a rebuttal that counters or distracts from the original message. A thrust-parry cycle is clearly identified by the timing of the response, and the contradictory content of the memes. The thrust-parry cycle sits at the center of the symbiotic relationship between meme and countermeme, frame and counterframe. Thus, the third research question:

RQ3: Is there evidence of a thrust-parry cycle structure in online social media discourse?

Research has not produced a sufficiently clear image of social network clusters. Social network clusters are collections of users with densely linked nodes and sparse external links (Mishra, Schreiber, Stanton, Tarjan, 2007). Social network clusters are different from echo chambers in that they do not necessarily need to be formed by individuals with similar viewpoints. For example, a social network cluster could be comprised of various individuals working for a given organization, even if their views are quite divergent.

Echo chambers emerge in homophilous community structures. These spaces are known as infoniches. At their most extreme, infoniches develop into echo chambers. Memes within these infoniches are in constant competition. Occasionally, these memes diffuse outside of their local informational ecologies. Echo chambers are especially prevalent in social media. Nicolov, Oliveira, Flammini, and Menczer (2015) found that information diversity decreases significantly on social media as compared to a search baseline. Their results also suggested a lack of diversity in news traffic filtered through social media. Social media have caused a situation whereby

increased polarization and reinforcement of collective filters is extremely likely. The more similar people are, the more likely they are to engage in communication with each other (Liang & Fu, 2015). This is also applicable to communication link formation. José-Cabezudo and Camarero-Izquierdo (2012) found that as homophily increases, likelihood of opening and forwarding messages increases. Content diffusion is highly dependent on the presence of homophilic community clusters. People often adopt and receive information from their friends with similar viewpoints (Del Vicario et al., 2016, p.558).

The presence of homophilous social networks does not necessarily mean that an echo chamber effect will exist. Barberá, Jost, Nagler, Tucker, and Bonneau (2015) found that individuals with discrete political views and separate social networks consistently interact in the deliberation surrounding current events. Twitter conversations about emerging current events are successful in penetrating echo chambers. Some research has even suggested that people who use social media sites like Twitter are likely to have relatively diverse social networks (Lee, Choi, Kim, & Kim, 2014). This research can be directly applied to the multilevel model of meme diffusion, specifically, the structural social network level.

Spitzberg (2014) briefly explores the tension between heterophily and homophily. It is posited that in order to diffuse successfully, a meme needs relative internal homophily within social networks, but moderate degrees of structural heterophily at the boundaries of the network in order for information to escape the confines of an echo chamber. Memetic diffusion is positively related to boundary heterophily. Memes that successfully diffuse throughout social media are adopted differently from the majority of memes (Weng, Menczer, & Ahn, 2013). While most messages are trapped within polarized communities, viral memes spread amongst various social clusters freely. This suggest that while online communities tend to be quite homogenous, a degree of boundary heterophily does exist. There is evidence to suggest that certain cross-ideological links are present in communities (Nahon & Hemsley, 2014). These links are not utilized as loci of discourse, but are instead used to “strengthen previously held political stances of the users who create them and negatively portray and reframe content of alternative views” (p. 1309). While connections of this type appear to be cross-linking, they are in fact homophilous nodes.

Therefore, a curvilinear relationship exists between heterophily, homophily, and message diffusion. Generally, homophily facilitates diffusion within networks. Heterophily at the

boundary is necessary for diffusion across communities (Liu-Thompkins, 2012). In the context of political ideology, the diffusion of political messages thus relies on an interaction of conservative and liberal social networks. Without some form of interaction, a meme will likely go extinct, or merely perpetuate its own narrow ecological niche.

Twitter has emerged as the medium of choice for disputes among prominent members of the political and celebrity world. Twitter is increasingly being used as a public means of settling disputes and contradicting opponents. It is in this regard that Twitter has found a unique niche in political campaigning. Where previously, candidates would be forced to rely on the media for dissemination of statements and positions, social media have allowed political candidates to circumvent the need to disseminate their positions through third parties. Arguments and claims against opponents can be levied using Twitter. Weber, Garimella, and Teka (2013) explain how hashtags are used by politicians as a means of competition and argument. There is currently a stark lack of academic research focused on understanding the phenomenon of Twitter wars, it is therefore necessary to develop a typology of memes that are used in political deliberations on Twitter. Shifman (2013) identifies memes through their general attributes that are derived via context and through specific quiddities. She describes quiddities as recurring attributes that are unique to a meme family. Much scholarly research concerning memes has followed a similar thread in attempting to establish an understanding of meanings derived from and created by memes. Where previous research has attempted to map the thematic variations of memes, this research seeks to establish a form-based typology. It is compelling to shift focus from the content of memes and instead focus on the different forms that a meme may take. It is therefore relevant to address the following question:

RQ$_4$: Do distinct types of political memes emerge from a presidential election?

M^{3}D looks at the presence of ideological or sentiment frames and their counter-frames as an important component of meme diffusion. The idea of a frame is akin to that of an actual picture frame. Goffman (1974) argues that *frames* are abstractions that organize meaning and provide emphasis for certain ideas. Frames control attention by selecting what information should be considered relevant (Snow, 2004). In direct opposition to these frames exist counter-frames. Counter-frames are opposing frames of reference and emphasis that vie for legitimacy with an individual's primary framework. Social networks seem to generate around certain ideological frames. These ideological frames may be signaled by their sentiments.

One of the ways researchers have attempted to differentiate social networks is by looking at sentiment analysis. Various methods have been developed to analyze sentiment analysis. Wang, Li, Xu, and Wu (2017) found that sentiment analysis could be used to detect communities in social networks. Cambria, Schuller, Xia, and Havasi (2013) outline the two basic tasks accomplished by sentiment analysis: Polarity classification and agreement detection. Polarity classifications use pro and con statements as ways of understanding whether or not a product or statement is well received. Agreement detection is the second basic task of sentiment analysis. Opinion mining programs attempt to position an opinion on a continuum of values ranging from positive to negative. The use of multiple classifiers in a hybrid manner (Prabowo & Thelwall, 2009), lexicon-based approach (Taboada, Brooke., Voll, & Stede, 2011), and machine-based learning focused on sentiment analysis (Nasukawa & Yi, 2003) all illustrate distinct approaches that can be used for sentiment analysis. Research on sentiment analysis has been used to identify social network clusters, and to predict elections, measure a population's overall happiness, and even look at the overall mental health of the United States (Thelwall, Buckley, & Paltoglou, 2011). Sentiments may represent attempts at emotional contagion and influence, and may signal or frame competing social networks. This research suggests that sentiment analysis could also be used to detect differences between political groupings. Thus, it would be compelling to answer the following question:

RQ$_5$: Does sentiment analysis differentiate social groups?

METHODOLOGY

DATA COLLECTION

A team of researchers at a large public southwestern University developed a Python script that allows researchers to collect the most recent 3,200 tweets created by a specified user, or handle. Instead of capturing all of the tweets relevant to a query, this python script focuses on the tweets of a single specified user (https://github.com/HDMA-SDSU/HDMA-SocialMediaAPI/tree/dev/API-Twitter). Tweets collected in this way provide various different information such as the date and time of the post, the text of the tweet, urls contained in the tweet, hashtags that were used, whether or not it is a retweet, and how many times the message was retweeted.

The current study utilized a unique approach in the study of conversations on social media. Instead of attempting to capture the totality of messages that relate to a specific topic of

conversation, the tweets of political opinion leaders were selected for analysis. In total, 25 accounts were selected for analysis. Two separate sets of selection criteria were utilized. First, all of the accounts selected were required to be political accounts. Political accounts were operationalized as any Twitter handle whose posts and tweets were primarily regarding the current state or goings on of modern day American politics. The face validity of each of the selected accounts was verified by analyzing account pages for words, descriptions, biographies, or posts that specifically referenced American politics. Following initial data collection criterion validity was tested through a search that counted the number of posts that directly referenced the 2016 election and American Politics. The search criteria utilized a series of keywords (i.e. trump, hillary, election, etc.) to check for participation in election-based conversations.

In order to generate a well-rounded cross-section of influentials that participated in Twitter conversations concerning the election, the selection was split among three distinct groups: Conservative, liberal, and moderate. From the conservative and liberal selections, five key accounts (opinion leaders) were selected based on their positioning within political conversations on Twitter. These five accounts were subjected to the following criteria: (1) one must be a presidential candidate, (2) one must be a vice presidential candidate. For each ideological division, three distinct types of opinion leader were also collected, (3) a news opinion leader, (4) an all-purpose American opinion leader, and a (5) major political news organization.

Opinion leader was operationalized as any political account with more than one million followers. Having at least one million followers as a political account points toward centrality in American political conversations. Having one million followers is often cited in literature as a critical threshold for indegree centrality (Cha, Haddadi, Benevenuto, & Gummadi, 2010). The selection of news opinion leaders exclusively included handles that claimed to present political news as the main focus of their posts. Each account's profile was examined for references to American politics in the bio in order to check the validity of each selection. This study defined general opinion leaders as accounts whose posts are not primarily associated with presenting the news, or a specific news organization. The selection for major political news organizations was limited to accounts that focused exclusively on American politics. The final criterion for selection required that each of the accounts represent a regular Twitter user.

Regular Twitter users were operationalized as posting, on average, at least 5 unique posts per day. A list of 5 potential accounts was generated for each of the conservative and liberal,

news opinion leader, general opinion leader, and major news political organization. One account was randomly selected from each list to be used in the final data analysis. These same criteria were used to generate a list of 15 moderate accounts. Two separate sources were used to generate a selection of potential moderate accounts. A portion was selected from Allsides.com, which uses a crowd-sourced voting system in order to determine the political leaning of specific news media sources. Moderate accounts were also selected in part based on a Pew Research Center (2014) article that investigated the favorite news media source of conservative and liberal respondents. News media sources graded as "mixed," meaning both liberals and conservatives felt that they were trustworthy, were included in the list of potential accounts. Of the 15 moderate accounts, five accounts were randomly selected for inclusion.

The second set of criteria for inclusion utilized Brandwatch's (2016) list of the five most influential Democratic and Republican Twitter accounts. This list was based on influence scores created by Brandwatch's proprietary social media analytics software. Brandwatch utilized three different measures in order to gauge the relative influence of all political Twitter accounts. First, they took the total number of times that an account was retweeted. They combined this metric with the number of mentions an account received, and the total number of interactions they have with other accounts.

METHODS

Using the individual user historical tweet collection Python script, the most recent 3,200 tweets for each of the 25 accounts listed in Appendix 1 were collected. The script was run twice, once on October 28, 2016, and again on November 9, 2016. The tweets from the second batch were cleaned to remove duplicate entries that resulted from the script gathering some of the same 3,200 tweets on the less active accounts. This process yielded 95,875 total tweets. In order to narrow down the collected tweets to the presidential election, any tweets before July 2016 were excluded from analysis. In July 2016 both of America's major political parties officially nominated their candidates for president. Collection at these two points in time allowed for the collection of mostly election-related tweets from each candidate, their surrogates, and news organizations. A total of 68,722 tweets fell within the desired range (Jul. 1 – Nov. 9) and were included in the final analysis. This data range encompassed many of the major events that transpired near the end of the election cycle. Presidential elections begin in earnest once each major political party officially nominates their candidate for president.

Word Clouds were created using the Text mining function of the tm R package, and wordcloud R Package. Tm is developed and maintained by Ingo Feiner (https://cran.r-project.org/web/packages/tm/tm.pdf). The wordcloud package is developed and maintained by Ian Fellows (https://cran.r-project.org/web/packages/wordcloud/wordcloud.pdf). A qualitative approach was utilized to analyze thrust-parry cycles. A content analysis was performed to create a typology of thrust-parry attacks and responses. The content analysis specifically looked at the text of the messages, including the URLs, and hashtags in comparison to a timeline of @mentions between each candidate and their surrogates. Memes taking similar forms were coded and assigned a name. The size of the dataset prevented the analysis of every tweet; instead selected tweets were chosen using target selection.

Sentiment analysis was performed using Azure Machine Learning (AML) for Excel. AML uses the MPQA Subjectivity Lexicon. Its dictionary is comprised of 2,533 positive words and 5,097 negative words, each of which is allocated a strong or weak polarity (Jelen, 2016). AML computes a value from 0 to 1, with 0 being extremely negative and 1 being extremely positive. These values are placed in a new column of the Excel spreadsheet and are given the descriptor of positive, negative, or neutral.

RESULTS

Each presidential election within the United States tends to focus on certain unique issues that occur throughout the course of the election cycle. The election in 2016 was beset by a plethora of headlines that dominated the news cycle and political conversations. These major events are often of central importance to the presidential campaigns. Each of these events resulted in exceptionally active Twitter days. In order to provide context for these findings, it is helpful to include a timeline of the major political events that occurred from July 2016 – November 2016 (see Appendix 2). These events often dominate the Twittersphere for days or weeks after they occur. It is important to make note of these occurrences as they often spawn their own hashtags, conversations, and themes.

THE VOTE

In order to determine whether there is a correlation between retweets and candidate popularity, a correlation was performed in SPSS. An 18 x 10 matrix was created. The matrix included values from the conservative and liberal accounts for 18 weeks of data. The median number of retweets was selected first by day, and then by week. The values included for USC

Dornsife and RealClear Politics were lagged one week so as to account for polling delays. A correlation was performed to determine the strength of association between the median number of retweets each week and candidate popularity from RealClear Politics. In addition to the first correlation, another correlation between retweets and USC Dornsife's Daybreak Poll was performed. The USC/Dornsife poll was utilized because it has accurately predicted the last few presidential elections with great precision. A matrix including the correlation coefficients for each variable can be found in Appendix 3.

The first research question sought to answer whether the number of retweets received by influentials could predict candidate popularity (see Figure 1). Four separate correlations were run to investigate whether candidate popularity ratings and median number of influential retweets are associated. A correlation was run to determine whether RealClear Politics' candidate popularity ranking and the median number of retweets across liberal Twitter posts throughout the election are associated. There was a significant positive correlation between the two variables ($R = .645$, $P \leq .01$, $N = 18$). A correlation was also performed to determine the association between USC Dornsife's Daybreak Poll and the median number of retweets across liberal Twitter posts. There was no significant association between the two variables ($R = .329$, $P = .183$, $N = 18$). No significant association was found between RealClear Politics' candidate popularity ratings and median number of retweets across conservative influentials' accounts ($R = .283$, $P = .207$, $N = 18$). Finally, there was no significant association between USC Dornsife's election forecast and median number of retweets across conservative influentials' accounts ($R = .312$, $P = .207$, $N = 18$).

@ECHO #ECHO RT ECHO

Linguistic community detection through Gephi revealed distinct social network clusters present in political conversation on Twitter. Gephi graphs social networks based on similarity of attributes. The tweets with the most similarities are classified into specific modularity classes (see Figure 2). Gephi identified 15 modularity classes after performing a test for modularity. Four communities accounted for 65% of the modularity present in the graph. Modularity classes six and 15 accounted for 43% of the selected tweets. These two modularity classes consisted predominately of Trump supporters. Modularity classes 14 and 19 accounted for 22% of the selected tweets. These two classes were comprised of supporters of Hillary Clinton. The results of the social network analysis suggest that members of distinct social groupings typically

reference many of the same users. Research question two sought to answer whether political conversations on Twitter reflect structures interpretable as communities. The results of Gephi's test for community detection suggest that there are online communities present in political conversations on Twitter.

The second research question also sought to answer whether there is evidence to suggest the presence of an echo chamber effect in online political communication, and whether there is competition among distinct social groupings. Word Clouds were created to map out the distinct communities present in the data. The conservative word clouds share many of the same hashtags (see Figures 3 and 4). For example, #MAGA and #MakeAmericaGreatAgain are the two most commonly used hashtags across all conservative accounts. The liberal hashtag word clouds also reveal a few commonalities among liberals that do not carry across to the Republican users (see Figures 5 and 6). In this instance #StrongerTogether and #ImWithHer could be seen as markers for liberal influential. All of the accounts included in this study used one of these four phrases at one time in a tweet. If one of the accounts used a conservative marker, such phrases were used too infrequently to show up in a word cloud. The accounts that utilized conservative markers did not use the liberal markers. Additionally, if any accounts made use of a liberal marker they did not utilize conservative markers. This suggests that hashtags can be used to define the boundaries of distinct communities on Twitter. People who use the same political hashtags can be considered to be a part of a specific political community. In this instance, users who included hashtags such as #DrainTheSwamp, #MAGA, #AmericaFirst, #crookedHillary, #ImWithYou, #TrumpTrain, could reasonably be expected to belong to the conservative group. Accounts that used hashtags like #ForwardTogether, #BetterThanThis, #LoveTrumpsHate, #DisarmHate would be expected to belong to the liberal group. This suggests that there is some evidence that an echo chamber effect is present in political conversation on Twitter. For contrast, the moderate word cloud revealed modest overlap with the liberal semantic clouds (see Figure 7).

A content analysis of the collected tweets was performed in order to determine whether political conversations occurring on Twitter are representative of competing echo chambers. The following table details specific references to each political candidate (Table 1). This information is helpful in determining whether conversations span across political groupings. While the results tend to suggest that there is division among party lines, there is still overlap among the groups. Influentials on Twitter regularly interact with and discuss members of the opposition

through @mentions. This suggests that the political conversations of influentials on social media have the ability to escape the confines of their echo chambers.

A Chi-square test for independence was performed comparing the frequency of candidate mentions by political grouping (Table 2). A highly significant association was found ($\chi^2 = 2227$, df = 37356, $p < .01$). The table below includes the results of the Chi-square. The cells clearly demonstrate an association beyond what would be expected by chance. For example, there are far fewer liberal mentions of @realdonaldtrump than expected by chance (114 vs. 616), far more conservative mentions of @realdonaldtrump than expected by chance (870 vs. 437), and far fewer conservative mentions of "donald trump" (1545 vs. 2188).

THRUST-PARRY TYPOLOGY

This study developed a form-based typology of the memes utilized in political social media argumentation. Using qualitative date analysis, five unique meme forms were identified as thrust-parry memes. The forms identified were urls, images, hashtags, videos, and RTs. In order to generate these typologies, a search was performed in the text of the tweets that mentioned either political candidate by name or by handle. Two exemplars were chosen to illustrate each of the forms. These exemplars include the original meme, and its counter-meme issued by the opposing political candidate.

URLS

Each of the candidates used urls and links to other websites or news outlets to argue against their opponents. There was an extensive exchange on Twitter between Donald Trump and Hillary Clinton following the release of story by the New York Times claiming that Donald Trump had paid almost nothing in taxes for many years. On 10/2/16 at 3:48, @HillaryClinton tweeted “Trump ‘apparently got to avoid paying taxes for nearly two decades while tens of millions of working families paid https://t.co/s6KgRcoICM.”

At 11:22 @realDonaldTrump responded “I know our complex tax laws better than anyone who has ever run for president and am the only one who can fix them. #failing@nytime.” Hillary Clinton responded with two Tweets that each linked to unique pages in opposition to Donald Trump. At 17:54 @HillaryClinton tweeted “Try our new tool! See how much you'd pay in federal income taxes if you paid the same as "billionaire" Donald Trump (see Figure 8). https://t.co/CD0yzPDqhw”.

Additionally, @HillaryClinton linked to a previous tweet from Donald Trump in 2012

decrying the amount Americans who do not pay income tax. She tweeted the following message: “Now that's pretty rich coming from a guy who paid $0 in taxes for 18 years.” This message linked directly to an article on Hillary Clinton’s website attacking Trump for not paying his taxes (see Figure 9).

At the end of August, each candidate was pressed to answer questions about their health. During that exchange on 8/28/2016 at 23:24, @realDonaldTrump tweeted “I think that both candidates, Crooked Hillary and myself, should release detailed medical records. I have no problem in doing so! Hillary?” Hillary Clinton responded the next morning by linking to an article on her website, calling into question a letter produced by Donald Trump’s physician. On 8/29/16 at 12:50 Hillary Clinton tweeted “We have some questions about this letter from Donald Trump's doctor. https://t.co/0wd7ZSAUx.”

Images. In response to @HillaryClinton’s tweet on 9/27/16 1:10 “We have to build an economy that works for everyone, not just those at the top. #DebateNight https://t.co/XPTvh4Dovf,” @realDonaldTrump posted the following image at 1:32 (Figure 10). In response to @realDonaldTrump’s tweet on 10/20/16 at 1:42 “@HillaryClinton's tax hikes will CRUSH our economy. I will cut taxes -- BIG LEAGUE,” @HillaryClinton responded with the following Tweet and image at 1:43: “@TheEconomist ranked Donald Trump and his economic policies as tied for 4th among the greatest risks to the world” (see Figure 11).

Hashtags. In response to the Hillary Clinton campaign and supporters use of the hashtag #ImWithHer, Donald Trump began to use the phrase and hashtag #ImWithYou. He utilized this hashtag as a means of contrasting Hillary Clinton’s message by appealing to the populist vote. The message was crafted at a time when Trump was attempting to rebrand himself as a caring and empathetic choice for president. Another example of the strategic use of a hashtag in a thrust-parry cycle occurred on 07/25/16 at 22:18. During the days leading up to the Democratic convention, @realDonaldTrump continually made reference to @hillaryclinton as “Crooked Hillary” and on 07/25/2016 at 16:46 he tweeted #MakeAmericaGreatAgain. After winning the Democratic nomination @HillaryClinton responded with her first use of the hashtag #LoveTrumpsHate. She utilizes this hashtag as a direct rebuttal of the messages @realDonaldTrump had been sending prior to that point in the election. She continued to make use of the hashtag in a similar fashion for the remainder of the election cycle.

Videos. During the 2016 Presidential election, both camps also made extensive use of videos. On 8/22/16 there is an exchange between the candidates that tries to appeal to black voters. Each of the candidates tweeted videos that attempted to paint their opponent as racist. Donald Trump began the exchange with the following tweet at 1:19 “"@Jimbos2002: @Morning_Joe Video: Hillary referring to blacks as super predators that need to be brought to heel. https://t.co/pMIHWayMRw." At 2:03 @HillaryClinton responded with, “This week, Donald Trump made a shockingly ignorant pitch to African American voters. https://t.co/acxeolbsuv”. This tweet linked to an article with two videos portraying Trump as racist.

Another example of videos being used during a thrust-parry interaction develops in response to Donald Trump’s comments about Mr. and Mrs. Khan, parents of a Muslim American soldier who was killed in Iraq. Trump’s comments forced him on the defensive after many people expressed disdain for how he treated Mr. Kahn. On 8/1/16 Trump tries to deflect he criticism with the following tweet, “Mr. Khan, who does not know me, viciously attacked me from the stage of the DNC and is now all over T.V. doing the same - Nice!” Hillary Clinton responds with an ad posted on 9/7/16 at 1:00 stating, “’I think I've made a lot of sacrifices.’ Trump's response to the parents of Humayun Khan, who died serving in Iraq https://t.co/B3Av1YtocK.”

RTs. Donald Trump and Hillary Clinton both used RTs during the 2016 Presidential election as a means of arguing their points and contesting the positions of the other candidate. For example, in response to @HillaryClinton’s tweet 10/10/16 at 1:12 “‘I have great respect for women.’ @realDonaldTrump, who said all of these things. #Debate https://t.co/BsW2pUz0hC,” Donald Trump responded at 1:16 with the following retweet: “RT @TeamTrump: Quite simply, @HillaryClinton mistreats women. #BigLeagueTruth #Debate2016”

On September 10, Hillary Clinton and Donald Trump exchange a series of Tweets that illustrate the strategic use of retweets in political thrust-parry cycles. This exchange centered around Hillary Clinton’s comments at a campaign event, that Trump supporters a “basket of deplorables.” At 18:18, @realDonaldTrump tweeted “While Hillary said horrible things about my supporters, and while many of her supporters will never vote for me, I still respect them all!” @HillaryClinton responded by retweeting Donald Trump’s message at 19:04 with the following text: “Except for African Americans, Muslims, Latinos, immigrants, women, veterans and any

so-called "losers" or "dummies." https://t.co/rbBg2rXZdm. Finally, Donald Trump parried with the following at 20:46, “RT @BarackObama: RT if you agree: We need a President who is fighting for all Americans, not one who writes off nearly half the country.” This exchange clearly demonstrates not only the retweets of an opponent, but of a third party used as a parry to an attack.

Presidential elections generated their own unique memes. The fourth research question asked whether distinct types of political memes emerge from a presidential election. Content analysis revealed that novel memes are commonly used in digital political deliberation. The typology developed herein outlines a few of the unique meme forms present in the 2016 presidential election.

SENTIMENT

Sentiment analysis was performed on the entire corpus of tweet texts for each political grouping. The range of the sentiment quotient goes from 0 to 1. A tweet with a sentiment score of 0 would be identified as being extremely negative. For example, on 10/10/16 Donald Trump tweeted “CNN is the worst – fortunately they have bad ratings because everyone knows they are biased.” This would be rated by AML as a negative tweet. In contrast, a tweet with a score of 1 would be characterized as extremely positive. Hillary Clinton’s tweet on 11/9/16 “You represent the best of America, and being your candidate has been one of the greatest honors of my life," would be classified as having a positive sentiment. Tweets ranging from .450 to .550 are classified as having a neutral sentiment. Donald Trump’s tweet on 8/17/16, “Join me in North Carolina – tomorrow at 7:30pm!” is an example of a neutral tweet. Neutral tweets included invitations to campaign events, links to outside websites, and other messages that did not make use of negative or positive words. The results of the sentiment analysis can be found in Tables 3, 3a, and 3b below. The results reveal that the conservative, liberal, and most influential liberal all have a generally neutral sentiment. The most influential conservative had a positive sentiment overall. The moderate news outlets were the only group to have a negative sentiment overall.

The sentiment score for 25 randomly selected tweets was also computed for each of the groupings using specific search terms. The tweets of realDonaldTrump and HillaryClinton were also subjected to the same search. These terms included Trump, Clinton, Democrat, and Republican (Table 4).

The fifth research question sought to determine whether sentiment could differentiate social groups. The results of the sentiment analysis suggest that while each social group was not generally more positive or negative, they can be distinguished using sentiment at the issue level. When looking at sentiment across party lines, liberals reference conservatives much more negatively and conservatives are more negative when referring to liberals (Table 5). Sentiment analysis was able to differentiate the social groupings present in political deliberation on social media.

DISCUSSION

This study sought to clarify the process of political deliberation on social media. Data from Twitter was applied in a novel and unique way in order to illuminate the process of meme diffusion in digital settings. Political communication research has just started the process of using data from Twitter to explain phenomenon in the real world. It is important to consider whether the digital political world mirrors the physical, or is itself a wholly different domain of political deliberation. Previous literature has attempted to use Twitter as a means of understanding various political trends. By incorporating the Multilevel Model of Meme Diffusion, this research seeks to utilize Twitter data as a means of understanding presidential elections. This study contributes to literature on memes and political deliberation and expands on the network and societal levels of the M^3D framework.

The M^3D framework was employed as the basis of understanding how ideas are transmitted through social networks. At the core of any process of memetic diffusion there is a requirement for replication. Retweets are therefore considered to be indicators of influence and resonance. M^3D also predicts that there must be a moderate amount of heterophily in order for a meme to diffuse throughout a social network. It predicts the presence of counter-memes and counter-frames that compete for attention. There is evidence to suggest that political conversations on Twitter can be classified within this framework.

Using tweets from 25 influential political Twitter accounts, the following six implications became evident. First, retweets do not seem to be directly linked to other measures of popularity. This is a potential limitation of the M^3D model. The model regards retweets as an indication of influence. The results of this study revealed a weak correlation between retweets and candidate popularity for Hillary Clinton but no correlation between Donald Trump and the other polls. The reason for this lack of consistency is perhaps explained by the variety of reasons

people might have for retweeting a message, and the ever-changing number of followers that influential accounts possess. As a result of these factors, retweets are not an accurate tool for measuring candidate popularity. It may be that retweets are better indicators of echo chamber reinforcement than attitude distribution generally. The social network structures evident in digital political deliberation restrict the utility of the retweet as a metric for measuring the general public's political attitudes. The variety of ways a retweet can be employed also add to the ambiguity of their meaning. For example, as shown in the typology of thrust-parry cycles, a retweet can actually be used to parry the attack of a user. Certain accounts like AppSame and ChristiChat retweet messages regardless of the content of the message. Additionally, popular Twitter accounts are expected to grow gradually the longer they exist. This can lead to an overall increase in retweets even though there may not have been a significant amount of change in popularity. Future research must account for this shift in followers if it hopes to use retweets as an indicator of candidate popularity.

The findings further suggest that there are distinct social groupings in political conversations online. Social network analysis revealed distinct online communities. Conservative and liberal groups clustered around other users with similar political views. The liberal accounts referenced and linked to many of the same nodes, while conservative accounts were linked by separate nodes. This means that there is evidence to suggest that certain digital political communities do exhibit the characteristics of echo chambers. One unique way to delineate distinct political groupings is through the use of hashtags. Different members of social networks will use group specific hashtags. These hashtags are almost entirely used by members of the in-group. While each social grouping exists in opposition to each other, they still regularly interact with each other. Occasionally, other social groupings will attempt to alter a hashtag and repurpose for their own network. This supports M^3D's characterization of rival social network clusters. The conservative and liberal factions on Twitter are constantly competing for the limited attention of their followers. The thrust-parry cycle exhibited during the election campaigns shows that there exists a certain amount of heterophily in social networks and a structural level of symbiosis. Each of the candidates and their surrogates attempt to respond directly to the messages of their opponent.

The results of the chi-square test for independence on candidate mentions provides additional evidence for the presence of distinct social network clusters. Users tend to reference

members of their own social networks more often than outsiders. The difference in mentions suggests there is a certain degree of competition for attention among political groupings. One unique discovery found during data analysis was the ability to group users by sentiment. Sentiment analysis provided additional evidence for the presence of rival social groups.

Sentiment analysis was unable to detect a general trend toward negative or positive sentiment for each social grouping. In fact, most of the accounts trended toward a more positive sentiment. This is not surprising as communication is generally more positive than negative. Numerous studies have shown that the valence of most communication exchanges tends to be positive (Hardy & Segerstrom, 2016; Serfass & Sherman, 2015; Stieglitz & Dang-Xuan, 2013; Tov & Lee, 2016). Despite the prevalence of positive memes, negative content has consistently been shown to be more influential (Baumeister, Bratslavsky, Finkenauer & Vohs, 2001; Rozin, Berman & Royzman, 2010; Rozin & Royzman, 2001; cf. Tov & Lee, 2016). Research tends to be a bit more divided when attempting to determine whether negative or positively valenced messages diffuse faster and farther. Hornik, Satchi, Cesareo and Pastore (2015) found that negative information is disseminated more often, and for longer periods of time than its positive counterpart. They claim that there is a negativity bias in the diffusion and spread of information online. The results of their study indicate that negative information is able to reach a larger number of people and is more easily assimilated into the belief structure of communities. In contrast to these results, Berger and Milkman (2013) found that positive content is more viral than negative content and it is instead arousal value that determines contagiousness. Ferrara and Yang (2015) posit a slightly more nuanced relationship between positive and negative messages. Certain groups of users are highly susceptible to negative messages. In spite of this, they found that positive and negative tweets are actually quite similar in terms of virality. The lack of clarity concerning valence is best explained through the following discoveries: (1) negative messages disseminate faster (2) positive messages reach more people (3) highly-anticipated events engender positive sentiment (4) unexpected events primarily engender negative sentiment.

Where sentiment was able to differentiate social groups was in topic specific analysis. Sentiment analysis was able to accurately distinguish between liberal and conservative groups on topic specific issue areas. This supports the findings of Wang, Li, Xu, and Wu (2017) that sentiment analysis can be used to discover online communities. Members of each social grouping were consistent in their sentiment concerning each of the political candidates. This

lends additionally credence to the existence of competing rival social groups. One way that the digital world mirrors the physical world is in partisanship. While the digital interface may add one extra step to an interaction, it does not obviate the divisions present in American politics. Sentiment analysis can be used to highlight the frames people use to understand messages online. In this instance, there exist two competing frames: The liberal and the conservative. The divisions along party lines in terms of sentiment reveals that there are competing frames utilized in digital spaces. Political conversations on Twitter tend to mirror the real world. Conservatives tend to have a negative opinion of liberals and vice versa.

Twitter feuds are unique communication phenomena that deserve further scholarly consideration. Arguments that occur on digital landscapes provide different means of producing counter-points and counter-memes. An election can be viewed as a feud between candidates. Twitter is often utilized as a battleground of memes/frames and counter-memes/frames. It is compelling to consider the ways that the feud develops in digital spaces. Ad campaigns often yield response ads; statements often beget statements of their own. Twitter seems to adhere to a similar style, albeit in a new and unique form. This study begins the process of generating a form-based typology of the Twitter thrust-parry cycle. Twitter exchanges take specific forms, and users can strategically choose from those different forms in order to effectively engage in digital political deliberation. There is evidence to suggest that the interactive exchange of positions present in offline interactions can also be found in online environments. The results of this study indicate the presence of a thrust-parry cycle to election related Twitter posts. Political deliberation online also has the ability to generate distinctive types of memes. These messages have the potential for significant disruption of political norms. The results of this study are important because to date, there is almost no social media big data research that utilizes the tweet or the tweeter as the primary unit of analysis. It is the interaction of tweets and tweeters that is the most important relationship to understand. While not every message is directly responded to, certain exchanges suggest an interactive exchange of memes and counter-memes competing for limited attention space.

Frames exist in a state of symbiosis with their counter-frames. Liberal and conservative frames engaged in a thrust-parry cycle illustrate the back and forth necessary for messages to diffuse throughout social networks. Different social groupings can also be distinguished based on linguistic ontology and social network analysis. The survival and replication of a meme is aided

by the presence of competition. Competition forces organisms to evolve and adapt. In much the same way, messages and ideas must be capable of replication and adaption if they hope to survive in a diverse political ecosystem. This competition becomes even more important in the political sphere, where countless opinions are promulgated in order to distract and confuse. Responses lend credence to messages, and serve to increase the longevity of a meme. Future research should attempt to look at the longevity of memes and how the different forms utilized in thrust-parry cycles affect their lifespan.

Validating M^3D is the first step towards understanding how messages are able to diffuse through digital technologies. M^3D provides a guide to understanding how messages are able to spread on social media sites. As a result of this research, and future applications of the M^3D framework, researchers can begin to develop a clear understanding of how messages mirror the evolutionary behaviors of genes.

Limitations

As an exploratory study focused on expanding and validating the Multilevel Model of Meme Diffusion, this study has the following limitations. First, data was collected exclusively from a list of American opinion leaders. The results of this study must be validated against a sample that draws from more members of the general public. There may be a difference in the political deliberation that occurs among the elite users and that which occurs between typical Twitter users. Political deliberation is likely to be very different in mid-term elections. Additionally, this study focused on the conversations that occur surrounding presidential elections. Future studies need to address whether similar tactics and phenomenon are present in Congressional, Senate, state, and local elections.

Finally, sentiment analysis is still a relatively new tool. The use of sentiment analysis as a method of data analysis presents its own unique limitations. For example, Azure Machine Learning has difficulty classifying double negatives and assigning the correct polarity to messages that make use of double negatives. It is also hard to truly delineate between levels of the sentiment analysis scores. On a 0 to 1 scale it is quite difficult to accurately distinguish between what should be classified as very positive or very negative and positive or negative. Additionally, the sentiment analysis performed utilized a lexicon-based approach to determine sentiment scores. The lexicon utilized by AML includes over 7,500 words. While this is a sizable amount, it is feasible that other negative or positively valenced words could have been

present in the data collected. Other sentiment analysis programs have attempted to solve some of these problems by making use of natural language processing programs. Unfortunately, Azure Machine Learning did not have a similar functionality.

Conclusion

The Internet has revolutionized modern society. What is becoming ever more apparent is its profound effect on politics. Aristotle wrote that man is a political animal. Politics are a central component of the American life. Social media have ushered in the era of the digipolitical animal. Researchers in many different fields have begun to explore the dynamics of digital politics. This fervor is only going to increase as social media take a more prominent role in everyday interactions. Donald Trump's presidency is but one example of the unique ways that social media can be employed in national politics. Online political deliberation is a novel means of conversation that requires increased scholarly attention. Platforms such as Twitter provide researchers, politicians, lobbyists, and any other interested parties the ability to collect sizable amounts of easily accessible data. Big data has created the possibility of mapping political beliefs and tendencies in a way previously unfathomable. This study is one such attempt at mapping the digital landscape of political communication. American politics sits at a critical juncture in time. The entanglement of social media, digital technologies, and politics is just beginning. It is paramount that researchers continue to investigate human interaction in these digital spaces. Using this knowledge, an accurate representation of our digital social reality will begin to take shape.

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Table 1. References to Presidential Candidates

	@realdonaldtrump	@hillaryclinton	"Donald Trump" or Donald or Trump	"Hillary Clinton" or Hillary or Clinton	Most Frequent Words
Liberal	114	227	3524	2400	Trump: 3405 Donald: 1851 Hillary: 1735
Conservative	870	406	1545	1628	Trump: 4932 Hillary: 2634 Clinton: 2450
Moderate	1300	734	8174	5226	Trump: 8107 Clinton: 5073 Getty: 1475
MIL	54	233	1251	350	Trump: 1203 Donald: 463 Vote: 450
MIC	1337	835	3886	3264	Trump: 3615 Hillary: 2235 Clinton: 1426

Table 2. Candidate Mentions by Political Grouping

	@realDonaldTrump	@hillaryclinton	Donald Trump	Hillary Clinton	Row Totals
Liberal	114 (616.30) [409.39]	227 (408.35) [80.54]	3524 (3082.36) [63.28]	2400 (2157.99) [27.14]	6265
Conservative	870 (437.66) [427.09]	406 (289.99) [46.41]	1545 (2188.89) [189.41]	1628 (1532.46) [5.96]	4449
Moderate	1300 (1518.28) [31.38]	734 (1005.99) [73.54]	8174 (7593.47) [44.38]	5226 (5316.26) [1.53]	15434
MIL	54 (185.73) [93.43]	233 (123.06) [98.22]	1251 (928.89) [111.70]	350 (650.32) [138.69]	1888
MIC	1337 (917.03) [192.33]	835 (607.61) [85.10]	3886 (4586.39) [106.96]	3264 (3210.97) [0.88]	9322
Column Totals	3675	2435	18380	12868	37358 (Grand Total)

Note 1: The observed count, (expected count) and [cell χ^2 statistic]

Table 3. Composite Sentiment Analysis Scores

	Liberal	Conservative	MIL	MIC	Moderate
Sentiment	.483 (neutral)	.542 (neutral)	.530 (neutral)	.570 (positive)	.443 (negative)

Table 3a. Sentiment Analysis of Conservative Accounts

	realDonaldTrump	AnnCoulter	Foxnewspolitics	Mike_Pence	seanhannity
Sentiment	.550 (positive)	.510 (neutral)	.488 (neutral)	.643 (positive)	.535 (neutral)

Table 3b. Sentiment Analysis of Liberal Accounts

	HillaryClinton	ChuckTodd	CNNpolitics	Maddow	TimKaine
Sentiment	.522 (neutral)	.544 (neutral)	.425 (negative)	.532 (neutral)	.536 (neutral)

Table 4. Sentiment Analysis with Specific Search Terms

	Liberal	Conserv	MIL	MIC	Moderate
Trump	.413 (negative)	.594 (positive)	.402 (negative)	.611 (positive)	.504 (neutral)
Clinton	.536 (neutral)	.427 (negative)	.613 (positive)	.425 (negative)	.509 (neutral)
Democrat	.491 (neutral)	.317 (negative)	.600 (positive)	.384 (negative)	.435 (negative)
Republican	.419 (negative)	.567 (positive)	.360 (negative)	.611 (positive)	.449 (negative)

Table 5. Sentiment Analysis by Candidate with Specific Search Terms

	Trump	Clinton	Democrat	Republican
realDonaldTrump	.683 (positive)	.349 (negative)	.328 (negative)	.611 (positive)
HillaryClinton	.347 (negative)	.672 (positive)	.621 (positive)	.398 (negative)

Figure 1. USC Dornsife/LA Times Presidential Election “Daybreak” Poll

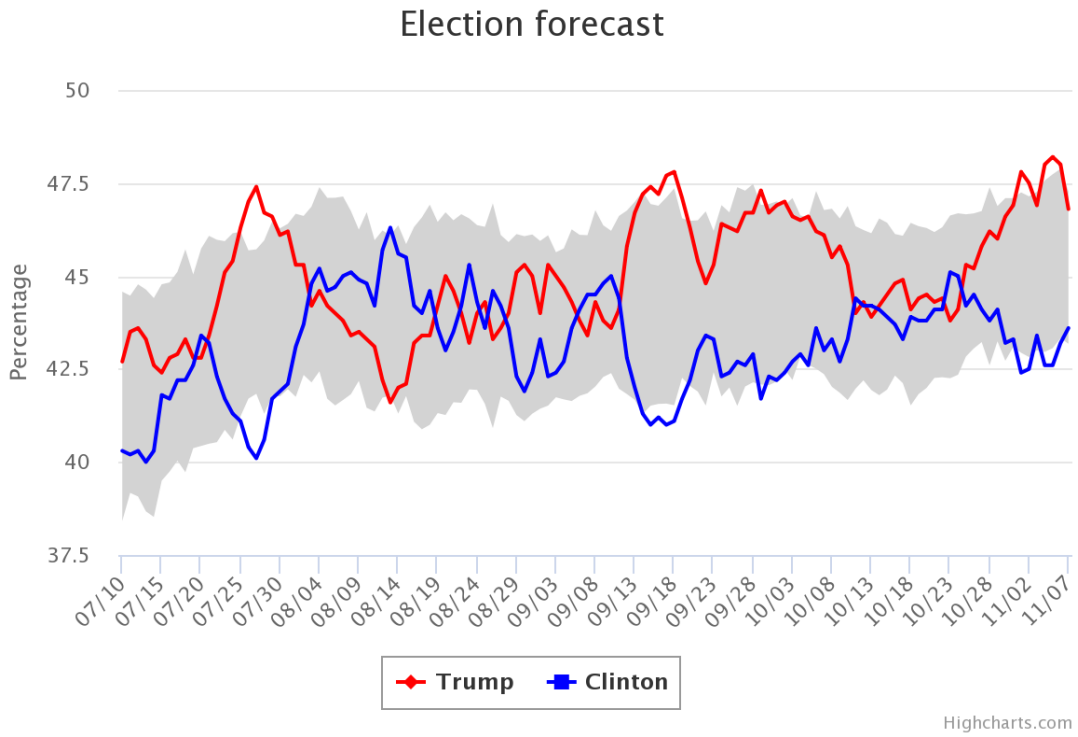

Figure 2. Social Network Clusters

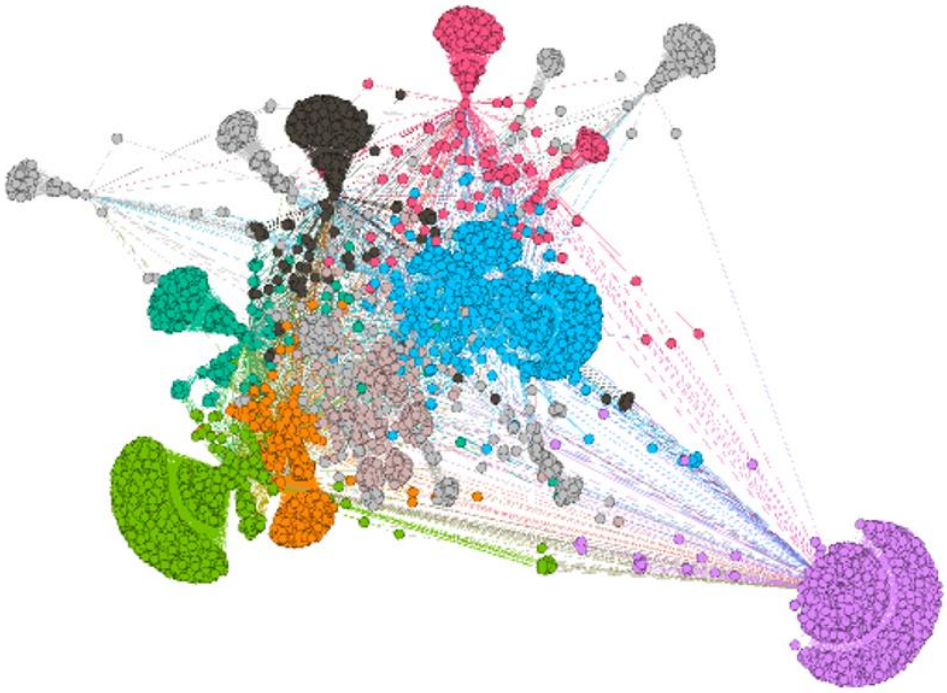

Figure 3. Conservative Hashtag Word Cloud

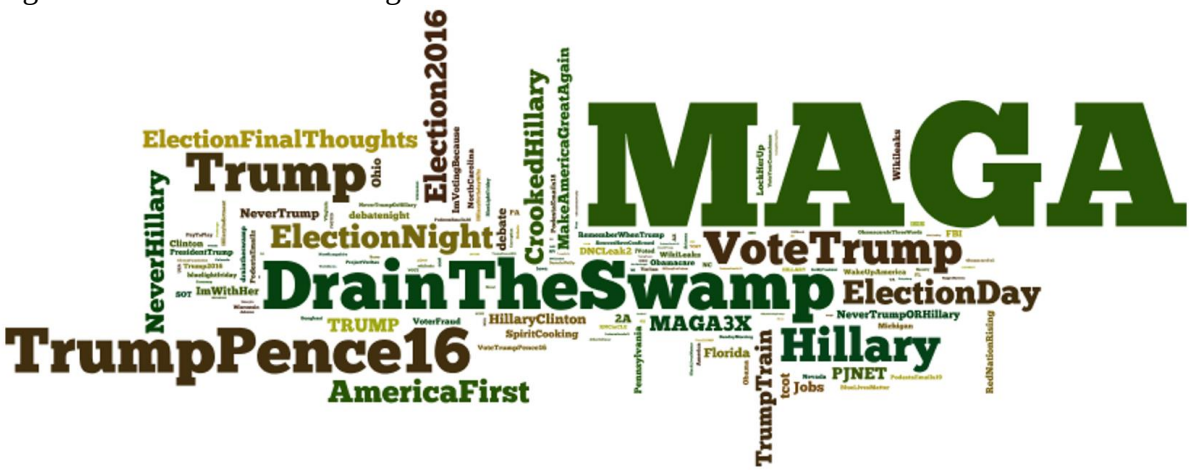

Figure 4. Most Influential Conservative Hashtag Word Cloud

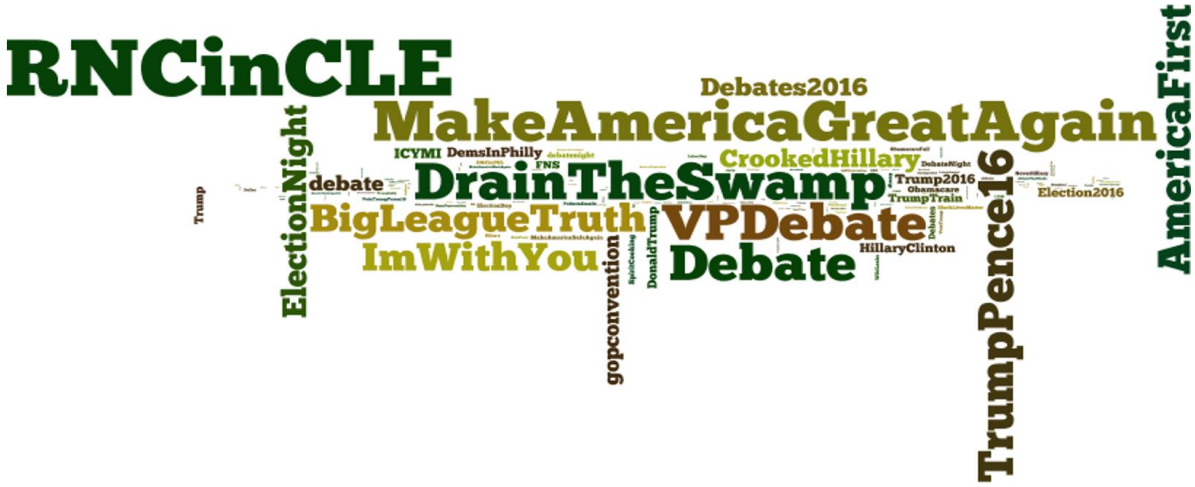

Figure 5. Liberal Hashtag Word Cloud

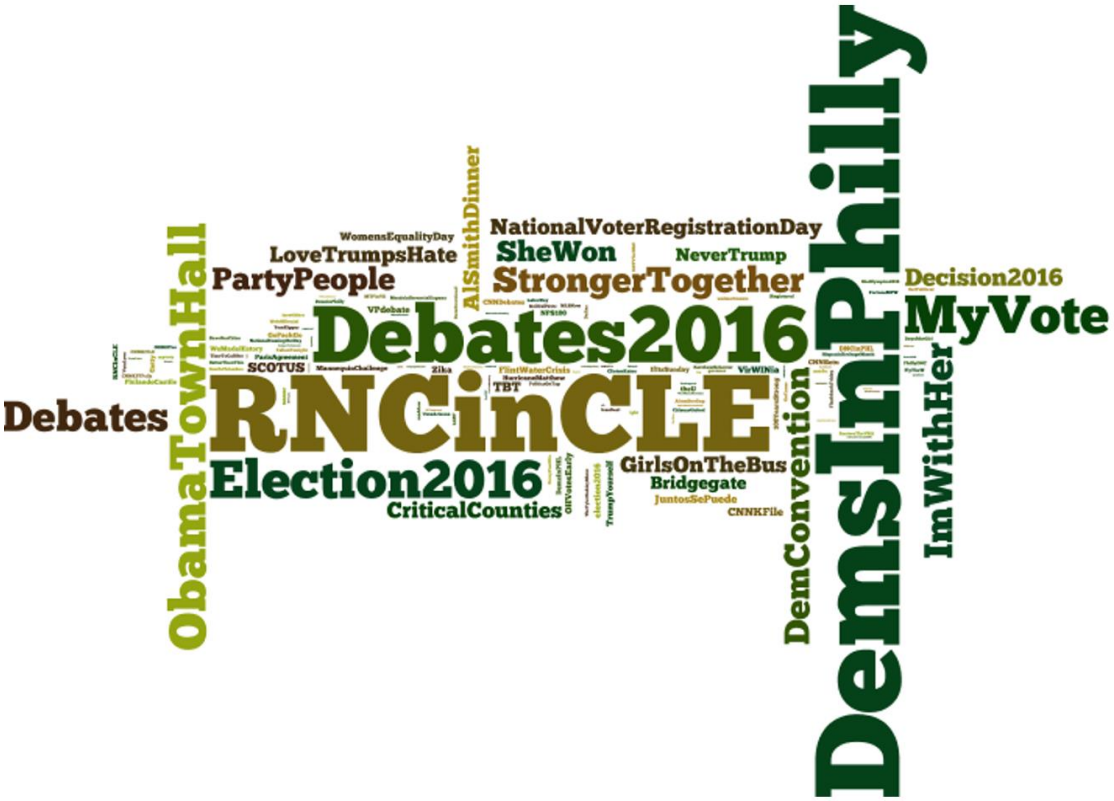

Figure 6. Most Influential Liberal Hashtag Word Cloud

Figure 7. Moderate Hashtag Word Cloud

Figure 8. Smart Tax Calculator

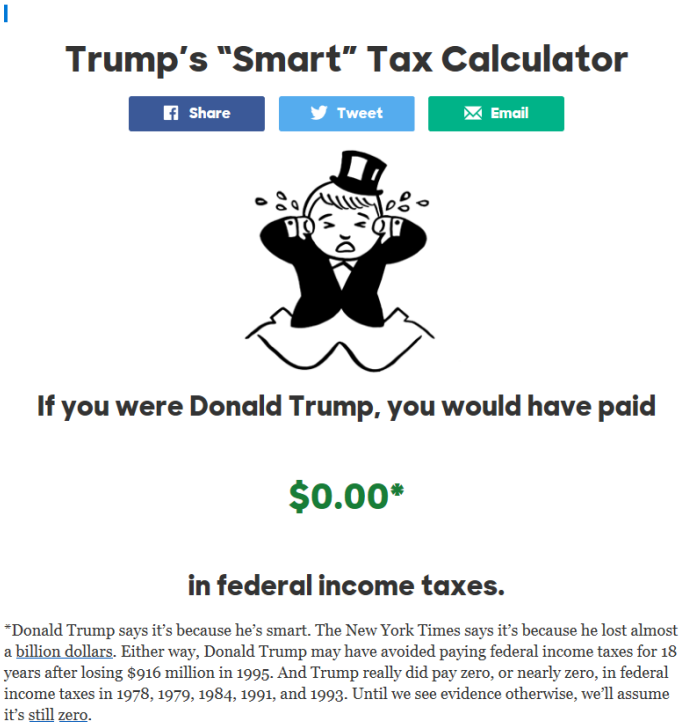

Figure 9. Pay Your Taxes

Donald Trump might have gone decades without paying taxes—but he's not afraid of telling you to pay yours.

Here's what we know about Trump's taxes.

October 2, 2016 by Sam Koppelman

Figure 10. Raise Taxes By $2 Trillion

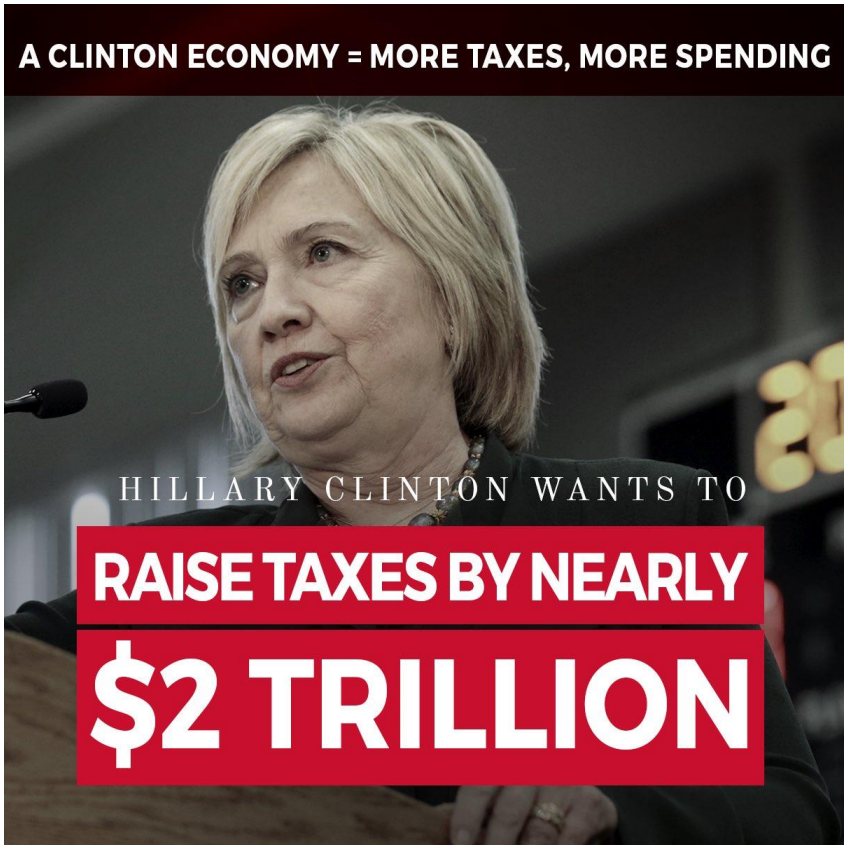

Figure 11. Risks to the Global Economy

Top 10 risks to the global economy

The Economist

Risk	Intensity
China experiences a hard landing	20
Beset by external and internal pressures, the EU begins to fracture	15
"Grexit" is followed by a euro zone break-up	15
Donald Trump wins the US presidential election	12
Currency depreciation and persistent weakness in commodity prices culminate in emerging-market corpo	12
The rising threat of jihadi terrorism destabilises the global economy	12
Chinese expansionism prompts a clash of arms in the South China Sea	12
Global growth surges in 2017 as emerging markets rally	10
Rising tide of political populism in the OECD results in a retreat from globalisation	9
A collapse in investment in the oil sector prompts a future oil price shock	4

APPENDIX 1. SELECTED TWITTER ACCOUNTS

Right Wing

1. Donald Trump (12.2M Followers) Presidential Candidate @realDonaldTrump
2. Mike Pence (332K Followers) Vice Presidential Candidate @mike_pence
3. Sean Hannity (1.67M Followers) News Opinion Leader @seanhannity
4. Ann Coulter (1.02M Followers) Opinion Leader @AnnCoulter
5. Fox News Politics (680K Followers) Major Political News Source @foxnewspolitics

Left Wing

1. Hillary Clinton (9.5M Followers) Presidential Candidate @HillaryClinton
2. Tim Kaine (349K Followers) Vice Presidential Candidate @timkaine
3. Rachel Maddow (5.28M Followers) News Opinion Leader @maddow
4. Chuck Todd (872K Followers) Opinion Leader @chucktodd
5. CNN Politics (972K Followers) Major Political News Source @CNNPolitics

Moderate/ Non-Affiliated Political Twitter Accounts

1. Politico (2.03M Followers) @politico
2. NPR Politics (2.33M Followers) @nprpolitics
3. The Hill (1.37M Followers) @thehill
4. AP Politics (106K Followers) @AP_Politics
5. Reuters Politics (106K Followers) @ReutersPolitics

Most influential Conservative Twitter accounts based on data collected from BrandWatch:

1. AppSame (1.11M Followers, IS: 88) @AppSame
2. Sarah Palin (1.28M Followers, IS: 86) @SarahPalinUSA
3. I'm Chuck, Dude! ;) (111K Followers, IS: 86) @ChuckNellis
4. Michelle Malkin (1.44M Followers, IS: 85) @MichelleMalkin
5. 5. CC (163K Followers, IS: 85) @ChristiChat

Most influential Liberal Twitter accounts based on data collected by BrandWatch:

1. Donna Brazile (555K Followers, IS: 86) @donnabrazile
2. Nancy Pelosi (840K Followers, IS: 85) @NancyPelosi
3. The Democrats (625K Followers, IS: 83) @TheDemocrats
4. Joe Biden (1.22M Followers, IS: 81) @JoeBiden
5. Harry Reid (357K Followers, IS: 81) @SenatorReid

APPENDIX 2. TIMELINE OF MAJOR EVENTS

	Major event
July 12	Bernie Sanders endorse Hillary Clinton
July 15	Trump announces Mike Pence as running mate
July 18-21	RNC
July 23	Clinton announces Tim Kaine as running mate and Wikileaks releases 20,00 emails obtained from DNC
July 25-28	DNC
August 17	Kellyanne Conway promoted to Trump campaign manager
September 10	Clinton calls Trump supporters a basket of deplorables
September 26	First Presidential debate
October 4	Vice Presidential debate
October 7	Tapes leak showing Donald Trump and Billy Bush bragging about sexual exploits
October 9	Second Presidential debate
October 12	Women accuse Trump of inappropriately touching them
October 19	Third Presidential debate
October 28	James Comey announces the FBI is investigating newly discovered emails from Clinton
October 31	CNN parts with Donna Brazile after emails reveal debate questions were leaked
November 6	Comey tells Congress no evidence for Clinton to face charges
November 8	Election Day

APPENDIX 3. RETWEET CORRELATIONS

		USC Trump	RealClearPolitics Trump	USC Hillary	RealClearPolitics Hillary
Conservative	*r*	.312	.283	.371	.491
Compiled	*N*	18	18	18	18
Liberal Compiled	*r*	.440	.348	.329	.645**
	N	18	18	18	18
AnnCoulter	*r*	.213	.198	.307	.403
	N	18	18	18	18
FoxNewsPolitics	*r*	.163	.149	.342	.459
	N	18	18	18	18
MikePence	*r*	.398	.432*	.177	.261
	N	18	18	18	18
realDonaldTrump	*r*	.192	.154	.370	.457
	N	18	18	18	18
Seanhannity	*r*	.284	.236	.272	.401
	N	18	18	18	18
ChuckTodd	*r*	.414	.298	.355	.352
	N	18	18	18	18
HillaryClinton	*r*	.323	.250	.259	.586**
	N	18	18	18	18
TimKaine	*r*	.500	.250	.122	.441
	N	18	18	18	18
Donna Brazile	*r*	.408	.412	.155	.444
	N	18	18	18	18
TheDemocrats	*r*	-.099	-.233	.463*	.658**
	N	18	18	18	18

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).