#Polarized2016:

Affective campaign rhetoric and mass polarization in social media

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Introduction

The 2016 presidential race was considered by many to be one of the most divisive, uncivil, and polarizing political races in recent American history. According to recent polling by Zogby Analytics, 68% of Americans viewed the contest between Hillary Clinton and Donald Trump as being "extremely or very uncivil" (PR Newswire, 2016). This represented a more than three-fold increase over Americans' views regarding the "extremely or very uncivil" nature of prior presidential contests between Barack Obama and Mitt Romney in 2012 (20%), Barack Obama and John McCain in 2008 (18%), and George W. Bush and John Kerry in 2004 (15%). An open animosity between candidates and their campaigns was evident on the campaign trail, in political advertisements, during debates, and in television reporting. In turn, this behavior produced a super-charged political environment ripe with examples of elite polarization. Such conditions provided an excellent opportunity to study what effects, if any, elite polarization has on mass polarization.

The phenomenon of rising elite polarization has also been accompanied by a concurrent rise in the use of social media as a vehicle for political communication. One particularly popular social media platform for this type of communication has been Twitter, which allows users to instantly share thoughts, opinions, and reactions via words, images, and HTML links. One of the most valuable aspects of Twitter is that it provides an immediate snapshot of a person's state of mind; reactions to external stimuli can be measured in near real-time. Just as the conditions of the 2016 presidential race provided an excellent opportunity to study possible links between elite polarization and mass polarization, the emergence of social media as a popular form of political discussion provides an extremely valuable tool for measuring such possible links.

This research examines the extent to which polarizing behavior on the part of elites translates into polarizing behavior on the part of the mass public on social media. Additionally, it measures whether or not messages by candidates have a different amount of influence than messages by the candidates' respective political parties. This research is relevant to the state of the parties, as it contributes to our understanding of social media as a strategic resource for political parties and their candidates. Further, this research adds to the political polarization literature by shedding new light on how the relationship between elite cues and mass polarization is modified by the dynamic environment of social media networks, while also observing how this relationship varies depending upon the mode of delivery.

Political Polarization

Elite Polarization and Mass Polarization

Political polarization is a defining feature of the contemporary American political landscape. By most measures, polarization amongst political elites has reached record levels (Hetherington 2009). A primary tool for measuring polarization among elites is DW-NOMINATE (Dynamic Weighted Nominal Three-Step Estimation), originally developed by Keith T. Poole and Howard Rosenthal in the early 1980s. This tool utilizes roll-call vote records by members of Congress as a means for estimating their position on the liberal/conservative ideological continuum. After multiple iterations over multiple congressional sessions, trends have emerged over time which demonstrate a clear ideological divergence in voting behavior among political elites. In short, Republicans are voting in a more exclusively conservative manner, Democrats are voting in a more exclusively liberal manner. More importantly, there has been progressively less overlap in the moderate areas of liberal Republicans and conservative Democrats.

Recent research suggests polarization in Congress has become so pronounced that congresspersons sharing district borders, yet representing different parties, consistently vote in opposition to each other – even when congresspersons share heavily gerrymandered borders where one would expect some geographical common interests (Andris 2015). These phenomena are indicative of the widening levels of polarization amongst American leaders and are widely considered to influence our political system in a way that causes more harm than good. For example, an increasingly polarized U.S. Congress faces more scenarios where compromise is difficult to achieve, leading to gridlock and – in some cases – threats of a government shut down (Farina 2015).

The extent to which polarization manifests itself in the American electorate is still an open question. Fiorina has provided strong support for the argument that most voters have not been influenced by increased levels of polarization amongst elites (2011). At the same time, polarization can be observed through increased levels "sorting", wherein voters' party identification and ideological self-placement are increasingly aligned (Levendusky 2009). Polarization is also evidenced by a tendency of supporters of one party to follow to demonize supporters of the opposing party (Abramowitz 2013). Further, there is evidence to suggest mass polarization is fueled by deep-seated psychological impulses of "fear and loathing" of members in the opposing political party, especially amongst those who are in the "out party" (Kimball, Summary, & Vorst 2014).

Recent national polls support the conclusion that the American public is increasingly divided along party lines and, more importantly, separated by an increasing gap of partisan identification. The Pew Research Center (2014) found the percentage of Democrats who were consistently more liberal than the median Republican rose from 70% to 94% from 1994 to 2014.

Similarly, the percentage of Republicans who were consistently more conservative than the median Democrat rose from 64% to 92%. During the same time span, the levels of antipathy towards members of the other political party more than doubled, with the percentage of Democrats viewing Republicans very unfavorably rising from 16% to 38% and the percentage of Republicans viewing Democrats very unfavorably rising from 17% to 43%.

Just as levels of elite polarization can be measured by observing behavior on the part of political elites such as voting records or other elite cues, levels of mass affective polarization can be measured by observing variances in mass affective rhetoric. Questions remain as to whether or not high levels of affective polarization translate into high levels of mass political polarization. However, it is reasonable to believe that such a relationship could exist, as an atmosphere filled with strong psychological divisions could be primed for divisions along other lines, given the proper elite cues are delivered.

Such a possibility appears more likely when one considers the possibility that expressions of political polarization in the form of elite cues may have a kind of framing effect on the mass public, wherein expressions of political polarization by elites influences and shapes the mass public's understanding of political reality. Broadly defined, political framing occurs when a story or issue is portrayed using a specific perspective or through a particular lens. Despite being presented with the same set of facts, a person may reach different conclusions depending upon the way an issue is framed. Framing has the potential to be a powerful persuasive tool, as it occurs in a manner that is far less obvious than the traditional means of outlining an argument based upon clearly stated premises and conclusions.

If viewed from a framing theory perspective (Blumler 2015), the framing potential of elite cues would equate to elites affecting not only polarized behavior on the part of the mass public (or, "what to think about") but also potentially affecting polarized political positions on the part of the mass public (or, "what to think about it"). Given the influence of political figures' ideological differences on affective mass polarization (Rogowski and Sutherland 2015), such a causal link is not out of the question. At the same time, it must be noted that in attempting to answer questions regarding the extent and effects of mass polarization on political participation, the vast majority of research has been conducted through the lens of traditional forms of communication, such as mass media messages, candidates' campaigning tactics, or voting behavior of elected officials.

Affective Rhetoric, Incivility, and Affective Polarization

An increasing body of literature is defining mass polarization in terms of affect. While related to the concept of emotion, affect is best defined as "emotion that persuades". When applied to political polarization, this school of thought argues that rather than being driven by political ideology, political divisions in the mass public are driven by hostility towards the opposing party. Instead of a person with one party identification opposing someone with a different party identification based upon ideological differences or policy disagreements, such hostility is the product of psychological mechanisms. Drawing upon a definition of affect as emotional persuasion, it can be viewed as a type of argument that is less cerebral and more base.

When such persuasion is married to party identification and infused within political debate, the results can be detrimental to reasoned discussion. Such partisan discrimination fuels levels of affective polarization that can, in some cases, be equally as strong as levels of polarization based on race (Iyengar and Westwood 2015). These tendencies are troubling, especially given what social scientists know about the myriad divisions rooted in race related issues.

Regardless of whether a causal linkage exists that flows from elite polarization, through elite cues, affective rhetoric, and affective polarization, and results in mass polarization, the political communications literature can be strengthened by better understanding how different types of elite cues influence affective polarization in different types of interpersonal environments. This understanding is especially important with respect to how elite cues delivered in a live, confrontational, and politically charged atmosphere contribute to affective polarization which, in turn, may be creating conditions that may foster mass polarization in online spaces.

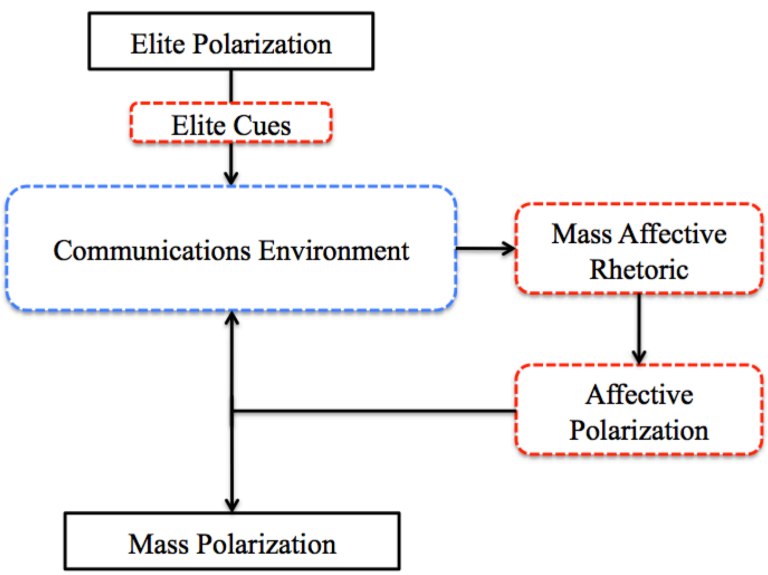
Areas for Growth in the Literature

The bulk of prior literature on political polarization has studied the phenomenon through the lens of the traditional media environment, while using methods appropriate for such settings. However, it is essential to acknowledge that the social media environment is vastly different than the traditional media environment, most notably with respect to the structural dynamics of social media that redefine what it means to be a political elite. As such, this research utilizes a mixed methods approach including social network analysis and visualization in order to better understand how members of social networks react to polarizing behavior on the part of elites.

One major benefit of studying social networks is that it allows researchers to examine how interpersonal relationships and social neighborhoods form in response to "real world" events. Prior research on causal links between elite and mass polarization has primarily relied upon evidence citing individuals' positions on public policy issues and party sorting (Fiorina and Abrams 2008; Hetherington 2009; Levendusky 2009; Abramowitz 2013). While these are definitely useful measures, any ostensible effects are often separated from their purported causes by a considerable amount of time. This time lag allows for a significant muddying of the waters, as individuals have increasingly more opportunities to be influenced by multiple intervening variables as the time horizon between cause and effect increases. Perhaps even more importantly, such measures of a causal relationship largely rely upon self-reporting and proxies, which are prone to subjectivity, reporting error, and imperfect comparisons.

Theoretical Model

I expand upon existing theories regarding the relationship between elite polarization and mass polarization in order to answer the broader question: Does elite polarization contribute to mass polarization in social media? This question is pursued using the following theoretical model:



This theoretical model proposes that potentially polarizing cues originate from elites and enter the communications environment. When the mass public is exposed to these cues, there is a likelihood of increases in mass affective rhetoric which, in turn, could contribute to increases in affective polarization. Due to the unique nature of the social media environment, the mass public is able to re-enter the communications environment to express polarized cues of their own – not unlike the cues originating from elites. In theory, this process could reinforce an increasingly polarized communications environment that creates spaces where mass political polarization can develop. In other words, social media allows for affective rhetoric to not only spread efficiently among the mass public, but to be amplified by members of the mass public as well. Further, it allows for individual communities of ideological homogeneity to form with far greater ease than was previously possible in the traditional media environment.

The vast majority of prior research on elite cues, political polarization, and media effects have been conducted within the context of the traditional media environment. However, a completely different approach is required when testing for potential causal relationships in the social media environment than the approach used when testing for potential causal relationships in the traditional media environment. Such a different approach is necessary because of fundamental differences between the two communications environments.

It is critical to acknowledge the unique nature of the social media communications environment, how it differs from the traditional communications environment, and why this matters when testing this theoretical model. Given the completely different structure of the social media communication environment, it is possible that the influence and reach of elite cues disseminated through social media sources will be different than the same elite cues would be in traditional media sources.

Hypotheses

The following hypothesis are used to measure the extent to which elite affect influences mass affect in social media. These hypotheses are tested using content analysis applied to time series analyses, network analyses, and network visualizations.

H1: Increases in elite affective rhetoric on social media lead to increases in mass affective rhetoric on social media.

H2: Elite affective rhetoric in the form of campaign speeches has a stronger influence on mass affective rhetoric than elite affective rhetoric in the form of social media messages.

H3: Social networks with high levels of affective rhetoric foster conditions conducive to mass polarization.

H4: Social networks with high levels of affective rhetoric enhance the reach and impact of strategic hashtags.

Data and Methods

Data Collection

This research draws upon a large, diverse, and growing set of data. The data set used to analyze candidate language in campaign speech was gathered via *The American Presidency Project*, which is an online source containing over 127,000 official presidential documents, dating back to 1789. The second data set was created by accessing the Twitter API via the NodeXL Excel template (Social Media Research Foundation, 2017) on a daily basis from September 1st, 2015, through the present. The full data is comprised of over 13,000,000 tweets and 260,000,000 words, although only a small portion of this full data set was used to test the hypotheses presented in this research. While other options exist for conducting Twitter API searches, NodeXL was chosen due to its ability to perform a wide range of search functions while keeping the financial costs to the researcher extremely low.

A primary limitation of using the Twitter API for data collection is that the results returned for high-frequency search terms represent a sample of approximately 1% all tweets during the specified search time frame. According to Twitter, these results are “a statistically relevant sample”. Such a rather vague explanation is somewhat bedeviling to social scientists, as it limits the ability to establish the extent to which this ostensibly “random” data is representative of the larger population. Recent research indicates that data acquired via the Twitter API may not be very random after all. For example, when comparing data sets compiled through multiple Twitter API searches, Joseph et al. (2014) found that on average, more than 96% of tweets found in one sample were also found in all other samples. Despite such similarities, the content found in the subset of non-matching samples did not differ significantly in terms of tweet structure or user popularity. It should be stressed that such limitations apply to any scientific study using high volumes of data acquired via the Twitter API.

Given that Twitter operates as a publicly-traded for-profit business, it is likely that Twitter has a financial motivation for not allowing potential business competitors to have insight into the nature of their randomization models, or any other type of proprietary algorithms or code. It is also worth noting that use of the Twitter API seems to be the preferred method for social media researchers, as the only option for avoiding Twitter's black box of "statistically relevant samples" is to pay for access to the Twitter "firehose" or to purchase data from companies specializing in storing hundreds of billions of archived historical tweets. Such access allows researchers access to every single tweet ever sent, typically acquired by purchasing a given volume of tweets (e.g. 100,000) mentioning a give key term (e.g. "Donald Trump") over a given time frame (e.g. 11/1/2016 – 11/31/2016). While such an option provides researchers with the ability to fine-tune the creation of their data sets without needing to perform daily searches, it is also an option that is often prohibitively expensive.

In sum, while there are limitations with respect to how representative the Twitter API's "random" data is of the larger population, these limitations are shared by most researchers in the social sciences. Rather than being a condition that disqualifies the validity or generalizability of results obtained through Twitter API data, it is more of a caveat to be considered when analyzing the results of any study using such data.

Content Analysis

Content analysis is a valuable method for quantifying the frequency of words in bodies of text. Typically, content analysis utilizes specialized dictionaries which organize words within specific categories. Through this process, various meanings and themes within the text begin to emerge. The primary tool for conducting content analysis was Lexicoder 3.0, a software application developed by Mark Daku, Stuart Soroka, and Lori Young at McGill University. This software was used in conjunction with the Lexicoder Semantic Dictionary (Daku, Soroka, and Young 2016). The Lexicoder Semantic Dictionary draws upon a dictionary of approximately 5,000 words and is designed to measure the positive and negative sentiment in political texts.

Network Analysis

When combined with content analysis, network analysis provides a picture of both the nature of political discussion and the efficiency with which this discussion spread throughout members in the network. For example, if content analysis on a specific date demonstrates a relatively high rate of aggressive affective rhetoric, but network analysis suggests a weakly connected network, one could infer that the impact of such rhetoric has been mitigated. Conversely, if content analysis alone was used in this scenario, the more likely inference would have been an overestimation of the affective rhetoric's overall impact on members in the network as a whole. Simply put, content analysis provides valuable aggregate measures – but network analysis puts these aggregate measures into context by taking into account the critical variable of network structure.

The emergence of social media – and of Twitter in particular – has provided a wealth of new opportunities to utilize social network analysis tools as a means for studying human behavior. Social network analysis goes far beyond the ability to produce “eye candy” in the form of striking and often beautiful visualizations. Social network analysis draws upon empirical data to provide context for relationships between individuals and, in doing so, reveals insight into issue trends, influential participants, and a treasure map for learning more about their predominant characteristics. In this respect, social network is a powerful tool for organizing massive amounts of empirical data and allowing the analyst to identify and focus upon empirical data that is most germane to his or her research question. Today, social network analysis is an invaluable tool for making sense of the millions of interactions that occur on an hourly basis across multiple social network platforms.

Increasing numbers of researchers have enjoyed improved access to powerful social network analysis tools in recent years, due largely to the convergence of social media’s widespread popularity with researchers’ access to progressively powerful computers at reasonable costs. Such a convergence allows social network analysts in the “Twitter Age” to design research frameworks capable of sufficiently accommodating Freeman’s four features of social network analysis. Twitter data provides information on the connections between actors and an application program interface (API) that allows for systematic collection of this data, while modern personal computers have the ability to process complex algorithms and convert them into graphical representations of social networks containing tens of thousands of actors. Additionally, powerful software is readily available that allows these graphics to be presented in a manner that clearly illustrates where neighborhoods of discussion form in relation to each other.

Despite the availability of such tools, academic contributions in the field of social network analysis have been sparse until recently. As Williams, Terras, and Warwick (2013) observed, only three academic papers published in 2007 focused upon Twitter in some form or another. This number rose to eight in 2008 and 36 in 2009, with the volume of academic research increasing significantly in the 2010's. It is likely that these increases was due to a combination of several factors. First, the 2010's saw a boon in the availability of progressively powerful and increasingly inexpensive hand-held mobile smart devices which were ideal for using a lightweight and easy-to-use application like Twitter. Second, researchers enjoyed a concurrent rise in computing power alongside a corresponding drop in cost. Third, third-party software developers began releasing numerous inexpensive open-source tools allowing researchers to access the Twitter API at little to no cost to the researcher.

As social network analysis has gained more acceptance within academia, researchers have begun to focus on the issue of political polarization in social media. Early examples include studies examining the extent to which Twitter users cross ideological lines (Himelboim, McCreery, and Smith 2013) and challenge conventional wisdom with respect to media echo chambers (Barberá et al. 2015). These studies have represented valuable efforts to examine and quantify the nature of mass polarization and filter bubbles in social media. There are also increasing numbers of studies drawing upon large *n* datasets spanning several months worth of Twitter messages, many of which are designed to better understand how political information is shared and discussed within social media networks as a whole (Gruzd et al. 2014; Morales et al. 2015).

Time Series Analyses

The first battery of analyses tests the first hypothesis: Increases in elite affective rhetoric on social media lead to increases in mass affective rhetoric on social media; and the second hypothesis: Elite affective rhetoric in the form of campaign speeches has a stronger influence on mass affective rhetoric than elite affective rhetoric in the form of social media messages.

Figure 1.1: Rates of Affective Rhetoric in Official Party Tweets

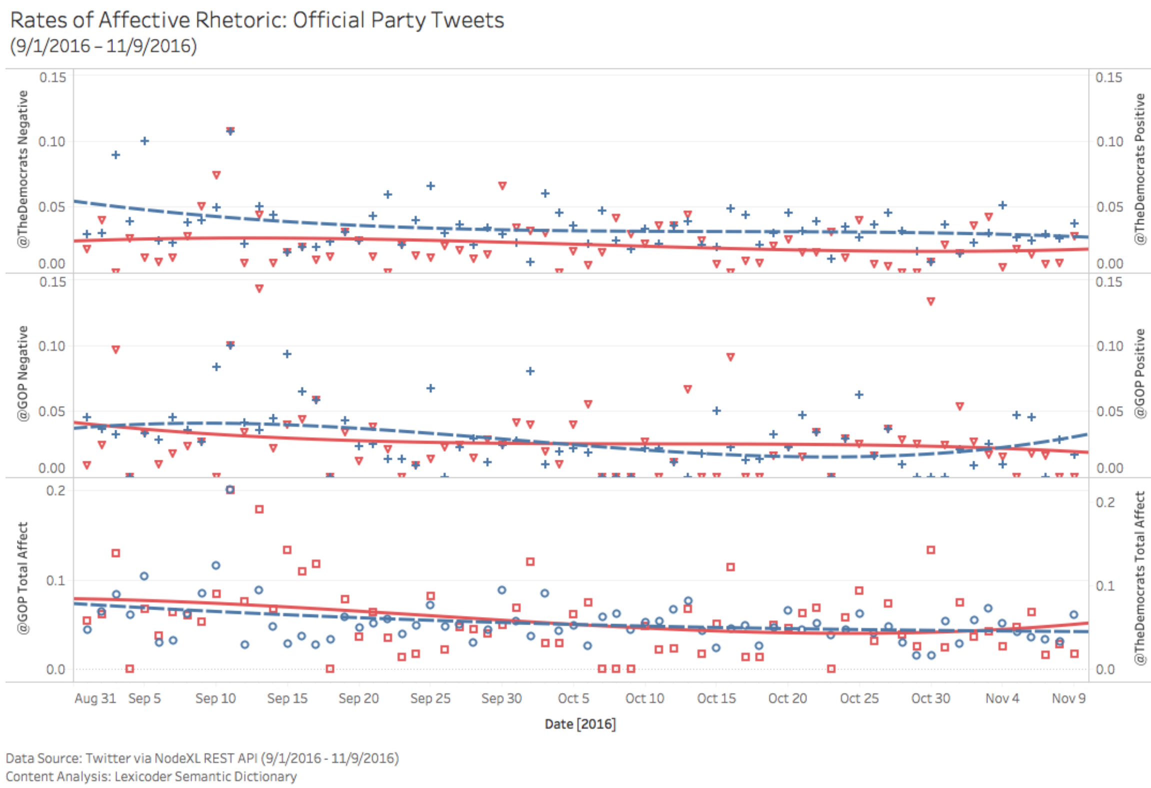


Figure 1.1 provides a general overview of the rates of affective rhetoric in tweets sent by the official Twitter accounts of the Republican (@GOP) and Democratic (@TheDemocrats) parties. Several observations can be made regarding this data. First, affect in @TheDemocrats tweets was consistently more positive than negative, while affect in @GOP tweets varied between mostly positive and mostly negative. There were also larger variances in the frequency of affect in @GOP tweets than there were in @TheDemocrats tweets. Last, when measuring for total rates of affect, both parties engaged in similar frequencies consistently over time.

Figure 1.2: Rates of Affective Rhetoric in Official Candidate Tweets

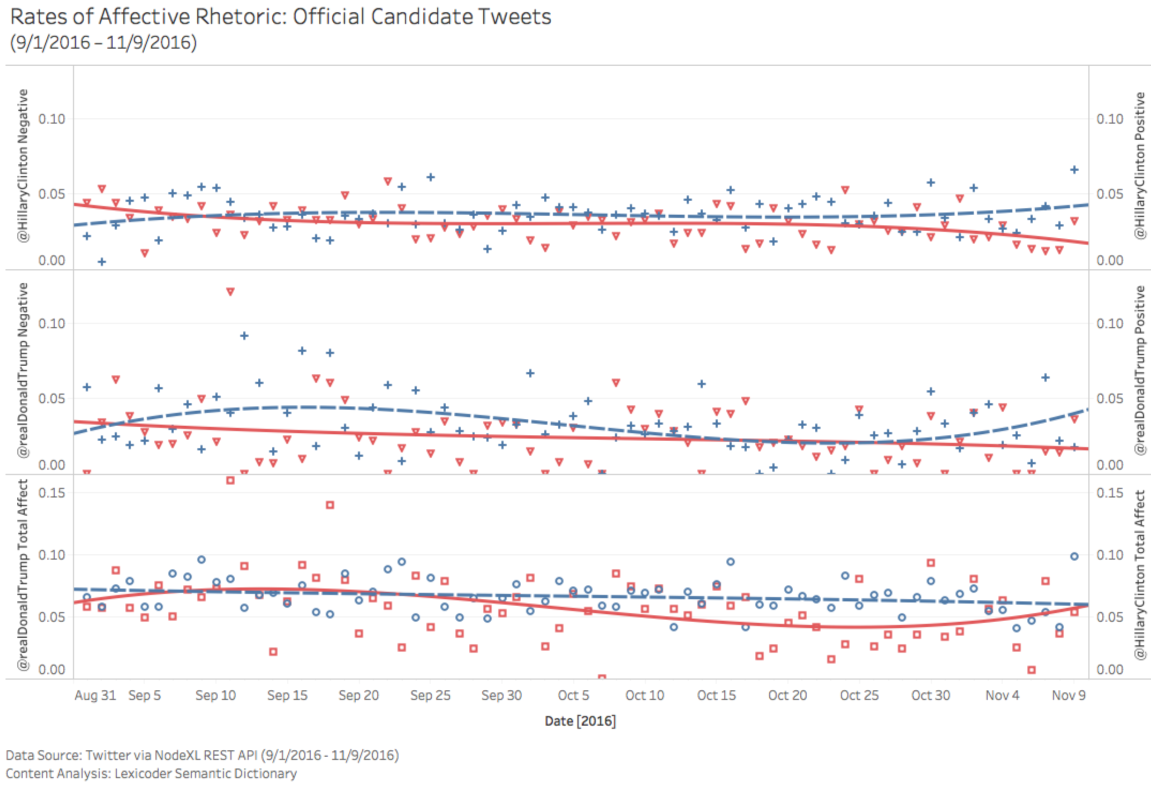


Figure 1.2 provides an overview of the rates of affect in tweets sent from the official Twitter accounts of Donald Trump (@realDonaldTrump) and Hillary Clinton (@HillaryClinton). As was the case with Figure 1.1, a number of observations can be made regarding the rates of affective rhetoric used in the candidates' official Twitter accounts during the final nine weeks of the election. First, the nature of affective rhetoric used by both candidates was consistently more positive than negative. This finding is somewhat surprising, as conventional wisdom would suggest that the candidates were far more negative than positive on social media. Second, the data shows that the use of affect in tweets by @HillaryClinton was quite consistent during the timeframe observed, with the notable exception being an increase in positive affect and a decrease in negative affect during the first week of observation and again during the last week of the election. Conversely, there were more fluctuations in @realDonaldTrump's use of affect, due to a slight lull in positive affect during mid-to-late October, 2016.

But in what ways, if any, did these rates of affect in tweets by the political parties and presidential candidates influence levels of affect in the mass public when the candidates were being discussed on Twitter? The following visuals address this question by analyzing whether there are similarities in the rise and fall in rates of affect that could provide evidence of a causal link between elite affect and mass affect in social media. Figures 1.3 and 1.4 test for this first by examining same-party effects, wherein affect by Republican political elites is compared to the mass public's discussion of the Republican candidate, and affect by Democratic political elites is compared to the mass public's discussion of the Democratic candidate. Figures 1.5 and 1.6 test for a relationship in opposing-party effects by examining whether affect by Republican political elites influences discussion of the Democratic candidate, and vice versa.

Figure 1.3: Effect of Republican Party and Democratic Candidate Affect on Same-Party Candidate Mentions

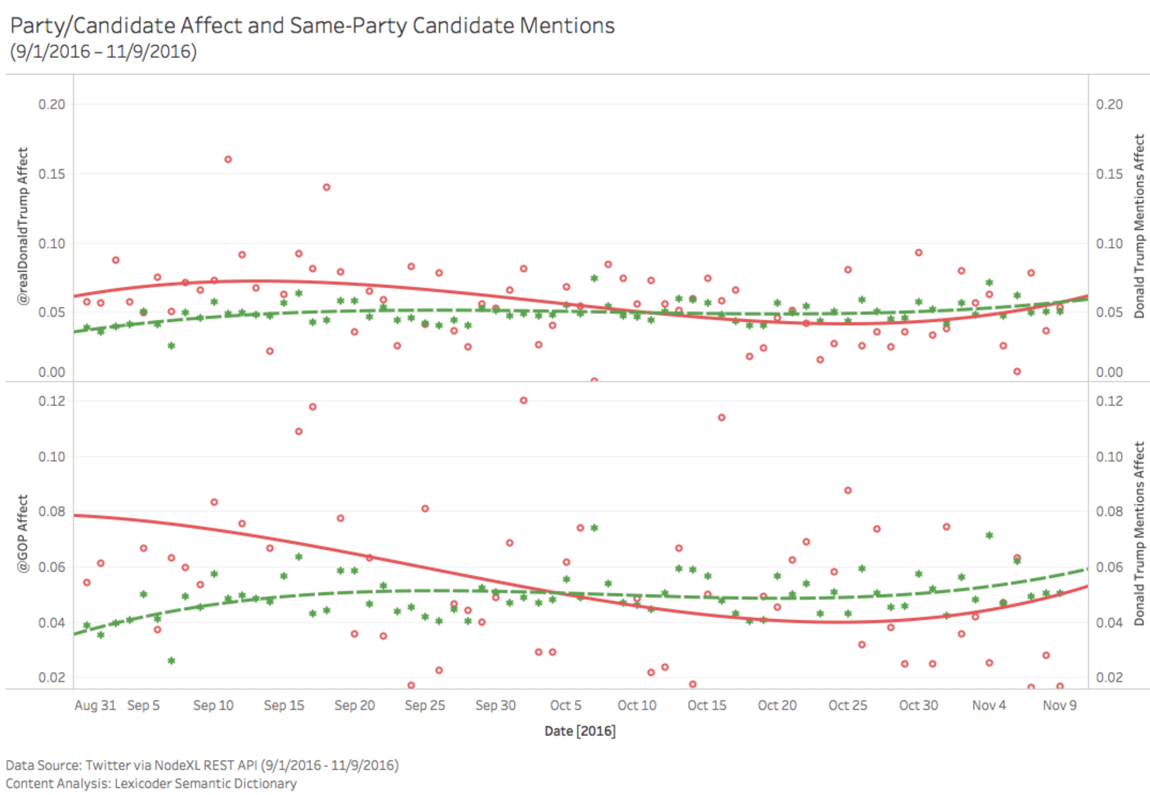
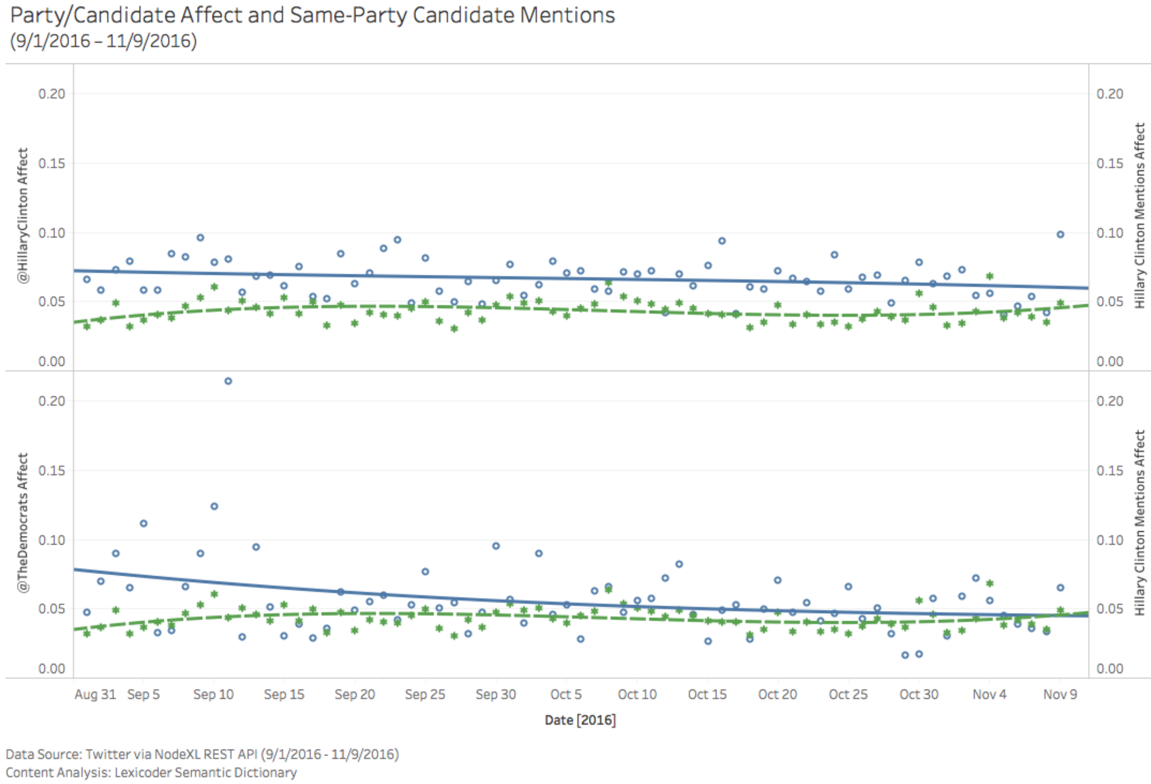


Figure 1.4: Effect of Democratic Party and Democratic Candidate Affect on Same-Party Candidate Mentions



At first glance, the data presented in Figure 1.3 appears to demonstrate a similarity between affect in @GOP and @realDonaldTrump tweets and subsequent affect variances in tweets mentioning Donald Trump. For example, there appears to be some relationship between affect in @realDonaldTrump tweets and tweets mentioning Donald Trump. However, such a relationship is not consistent throughout the time frame observed, even though a tantalizingly possible trend is observable during the early days of September and the later days of October. Such a trend is only observable during mid-to-late October when looking for a relationship between @GOP tweets and tweets mentioning Donald Trump. No such possible relationships can be seen in Figure 1.4. As such, there is little evidence in either of these particular tests to suggest that there is a causal relationship between affect in official party and candidate tweets and affect in tweets mentioning the candidate of the same party.

Figure 1.5: Effect of Republican Party and Republican Candidate Affect on Opposing-Party Candidate Mentions

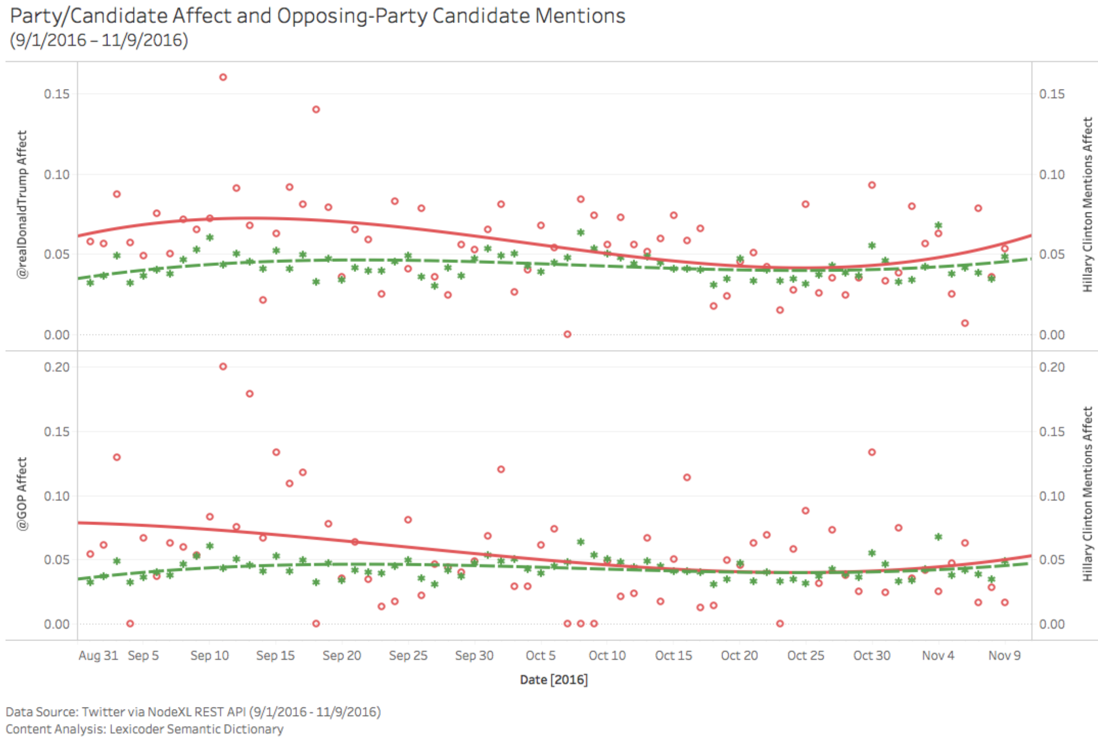


Figure 1.6: Effect of Democratic Party and Democratic Candidate Affect on Opposing-Party Candidate Mentions

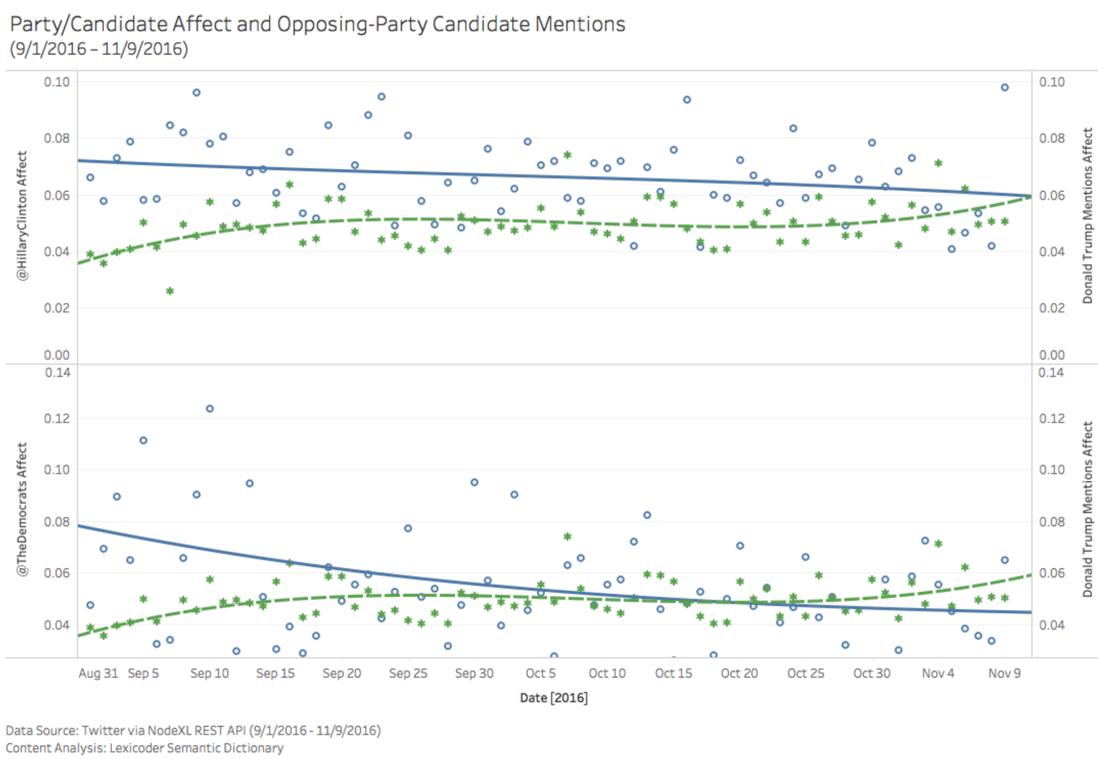


Figure 1.5 presents evidence similar in nature to that which was presented in Figure 1.3. Specifically, there appears to be some relationship between rates of affect in @GOP and @realDonaldTrump tweets and subsequent affect variances in tweets mentioning Hillary Clinton. Such a relationship appears especially evident in early September and mid-to-late October. No evidence of a relationship between rates of affect in @TheDemocrats and @HillaryClinton tweets and subsequent affect variances in tweets mentioning Donald Trump is observable in Figure 1.6.

There are two possible main reasons why there is lack of observable evidence of a causal relationship between elite affect and mass affect in social media as measured by these tests. First, it is possible that the dependent variables – as measured – lack a high enough level of accuracy with respect to actual discussion regarding the candidates. Given the random process of sampling when using the Twitter REST API, it is possible that the nature of this sample varied from day to day. This would result in an inaccurate measurement when observing rates of affect over time. A second possibility is that the mass public discusses candidates differently when using their full names (e.g. Donald Trump and Hillary Clinton) than they do when using their Twitter handles (e.g. @realDonaldTrump and @HillaryClinton). Future research can address these possibilities by using complete data acquired by paying for access to historical data from the Twitter Firehose. Of course, it is entirely possible that the results reported in the previous figures are indeed accurate. Again, future research using the aforementioned paid data sources would confirm or debunk this possibility.

In the absence of evidence of a relationship between affect in official party and official candidate tweets and subsequent affect variances in tweets mentioning the candidates, it is possible that other sources of elite affect could be contributing to the observed shifts in affect in tweets mentioning each of the candidates. A final set of time series analyses were conducted to take into account a more content rich and far-reaching form of candidate communication during the campaign: official campaign speeches.

Figure 2.1: Affective Rhetoric in Campaign Speeches by Donald Trump and Hillary Clinton

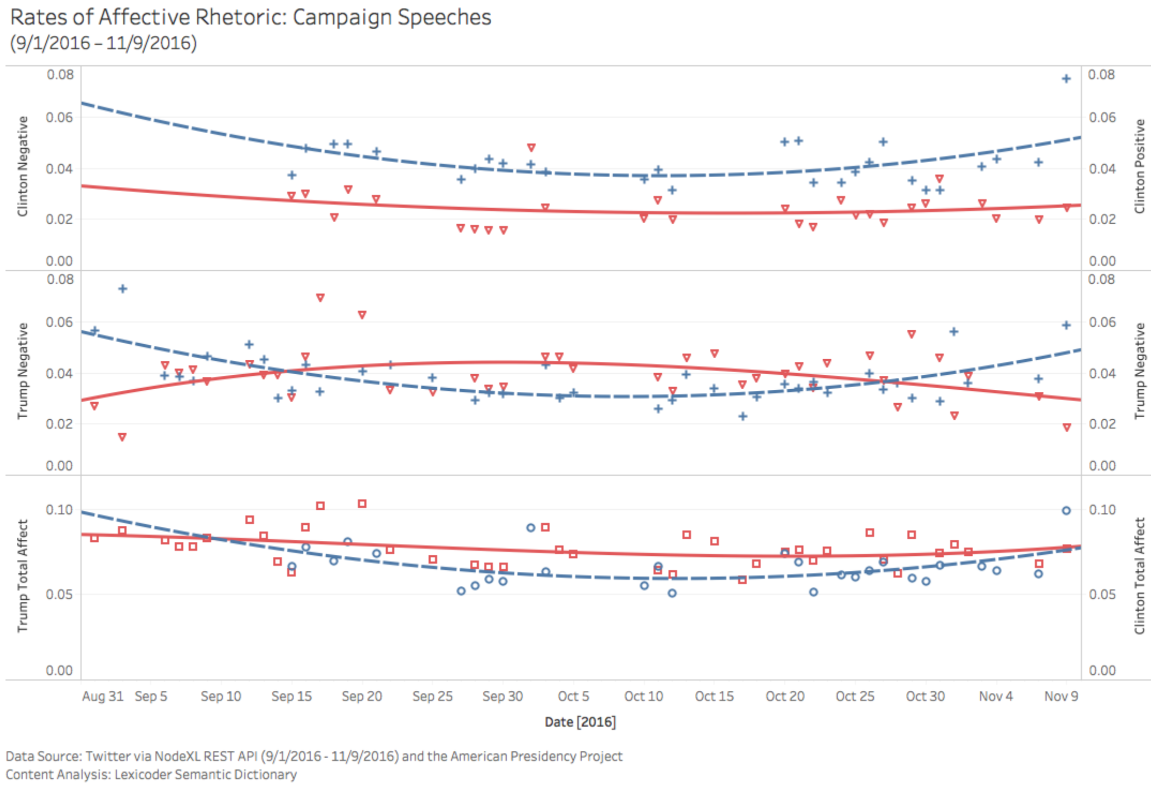


Figure 2.1 provides a general overview of the rates of affect in each of the presidential candidates' campaign speeches from September 1, 2016, through their respective acceptance and concession speeches on November 8 and 9, 2016. During this period, campaign speeches by Hillary Clinton contained, on average, almost twice the rate of positive affect than negative affect. Speeches by Donald Trump contained more positive affect than negative during early September and late October, while containing more negative affect than positive in the weeks between. In general, Donald Trump's speeches contained roughly 20% more affect than Hillary Clinton's speeches. The following figures examine whether or not these shifts in affect impacted same-party and opposite-party affect when the candidates were discussed on Twitter.

Figure 2.2: Effect of Affect in Republican and Democratic Candidate Speeches on Same-Party Candidate Mentions

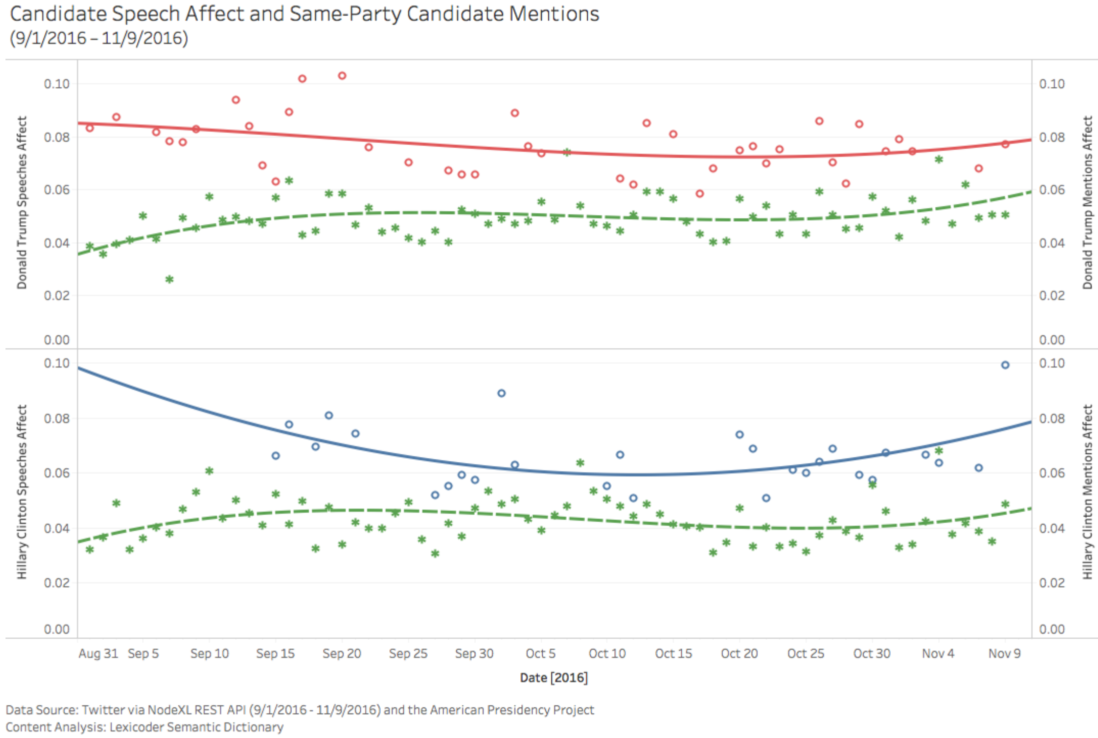
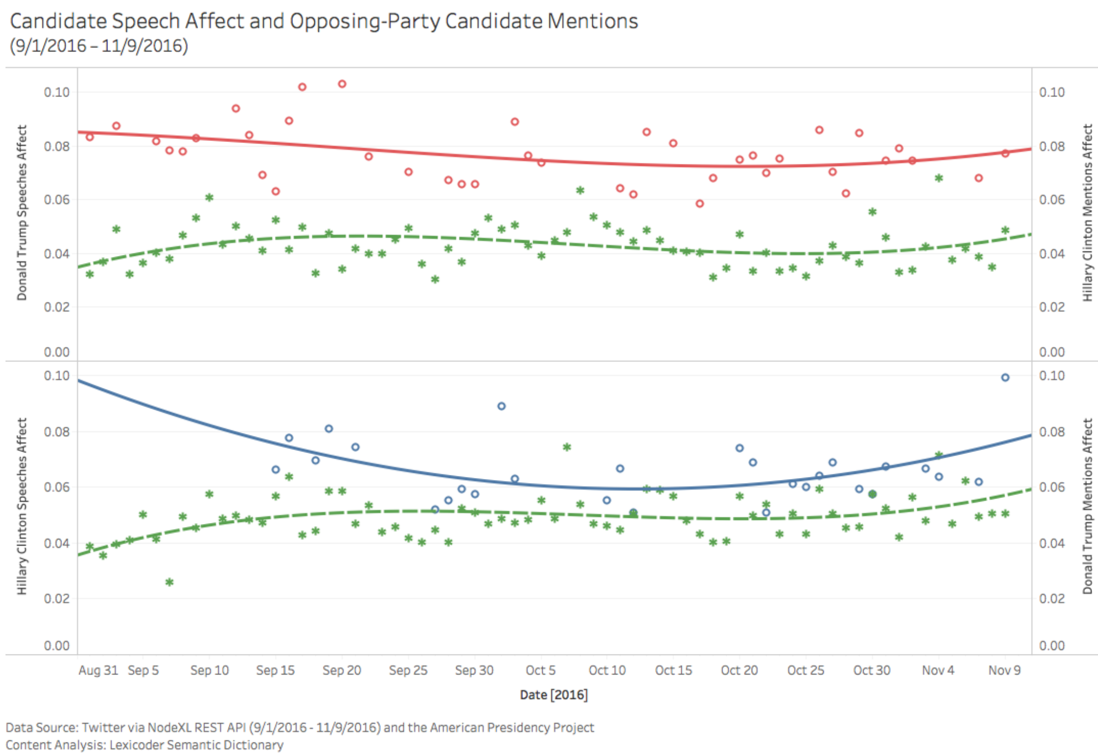


Figure 2.3: Effect of Affect in Republican and Democratic Candidate Speeches on Opposing-Party Candidate Mentions

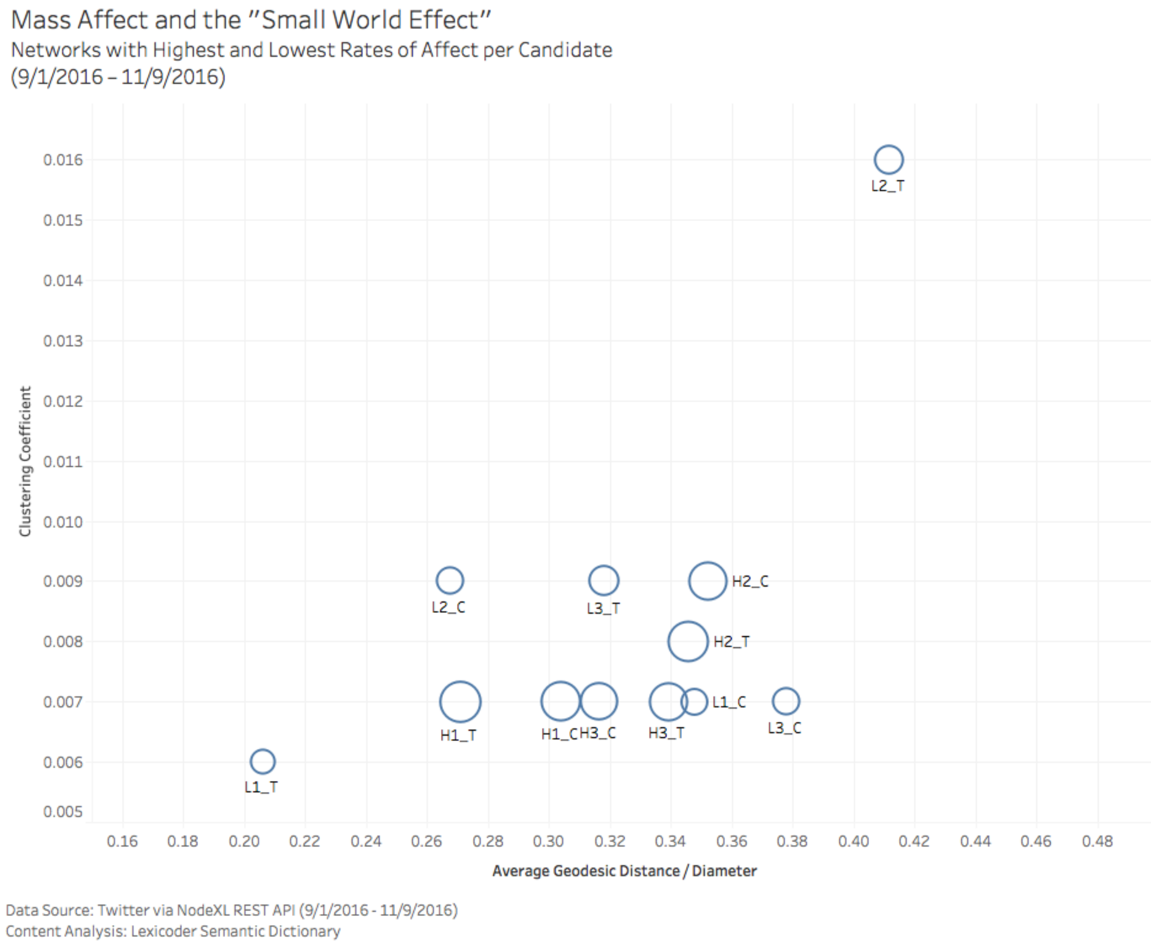


In contrast to previous figures, Figures 2.2 and 2.3 demonstrate a strong possibility of a relationship between affect in candidates' official campaign speeches and subsequent shifts in affect in Tweets mentioning the candidates. This possible relationship exists for both same-party candidate mentions as well as opposing-party candidate mentions, and is especially evident from early October through the end of the election. These findings are noteworthy in that they suggest the mode of delivery matters when measuring for a relationship between elite and mass affect. Specifically, there is evidence that elite affect delivered through televised events (such as campaign speeches) has an observable influence on levels of affect expressed in the mass public when discussing the candidates. However, further research is needed into whether or not such a relationship exists purely within the social media environment.

Network Analysis and Visualization

A final battery of tests was performed to assess the extent to which affective rhetoric fosters conditions in which mass polarization may develop. The first of such tests looked for evidence of a "Small World Effect" in networks with high levels of affect versus those with low levels of affect. A Small World Effect in networks is indicated by densely grouped communities with few connections with other communities in the network. In such a scenario, individuals are more likely to communicate within cliques and, as such, are less likely to be exposed to other individuals in the network. In short, networks exhibiting the Small World Effect are more likely to foster conditions where mass polarization may develop, as people's exposure in the network is limited. Figure 3.1 tests for indications of a Small World Effect in networks with the three highest and three lowest rates of affect in tweets mentioning each of the candidates.

Figure 3.1: Mass Affect and the "Small World Effect"



Two defining features of the Small World Effect are a high clustering coefficient (indicating a high incidence of network members forming dense communities) and a low average geodesic path length (indicating fewer overall "steps" from one node to the next in the network). Hypothesis #3 predicted that networks with high levels of affect would be more likely to foster the development of mass polarization. When comparing networks with the six highest rates of affect with networks with the six lowest rates of affect, there does not seem to be any pattern that would indicate a relationship between affect and the Small World Effect. If anything, networks with high levels of affect tended to demonstrate less clustering and more user interaction than networks with low levels of affect. These findings suggest that mass affect may serve a positive role in encouraging interaction between members in a network.

Despite the lack of evidence of a Small World Effect in networks with high rates of mass affect, an examination of these networks' ability to facilitate political messages still holds significant practical value. This is an area where network visualization offers a level of insight that is difficult to achieve through broad statistical measures of the overall networks. The final set of tests examines the extent to which affective rhetoric facilitates the spread of politically strategic hashtags. These tests focus on high affect and low affect networks both for tweets mentioning Hillary Clinton and tweets mentioning Donald Trump. For each of these four networks, pro-candidate and anti-candidate hashtags are isolated from a list of the top ten hashtags for that network on that day.

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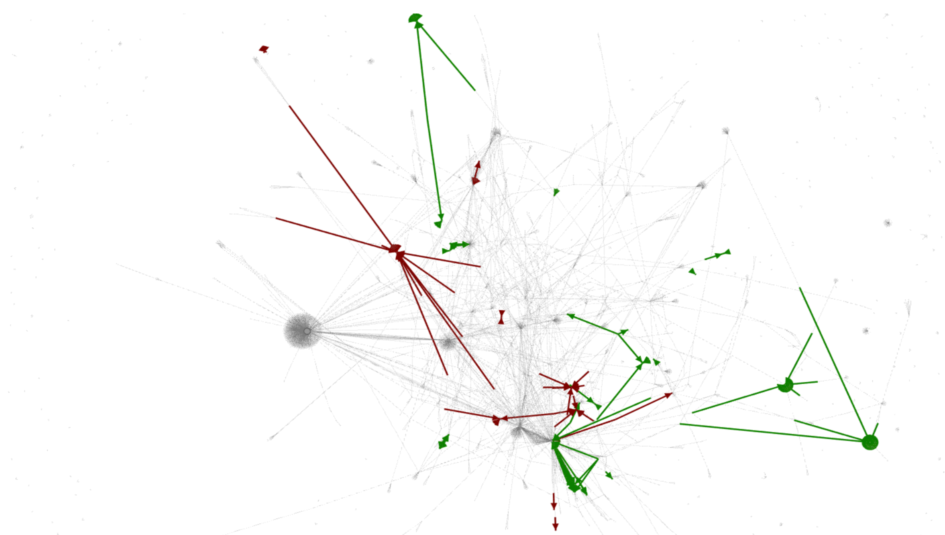
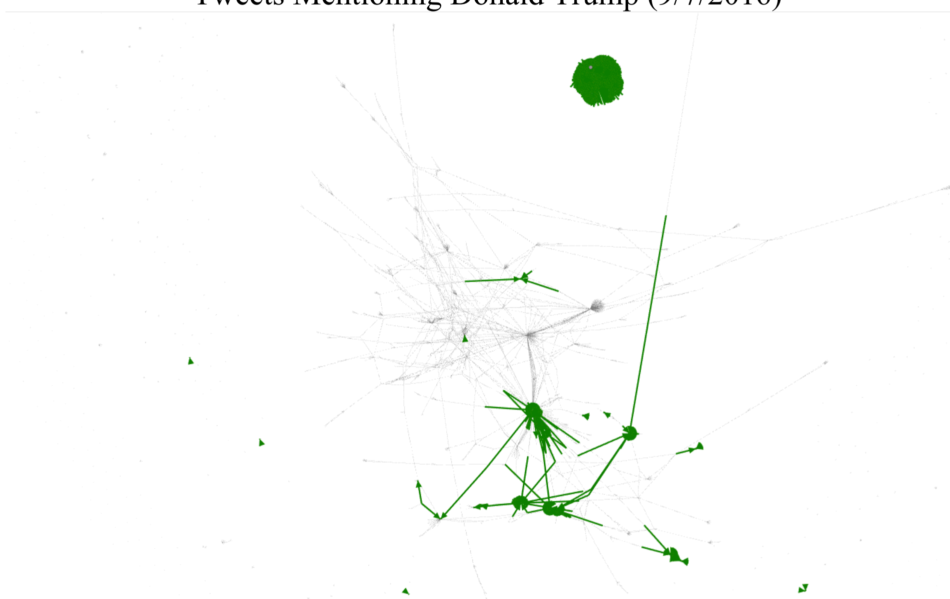
Figure 4.1: Reach and Impact of Strategic Hashtags, High Affect Network (0.713)
Tweets Mentioning Donald Trump (11/4/2016)



Top Hashtags in Network
trump
spiritcooking
podestaemails29
presidenttrump
qaeda
maga
nevertrump
trumptrain
draintheswamp
lockhimup

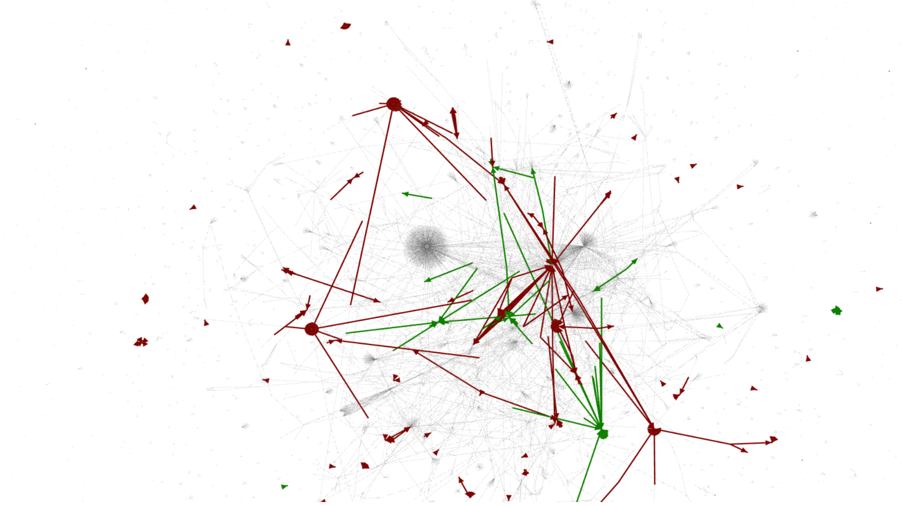
Figure 4.2: Reach and Impact of Strategic Hashtags, Low Affect Network (0.259)
Tweets Mentioning Donald Trump (9/7/2016)



Top Hashtags in Network
trumptrain
trump2016
maga
trump
americafirst
trumppence16
wednesdaywisdom
votetrump
donaldtrump
nbcnewsforum

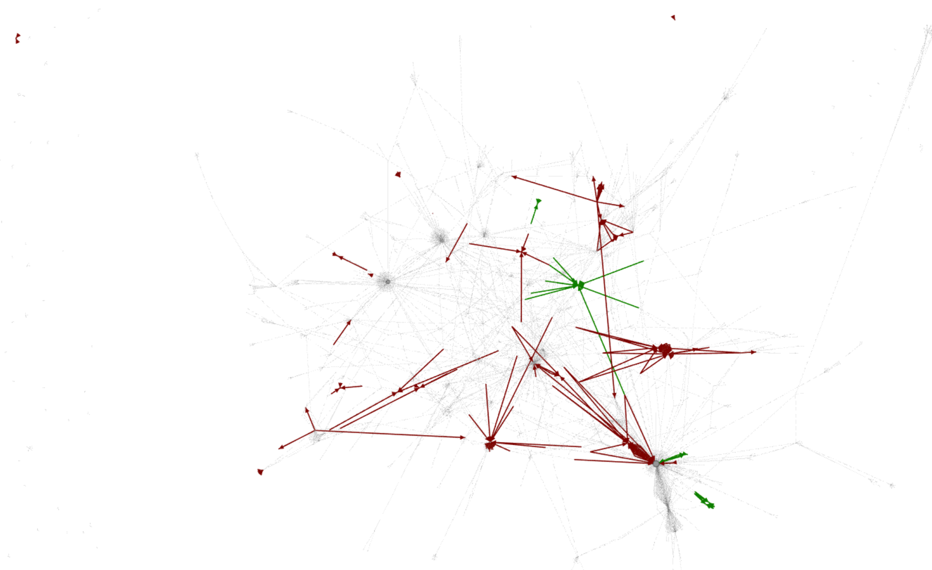
In Figure 4.1 and 4.2, pro-Trump and anti-Trump hashtags are highlighted in order to assess their reach and impact on the broader network. As shown above, the network with the highest rate of affective rhetoric was more effective in spreading both pro-Trump and anti-Trump hashtags than the network with the lowest rate of affective rhetoric. Videos with 3D rendering of these networks are available at http://bit.ly/2y37vvQ and http://bit.ly/2y2poLi .

Figure 4.3: Reach and Impact of Strategic Hashtags, High Affect Network (0.679)
Tweets Mentioning Hillary Clinton (11/4/2016)



Top Hashtags in Network
spiritcooking
trump
podestaemails29
maga
presidenttrump
qaeda
draintheswamp
nevertrump
trumptrain
lockhimup

Figure 4.4: Reach and Impact of Strategic Hashtags, Low Affect Network (0.309)
Tweets Mentioning Hillary Clinton (10/18/2016)



Top Hashtags in Network
hillary
maga
hillaryclinton
draintheswamp
clinton
trump
evangelicaltrump
podestaemails
imwithher
trumppence16

As was the case in Figure 4.1 and 4.2, pro-Clinton and anti-Clinton hashtags are highlighted in Figure 4.3 and 4.4 in order to assess their reach and impact on the broader network. Also similar to Figure 4.1 and 4.2, the network with the highest rate of affective rhetoric was more effective in spreading both pro-Clinton and anti-Clinton hashtags than the network with the lowest rate of affective rhetoric. Videos with 3D rendering of these networks are available at http://bit.ly/2ixqF6P and http://bit.ly/2h60eok .

Conclusions

The explosion in popularity of social media took most observers by surprise. This was also true in the field of political science, as researchers have scurried to play “catch up” in understanding the nature and implications of this new landscape of political communication. Likewise, researchers have been forced to develop new methods and tools to measure and explain phenomena in a manner that takes into account the unique nature of the networked communication environment. The mixed methods approach presented in this research represents an important step in developing such methods and tools.

Does elite affect influence mass affect in social media? The evidence presented in this paper is mixed. There are signs that affective rhetoric on the part of the political parties and candidates on social media does have some impact in the extent to which the mass public uses affect when discussing the candidates. However, greater specificity in how the dependent variables are defined and measured could make this relationship more clear. There is stronger evidence that elite affect expressed in the form of campaign speeches has a much more consistent influence in how the mass public uses affect when discussing the candidates in social media. As suggested earlier, this could indicate the power of televised communication – whether this communication is received by the viewer on an actual television or a streaming device like a mobile phone, tablet, or computer. Regardless, these are findings that warrant future research.

The most compelling findings were presented in the network analysis portion of this paper. These findings have the potential to provide an important addition to the political communication literature, as they present evidence that high levels of affective rhetoric in social networks is not necessarily a negative condition. Further, these findings suggest that measurements of network polarization alone are not sufficient to determine the extent to which a given message will be successful in achieving broad reach and impact in a network. If true, this would have significant implications not only to social scientists, but also to campaign managers, political strategists, and political marketing specialists.

While affective rhetoric can lead to affective polarization which, in turn, can lead to mass polarization, a great deal of this process may be dependent upon network dynamics that can be easily overlooked or inadvertently missed. This research has provided signs that high levels of mass affect could be beneficial, as such an atmosphere could more effectively facilitate discussion between individuals with opposing beliefs. Further, such an atmosphere could more efficiently facilitate the reach and impact of targeted political strategies dependent upon trending hashtags. The research and methods presented in this paper offer a flexible blueprint for measuring such phenomena in future research.

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