

The Elephant and the Bird: Republican Candidates’ Use of Strategy and Issue Framing in Twitter During the 2016 Republican Presidential Primaries

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Studies have demonstrated an increase in the use of strategy framing in coverage of political campaigns over the years, and during campaign cycles. Despite increases in politicians’ and voters’ use of social media, very little is known about the use of framing in e-campaigns. This study examines Republican presidential candidates’ Twitter activity during the 2016 primaries (more than 22,000 tweets). We find that only two candidates, Donald Trump, and John Kasich, have followed the news media tendency to emphasize strategy over issues. Also, candidates dedicated more than a third of their Twitter activity to updating followers on events and the campaign. Using time-series analysis, we found that the use of framing was dynamic over time, with issue framing increasing around debates and strategy around voting days. This study contributes to our understanding of the use of social media as a complementary and alternative method for direct communication between candidates and their voters.

Keywords: framing, elections, e-campaigning, candidates–voters communication, social media, unsupervised machine learning, content analysis

The 2016 race for the United States presidency was perceived by many to be unique because of the prevalence of “personal brawls . . . insults and name calling” (Bradner, 2016, para. 2), as well as a heightened candidates’ online activity in social media (Allcott & Gentzkow, 2017). However, both phenomena are not new to American politics and the media environment and could be seen as the apex of continuing trends. The discussion of politics through a focus on strategy, including emphasis on personalities and horserace perspectives has been on the rise for decades (Aalberg & Brekken, 2007, as cited in Aalberg, Strömbäck, & de Vreese, 2011; Cappella & Jamieson, 1997). Similarly, politicians’ use of social media as a

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Date submitted: 2019–03–17

¹ The authors would like to thank Alexander Castiglione and William Cantor for their assistance in coding the topics, as well as the anonymous reviewers for their constructive feedback to the drafts of this article.

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tool for direct communications with constituents had become central to campaign efforts (Evans, Cordova, & Sipole, 2014; Larsson & Kalsnes, 2014). Both the increase in strategy discourse and in online campaigning had received ample attention from scholars, but more information is needed on their intersection. To fill this gap in the literature, this study examines the use of issue and strategy frames by politicians in social media, to examine whether they use the relative freedom from editorial limitations to provide voters and followers with alternative communications that differ from what is offered in the mass media (Bode et al., 2016). As studies have found that the mass media's use of framing changes over the campaign time line, we examine the dynamics of social media framing as well.

This study explores these questions by examining Twitter communications by the 12 main candidates in the 2016 Republican presidential primaries, who have competed in at least the first primary cycle of the Iowa caucus (i.e., removing short-term candidates such as Scott Walker or Bobby Jindal). We chose to focus on the primaries and not on the presidential campaign to increase our sample size of candidates, as politicians' use of social media drops dramatically after they withdraw from the primary race. To capture the full primary time lines, we analyzed the candidates' use of issue framing on Twitter between July 30, 2015 (a day after the last candidate, Jim Gilmore, presented his candidacy), and June 7, 2016 (the day of the last primary contests), as well as their usage of nonissue messages, including strategy frames and campaign information messages. We examined the differences between the candidates in their Twitter activity, the pattern of their communication across the time line, and the relationship between major campaign events, such as debates, voting dates, and framing choices.

Because of the volume and complexity of the data, we employed a semiautomated method for the analysis that allowed us to reduce the vast number of messages to a manageable set of topics that could be analyzed as representing the full corpus (DiMaggio, Nag, & Blei, 2013). Specifically, we used topic modeling to extract the latent themes in our data set, and then manually analyzed each topic for its use of framing, a methodological move that allowed us to analyze the full universe of candidates' tweets using a reduced form of the corpus. This analysis effectively and efficiently quantified the amount of issue framing, strategy framing, and additional communications that are not part of candidates' framing efforts, such as campaign information (used to mobilize followers and supporters or inform audiences about campaign events; see "Campaign" and "Mobilization" in Evans et al., 2014) and nonpolitical communications (e.g., birthday wishes).

Political Campaigns in Online Media

Since the mid-1990s, "e-campaigning," politicians' presence and activity online, has become an essential complementary part of campaigns (Larsson & Kalsnes, 2014). By the beginning of the 2016 U.S. presidential campaign, social media had become a common practice among virtually all American politicians. Social media channels such as Twitter and Facebook allow candidates to directly communicate with potential voters (Schweitzer, 2008). Campaigning on social media is often relatively cheap (Vergeer, Hermans, & Sams, 2013), and provides a way to circumvent the limitations and gatekeeping functions of traditional news media (Hong & Nadler, 2011) and communicate directly with citizens, journalists, and other politicians (Verweij, 2012). In other words, it allows candidates to have greater control over their messages while avoiding traditional gatekeepers (new forms of gatekeeping exist online, but politicians do not need to adjust themselves to editorial standards and limitations when writing on social media).

Despite this potential, earlier use of online platforms by politicians generally adhered to traditional communication strategies (Schweitzer, 2008). However, e-campaigning kept developing, and contemporary online activity nowadays differs from traditional mass media counterparts in several ways. First, social media political platforms focus more strongly on personalized messages (Vergeer et al., 2013), emphasizing candidates over political parties (Hermans & Vergeer, 2013; van Aelst, Sheafer, & Stanyer, 2012). Second, social media allow politicians to increase citizens' involvement in campaigns, by mobilizing them to donate money, share messages, and attend events (Evans et al., 2014). Third, online communications provide a gatekeepers-free channel to introduce policies, and studies found that audiences who interact with politicians and perceive the communication to be nonmediated can develop more favorable responses toward the politicians (Lee & Shin, 2012) and their policies (Sundar, Kalyanaraman, & Brown, 2003).

One of the most popular social media platforms among politicians and news-seeking citizens (Gottfried & Shearer, 2016) is the microblogging platform Twitter. Twitter's centrality in the contemporary political environment was heightened further since 2015 as a result of candidate, and later on president, Donald J. Trump (Ott, 2017). The increase in Twitter's popularity and centrality during campaigns raises the question of whether this channel provides unique messages to audiences or merely amplifies messages similar to the ones found in traditional news coverage of campaigns. In this study, we examine the use of framing devices in candidates' Twitter activity. Past research on political campaigns have consistently demonstrated the lack of emphasis on issue frames (Aalberg et al., 2011) by, and about, candidates in traditional news media (Cappella & Jamieson, 1997). However, despite the growing centrality of social media to the electoral process, and the availability of automated methods for analyzing complex online data (Schwartz & Ungar, 2015), issue and strategy framing choices by primary presidential candidates in social media received little attention.

Issue and Strategy Framing

A highly prominent theory in communications and other fields, framing received several conflicting definitions by researchers (Cacciatore, Scheufele, & Iyengar, 2016; Entman, 1993; Gamson & Modigliani, 1989; Goffman, 1974; Tversky & Kahneman, 1981). Common to all is the focus on ways in which information can be presented to audiences, and its effects on perceptions and behaviors (Matthes, 2009). The current study relies on a prominent definition, asserting that "news frames highlight certain aspects of news and downplay others through selection, emphasis, exclusion, and elaboration" (Cappella & Jamieson, 1997, p. 77).

In the context of campaigns and elections, Cappella and Jamieson (1997) suggested the competing frames of issue and strategy. Strategy frames focus on winning and losing, use language of war and competition, focus on performance and style, and emphasize standing in the polls and candidates' character. In contrast, issue frames focus on questions of policy and decision making, identifying problems, solutions, and candidates' approaches to these questions (we elaborate more on the exact operationalization of frames in this study at the Material and Method section). Cappella and Jamieson (1997) argued that strategy frames with their focus on winning, losing and self-interest "draw the audience's attention to the motivation of the people depicted" (p. 84). As a result, strategy framing encourages cynicism toward politicians, campaigns, and the political system, through the induction of a belief that politicians' rhetoric and acts are not based

on genuine opinions, but rather on their ability to increase electoral success (Cappella & Jamieson, 1997). Issue framing, on the other hand, focuses the attention of audiences to policy, opinions, argumentation, and substantial political decisions.

Other scholars explored the extent to which traditional news media dynamically employ strategy and issue frames when covering political candidates and campaigns. For example, a study (Patterson, 1994) demonstrated that the share of strategy oriented news in the U.S. have steadily grown from below 50% in 1960 to more than 80% in 1992. Aalberg and Brekken (2007; as cited in Aalberg et al., 2011) found that the prevalence of strategy frames in electoral news coverage has not only grown over election cycles, but also within every cycle, with strategy framing intensifying as the campaigns nears election day. Looking into the dynamic use of framing along campaign time-lines, Patterson (1994) found that the use of strategy framing tended to increase around important primaries events such as Super Tuesday (a major event in American campaign time lines in which ballots are being cast in a large number of states on the same day). Aalberg and colleagues (2011) explained the increase in strategy framing as a result of the sophisticated nature of modern campaigns, the professionalization of political communications and political news media, the lower resources costs associated with production of strategy-oriented news, the proliferation of polling, and the growing focus on celebrity candidates.

Empirical studies demonstrated mostly small to moderate effects of strategy framing on audiences (Cappella & Jamieson, 1997). Moreover, the effects were moderated by factors such as political engagement, sophistication, and knowledge (de Vreese, 2005; Jackson, 2010; Valentino, Beckmann, & Buhr, 2001). Nevertheless, even if the effect on cynicism tends to be small, there is empirical evidence to support the notion that "strategy framing sells." For example, Iyengar and colleagues found that some audiences, especially highly knowledgeable, cynical, urban, and partisan ones, prefer strategy-oriented news (Iyengar, Norpoth, & Hahn, 2004). Supporting the commercialism argument is the fact that strategy framing is less prevalent in public media and elite newspapers compared with commercial outlets (Strömbäck & van Aelst, 2010).

Early studies on issue and strategy framing focused primarily on news content. However, recent examinations of candidates' personal use of framing also identified uses of both issue and strategy frames (Tedesco, 2001). Nevertheless, social media allowed candidates to include messages that were absent from news coverage, and recent studies have found that in addition to strategy and issue frames, candidates use social media for mobilizing voters and disseminating news about campaigns. For example, in the context of Congress races, Evans et al. (2014) examined how candidates use Twitter to communicate with constituencies to get them involved with the campaign, from encouraging donations to providing voting instructions. Moreover, candidates' Twitter feeds served as a "bulletin board" (Evans et al., 2014), informing voters about campaign events such as rallies. We refer to these uses by candidates as "campaign information." Evans et al. (2014) found that this type of communication accounted for about one-third of communications by candidates from the two big U.S. parties. Therefore, we expected many of the candidates' tweets to be used for mobilization. We hypothesized the following:

H1: On average (across politicians and over time), campaign information was the most common component in politicians' social media activity during the 2016 Republican Party presidential primaries.

However, evidence on the use of strategy framing by politicians in their own social media communications is currently scarce. According to the spiral of cynicism hypothesis (Cappella & Jamieson, 1997), the news media's focus on strategy frames might encourage politicians to use strategy framing in their own communication, thus reinforcing the emphasis on strategy framing in all media types. Thus, the commercial pressures that draw news organizations to focus on strategy may be also applicable to politicians' direct communication through social media. In a highly competitive information environment, if candidates assume that audiences are more receptive to strategy-oriented communication, and that such highly newsworthy communications will be more likely to be shared with other citizens (Trilling, Tolochko, & Burscher, 2016), they may want to use more strategy than issue framing. As the popular opinion about the 2016 Republican nomination was that it was highly personal and combative, we hypothesized the following:

H2: On average, politicians used more strategy framing than issue framing in their social media activity during the 2016 Republican Party presidential primaries.

Previous research showed that the prevalence of strategy frames in the news media often changed within the campaign cycle itself, with a general positive trend that peaks toward Election Day, and a rise in use of strategy frames around major political events such as Super Tuesday (Patterson, 1994). We therefore hypothesized that the relative use of different frames in politicians' social media communications will vary over the time line of the campaign. More specifically:

H3a: Strategy framing will increase over time.

H3b: Issue framing will decrease over time.

H3c: Fluctuations in frame emphasis will occur around major political events, such as debates and primary election days.

Material and Method

Data

With the largest pool of presidential candidates ever presented by the Republican party, we chose to limit our sample to the major candidates who sustained a relatively long campaign. This was done to collect data for candidates with sufficient campaign activity for analysis, and with a long enough time line to facilitate aggregated analysis. Therefore, we collected the full content of the Twitter feed for the 12 Republican presidential candidates who remained in the race long enough to compete at least in the first primary cycle at the Iowa caucus. We manually downloaded the Twitter feed content of these candidates between July 30, 2015, a day after Jim Gilmore, the last candidate to join the race, announced that he

would be running, and June 7, 2016, the date of the final five primary contests at which point Donald Trump remained the only viable candidate. Manual retrieval of webpages (followed by automatic parsing of whole webpages) was chosen due to the limited amount of accounts needed, making such procedure feasible, and more importantly to fully ensure that all data from each candidate feed is retrieved. A search query was performed using the candidates' official Twitter account handles during the chosen dates, and the text and date of publication of each tweet was manually collected. A custom-built Python script was then used to parse the retrieved HTML files into machine-readable data. A total of 22,005 tweets were collected, with the highest number of tweets posted by Donald Trump ($n = 4,829$), and the lowest number of tweets posted by Chris Christie ($n = 569$) and Rick Santorum ($n = 579$).

Procedure

Topic modeling is a semiautomated, unsupervised machine learning method that uses a Bayesian generative approach to "mimic" the writing process of a corpus of documents (Blei, Ng, & Jordan, 2003). Its main goal is in data reduction, reducing a large corpus into a smaller and more manageable set of topics: frequency distribution lists of words that tend to co-occur in the same documents, and are thus assumed to share a thematic meaning (Grimmer & Stewart, 2013). Topic models use observed sets of documents to infer the latent topic structure that could generate it. Like other clustering problems, topic models require input from the researcher about the number of clusters (topics), and other hyperparameters (e.g., the monotopical or multitopical nature of documents; see below). The model begins with a random (or semirandom) assignment of words to topics, and then reassigning them randomly over and over in an iterative process until the model converges.

This process provides researchers with two critical outputs. The first is lists of all words and the strength of their relationship with each topic (word–topic matrix). The higher the loading (coefficient between zero and one) for a word on a topic, the more likely the word is to appear with other words from the topic in the same tweets. However, some words, such as "people," tend to be associated with many topics, and while they may load strongly on a topic, they are not unique to that topic. Thus, to describe each topic, we examine words that are highly connected with that topic, but weakly connected with other topics. Therefore, we recalculated these relationships between words and topics, "penalizing" words for associating too strongly with multiple topics (often referred to as FREX words; see Roberts et al., 2014).

The second output is lists of topics prevalence for each document (topic–document matrix). In our case, the theta coefficient indicates how much of the language used in a specific document is associated with each topic. Importantly, topic models assume that each word has a probability to appear in each topic, and that each topic has a probability to appear in each document (thus allowing documents, or tweets in our study, to be represented as a mixture of several topics). Additional information about topic modeling can be found in introductory reviews (such as DiMaggio et al., 2013; Grimmer & Stewart, 2013; Maier et al., 2018). More in depth review of the algorithm used for this study (latent Dirichlet allocation with Gibbs sampling) can be found in Blei et al. (2003).

The texts were first preprocessed by removing links to images or websites, stop words, converting capital letters to lowercase, removing punctuations and numbers, and removing words that appeared only

once (in this order), based on guidelines suggested by Maier et al. (2018). We refrained from lemmatization or stemming due to their possible negative influence on topic stability. Next, we assessed the optimal number of topics for each case study as well as the optimal hyperparameters (to account for the fact that short tweets are expected to consist of fewer topics than longer texts such as news articles). To do that, we performed a grid search over α levels of 0.01 to 0.5, and topic numbers (k) of 2–100, using 10-fold cross validation and focusing on the most common measure for statistical goodness of fit for topic models, perplexity (Maier et al., 2018; Wallach, Murray, Salakhutdinov, & Mimno, 2009). The results of this analysis can be seen in Figure 1. Based on changes in diminished returns when increasing (k) and reducing (α) we decided on a model with 60 topics and an α level of 0.05. As we later aggregate multiple topics into frames, we chose to err on the side of too-many topics, with the possibility of some duplicate topics reducing the efficiency of the subsequent hand coding. The alternative, having too-few topics would have results in mixed topics, which would have reduced the reliability and validity of the subsequent hand coding.

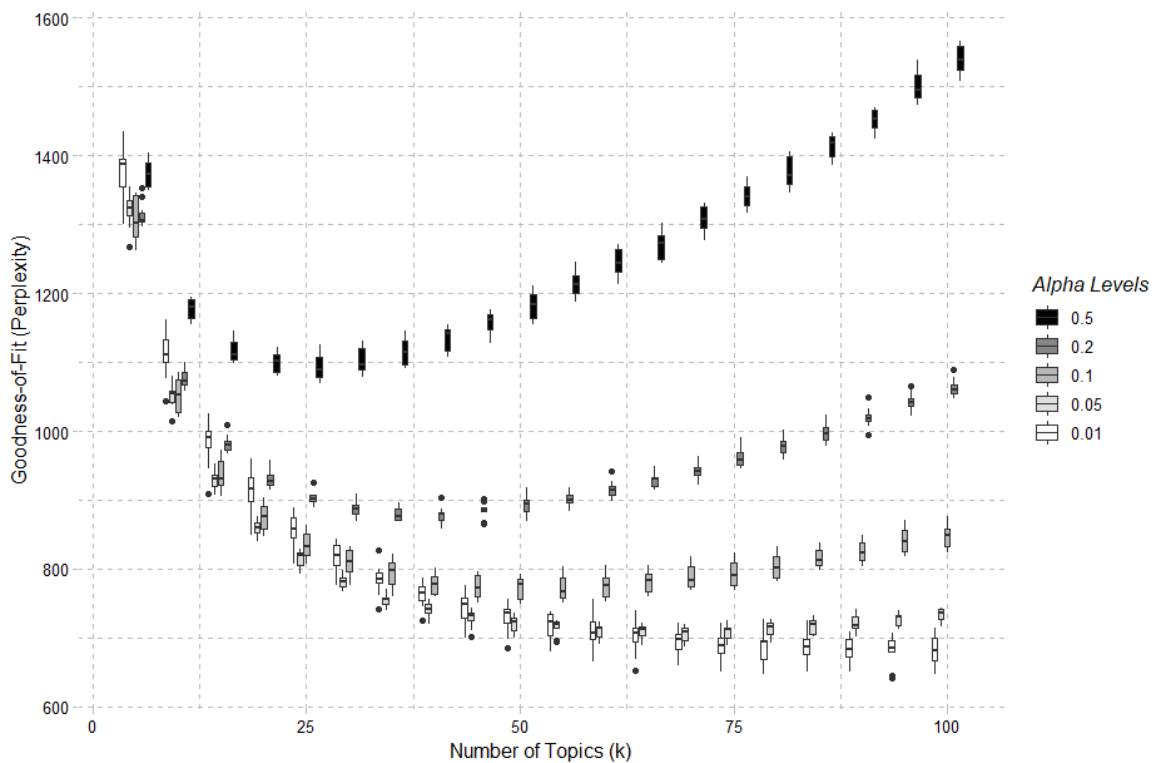


Figure 1. The goodness-of-fit (perplexity) indices for the grid search for models with k of 2–100 and α of 0.01 and 0.5.

To interpret the topics, we examined three types of information; the words with the highest loading over each topic, the words that are both prevalent and unique (exclusive) to each topic (Roberts et al., 2014), and the tweets most representative of each topic. Appendix 1 includes the top unique words for each topic to allow the readers to examine the various topics used for coding.

Measures

To account for the differences between codebooks that were created for the analysis of news content (Aalberg et al., 2011; de Vreese, 2005), and those that took into account the unique characteristics of Twitter (e.g., Evans et al., 2014), the coding of the topics was done in two stages and adopted items from all of these studies. First, coders decided whether or not a tweet included discourse about specific issues. If the tweet was only about issues it was coded 1. If the tweet was a mixture of issue and nonissue language (i.e., issue and campaign information, or issue and strategy, or all), coders evaluated which component was more dominant (2 = mostly issue, 3 = mixed, 4 = mostly nonissue). If the tweet included no issue language at all, it was coded as 5. In the second coding round, tweets that were coded as mostly nonissue (4) or nonissue (5) were coded again for the existence of campaign information, or any of the subframes of strategy language (war/game, character, media, etc.).

Two coders were trained on a different topic model ($k = 31$) of the same corpus, which means that word distributions were different from those used in the $k = 60$ model, to minimize potential biases in coding. The codebook was refined to account for disagreements during training. After training, both coders coded the $k = 60$ model. Topics that did not deal with politics at all (e.g., birthday wishes) were coded as "other." The rest of the topics were coded on a five-level scale (only issue frame, mostly issue frame, mixed, little issue frame, no issue frame), based on examination of the most prominent words, most prominent unique words (FREQ; Roberts et al., 2014), and the 30 tweets for which the topic was most prominent in. Next, the categories of "only issue" and "mostly issue" were collapsed to an "issue" category and "little issue frame" and "no issue frame" were collapsed into a "nonissue" category. This resulted in a three-level scale ("issue," "mixed," and "nonissue"), that reached an adequate reliability (Krippendorff's $\alpha = 0.9$). At the second stage, topics that were assigned to nonissue at the previous step were coded for their nonissue nature. This included campaign information (coded as 1), as well as common strategy framing subframes—namely, strategy/motives (2), winning/losing (3), character (4), media culture and celebs (5), or a mixture of the strategy subframes (6). Reliability for this category was found to be somewhat lower (Krippendorff's $\alpha = 0.7$). However, collapsing this item to a two-category item, campaign information (1) and common strategy subframes (2, 3, 4, 5, 6), resulted in a better reliability score (Krippendorff's $\alpha = 0.8$). Remaining disagreements for both questions between the initial two coders were resolved by a third independent coder based on the codebook.

To assess the validity of our method on the individual tweet level, we conducted two validation procedures using two data sets of manually coded tweets. Importantly, it should be noted that a challenge for such validation is the fact that our method does not simply classify tweets into discrete categories (i.e., issue, strategy, or campaign information), but rather estimates the percentage of language from each framing category in every tweet, while assuming that each tweet is a combination of all categories (as is always the case with topic modeling).

Validation

For the first validation procedure, we used a data set of 100 random tweets and treated the model prediction as a continuous variable estimating the amount of issue content in tweets. We coded individual

tweets following the codebook used to code topics, as described in the Method section. Our reliability for the manual content analysis was adequate ($\alpha = 0.85$). We correlated this ordinal variable, ranging from 1 (*only issue frame*) to 5 (*no issue frame*) with the model estimation of issue language. The Spearman correlation between the manual estimation and the topic modeling prediction was strong ($\rho = 0.72, p < .001$).

For the second validation procedure, we used a data set that included a random group of 33 tweets that were high on issue topics (more than 75% of the tweet content), a random group of 33 tweets that were high on strategy content, and a random group of 33 tweets that were high on campaign information content. We then manually coded these tweets as either "issue," "strategy," or "campaign information." Our reliability for the manual coding was 0.88. Using a confusion matrix, we examined whether the manual coding for each tweet was in accordance with the group from which it was retrieved. Our classifier achieved an accuracy level of 0.86. All in all, we found that the method was able to reasonably, efficiently, and automatically classify the various tweets to the frame used. However, we caution readers to remember that this method is not intended for classification, but rather for the estimation of mixed frame content in each tweet (as no tweet is composed of only 100% strategy, issue, or campaign information content).

Results

Descriptive Statistics

Table 1 presents the coding of topics into frames (a detailed table of top unique words for each topic can be found in Appendix 1).

Table 1. Descriptive Statistics for the 60-Topics Model.

Communication type	# topics	%	Topics included (see Appendix 1 for details on topics)
Issue	17	28	3, 12, 20, 24, 25, 26, 34, 44, 49, 50, 53, 54, 55, 56, 58, 59, 60
Mixed	4	7	1, 11, 15, 47
Other	4	7	22, 23, 40, 41
Nonissue	35	58	2, 4, 5, 6, 7, 8, 9, 10, 13, 14, 16, 17, 18, 19, 21, 27, 28, 29, 30, 31, 32, 33, 35, 36, 37, 38, 39, 42, 43, 45, 46, 48, 51, 52, 57
<i>Strategy/motives</i>	1	2	19
<i>Game/war/winning</i>	2	3	46, 51
<i>Characteristics</i>	3	5	4, 17, 42
<i>Media/celebs</i>	2	3	31, 32
<i>Strategy mixed</i>	6	10	5, 6, 9, 35, 37, 45
<i>Campaign info</i>	21	35	2, 7, 8, 10, 13, 14, 16, 18, 21, 27, 28, 29, 30, 33, 36, 38, 39, 43, 48, 52, 57

A total of 17 topics were coded as issue, 35 were coded as nonissue, and four topics were coded as not relating to politics (other). Of the 35 topics coded as nonissue, 21 were coded as campaign information and 14 as strategy. Lastly, of the 14 strategy-related topics, one was coded as strategy/motives, two were coded as game/war, three as relating to candidates' character, two to media and celebrities, and six were mixtures of strategy subframes.

To calculate the salience of frames in each document (tweet), we summed up the topic salience for the document over each topic corresponding with a specific frame. For example, the salience of the subframe "campaign information" was calculated as the sum of the salience of the 21 topics corresponding to that frame. Thus, our analysis examines frames as an aggregation of topics rather than treat topics as frames.²

Turning first to the volume of activity by candidates, Figure 2 presents the combined number of tweets posted by all candidates, with annotations for key political moments during the time frame. Dotted vertical lines indicate Republican debates, dashed lines indicate Democratic debates, and solid lines indicate major voting days. These included the first elections in Iowa (February 1), the last competitive elections in Indiana (May 3), and major election days in which five or more states participated.

As can be seen in Figure 2, the total number of tweets per day varied greatly over time. In terms of trend, volume increased toward the Iowa caucus (first primary elections) and began declining after that as candidates started withdrawing from the race. In terms of local fluctuations, volume corresponded to the Republican debates and major electoral events. The sharpest peaks in activity can be explained by either debates or major primary elections dates, but some lower peaks can also be observed that do not correspond with these events (though these peaks were minor compared with debates and election days). As for specific candidates, Donald Trump was the most prolific tweeter, with 4,814 tweets, followed by Ted Cruz (3,112) and Rand Paul (2,399). The candidates who tweeted the least were Jim Gilmore (789), Rick Santorum (575), and Chris Christie (569). Most candidates reduced their Twitter activity greatly after withdrawing from the race.

² It is important to note that we coded topics, not single tweets. Moreover, each tweet was considered by the model to be a mixture of topics. Thus, our method allows us to code the communication by candidates not on a binary issue versus nonissue scale, but as a mixture of all different frames. In addition, the prominence of the different topics was not identical, with some topics being more salient in the sample. Therefore, in the following analyses, when estimating the amount of frame usage, we incorporate the prominence of the topics (over time and between candidates) and the multitopical nature of the tweets into our estimation.

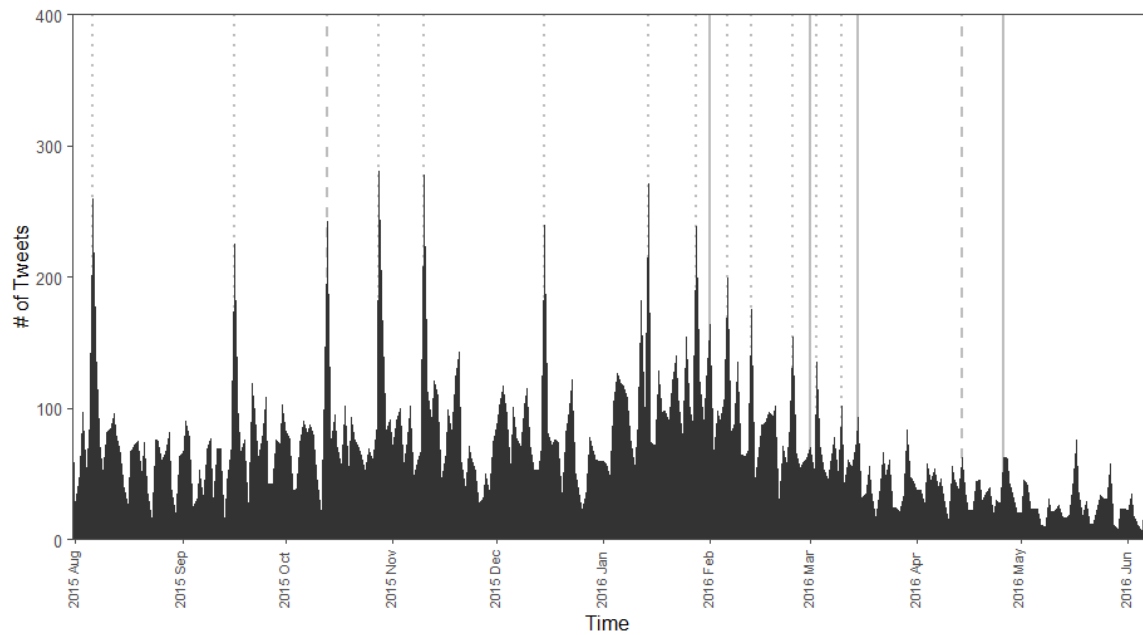


Figure 2. Total volume of tweets by the 12 candidates from July 30, 2015, to June 7, 2016. The dotted vertical lines indicate the 12 Republican debates, whereas the solid lines indicate major election dates (the first elections in Iowa, the last competitive elections in Indiana, and major elections in which five or more states participated). The dashed lines indicate the first and last democratic debates.

Strategy Framing

Figure 3 shows each candidate's percentage of tweets dedicated to strategy, issue, mixed, campaign information, and apolitical tweets (other). Candidates are ordered from left to right based on their relative use of the strategy framing. Importantly, as each tweet was modeled as a mixture of topics, the numbers in the figure indicate the percentage of language using each category, not the number of tweets that use that category.

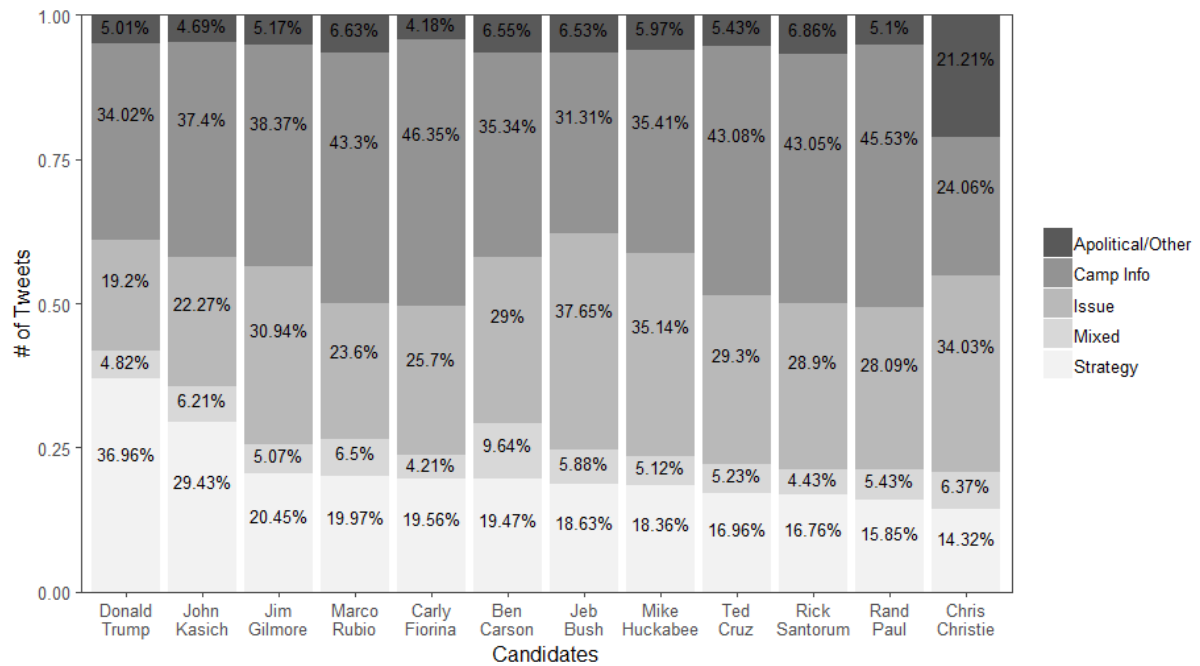


Figure 3. The average usage of frames per candidate. Percentages mark the relative salience the frames in each candidate’s communication.

According to H1, based on previous research on political candidates’ use of Twitter, we expected campaign information to be the most common framing in candidates’ online discourse. On average (i.e., for all candidates together and over time) candidates’ most common use of Twitter was for campaign information (38.1%) thus supporting H1. However, it should be noted that at the candidate level, three candidates had other frames as more common than campaign information (strategy dominant for Donald Trump, and issue dominant for Chris Christie and Jab Bush). According to H2, and based on existing research on traditional news media, politicians were expected to use more strategy framing than issue framing in Twitter. However, only two candidates, Trump (36.96% strategy vs. 19.2% issue) and Kasich (29.43% vs. 22.27%) used more strategy than issue framing. On average, and aside from candidates’ use of Twitter for campaign information, issue language was used more (28.65%) than strategy language (20.56%). However, because Donald Trump used Twitter much more often than the other candidates, the average amount of strategy language in the corpus was closer to, but still lower (23.45%), than issue (26.81%), and much lower than campaign information (38.1%). Therefore, H2 was not supported (aside for two candidates who used more strategy than issue framing on Twitter during the primaries. Notably the two were also the last candidates to remain in the race).

H3a predicted that the relative use of strategy framing will increase over time. Figure 4 shows that, on average, the use of strategy increased over time (though the increase after March 2016 is mostly due to Donald Trump’s activity, as other candidates withdrew from the race and reduced their Twitter use significantly). H3b predicted that the relative use of strategy framing would decrease over time. However, on average, there was

no change over time in the use of issue framing. Thus, the rise in strategy framing was on the expense of campaign information, which declined over time, as politicians began withdrawing from the race.

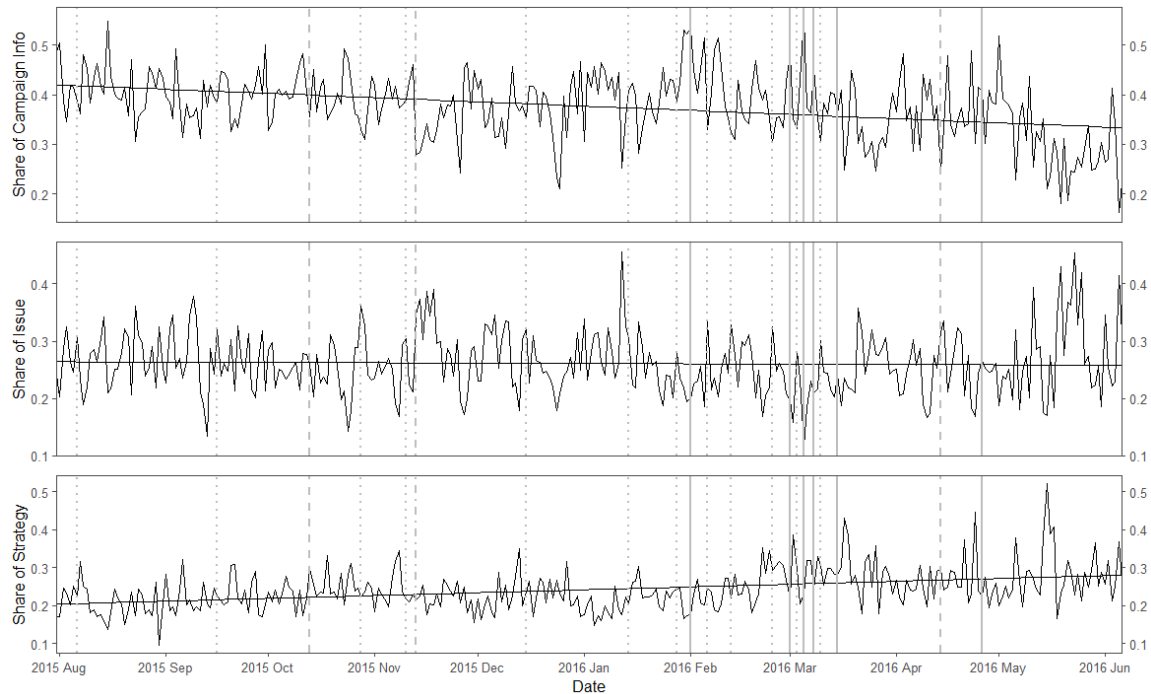


Figure 4. The average usage of strategy, issue, and campaign information in candidates' tweets, from July 30, 2015, to June 7, 2016. The dotted vertical lines indicate the Republican debates. The solid vertical lines indicate major election dates (the first elections in Iowa, the last competitive elections in Indiana, and major elections dates in which five or more states participated). The dashed vertical lines indicate the first and last Democratic debates. Lastly, the combined dash and dot line indicates the date of the 2015 Paris terrorist attack. The black horizontal line indicates the linear trend of the series.

Looking at the fluctuations reveals that strategy, issue, and campaign information were not stagnant and reacted differently to various political events. As can be seen in Figure 4, discussion of issues declined around major primary election days, and peaked during Republican and Democratic debates. Campaign information, on the other hand, peaked around major electoral events.

To assess these relationships statistically, while controlling for autocorrelations among observed and unobserved variables, we used Granger causality tests in vector autoregression time-series analyses (using the VARS package in R). The lag order of one day was chosen based on optimal lag values from four criteria (AIC, HQ, SC, and FPE). As the data were found to be stationary using an augmented Dickey-Fuller (ADF) test, we did not differentiate the data. Examining the relationship among the time line of debates, primary elections, and emphasis on issue, strategy, and campaign information, we found that (1) a positive relationship existed between debate events and issue emphasis ($b = 0.06$, $p < .001$), and (2) a positive relationship existed

between major voting days (first primary elections, last primary elections, and other primary elections in which five or more states participated) and campaign information emphasis ($b = 0.07, p < .01$).

Results for campaign information (3) remained virtually the same when accounting for all voting days and not just the ones where more than five states participated in, though the impact was lessened ($b = 0.04, p < .05$). Lastly, (4) a negative relationship existed between major election events and issue emphasis ($b = -0.04, p < -.05$). No other significant relationships were identified. These results lend support to the argument that major election events can influence the rate of campaign information messages and issue emphasis in candidates' direct communication via Twitter.

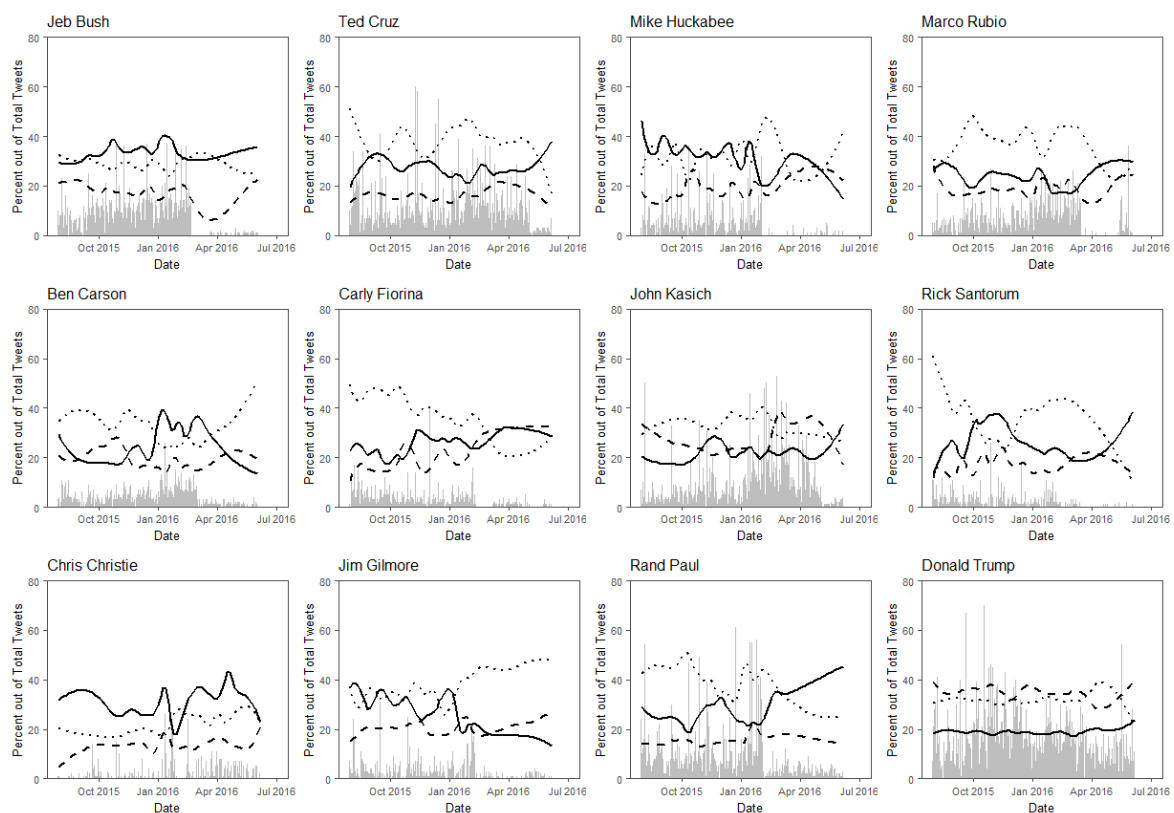


Figure 5. The usage of issue (solid line), strategy (dashed line), and campaign information (dotted line) in candidates' tweets. The horizontal trend lines represent the LOESS smoothed curve of activity, for easier observation of main trends, with the score indicating share of usage (0%–100% of total activity). The gray vertical bars indicate candidates' volume of activity over time in absolute terms (0–100 Tweets per day).

However, these events did not influence the rate of strategy frame usage in this case. Moreover, there were numerous peaks in all types of message activity that were not accounted for by these two types of events. For example, issue framing also increased in response to issue-related events, such as the Paris terror attack on November 15, 2015, thus indicating that events external to the campaign can also influence message strategy choice.

To sum, although strategy framing did not react to specific events but rather increased over time, issue framing and campaign information seemed to have been used interchangeably, with the first rising because of debates, and the second being used heavily around voting days. External events, such as terrorist attacks, may have also exerted influence over the use of framing. Therefore, H3c was generally supported, with the exception of strategy framing.

Discussion

This study examined Republican candidates' use of strategy and issue frames, as well as campaign information, in their social media activity during the 2016 primaries. We found that in contrast to what was consistently identified in traditional news media (Aalberg et al., 2011; Cappella & Jamieson, 1997; Patterson, 1994) and in initial results on social media activity in related contexts (Evans et al., 2014), politicians used more issue framing than strategy framing in their communication during this campaign. Only two candidates, the eventual winner, Donald J. Trump, and John Kasich, used more strategy than issue framing. Congruent with previous findings (Evans et al., 2014), most Twitter activity of all candidates was dedicated to disseminating campaign information. These findings suggest that candidates used Twitter as an alternative channel to directly communicate with their followers—both for mobilization and clarifying of positions—what they could not do as freely in gatekeepers-filtered traditional news media. It should therefore be seen as part of a large trend in the media landscape that allows elites to circumvent the limiting constraints of mass communication using social media.

An analysis of use over time revealed that on average, the use of campaign information declined over time, especially after candidates withdrew from the race. The use of strategy framing increased over time, influenced in part by the reduced activity by most candidates after their withdrawal and the increase in Trump's dominance in the information environment (because Trump used more strategy framing than the other candidates). The use of issue framing remained relatively stable over time.

An examination of the fluctuations showed that both issue framing and campaign information reacted strongly to political events. Specifically, campaign information increased around voting days, indicating the importance of communication with voters via Twitter for purposes of mobilization. Issue framing, on the other hand, increased around Republican and Democratic debates. If issue framing can have a positive impact on the political environment (Cappella & Jamieson, 1997), then this emphasis on issue framing can be seen as support for the importance of debates (McKinney & Rill, 2009), which influence voters not only directly but also affect the message strategy of the candidates themselves, forcing them to pay more attention in their communication to actual issues (even if this impact is rather brief).

However, it should be noted that our analysis observed only whether the two types of events, voting days and debates, influence candidates' discourse on Twitter. Although the results of this analysis were statistically significant (showing events Granger-caused changes in Twitter activity), these events are in no way the only influencers on framing and campaign information. Aside from campaign-oriented events, other extraneous events could influence discourse. This can be observed, for example, when examining the discourse surrounding the terrorist attacks in Paris on November 15, 2015. These horrendous events were able to increase the rate at which candidates discuss actual issues that are relevant to the campaign while temporarily decreasing their mobilization efforts. However, similar to the impact of the 12 debates, this impact was relatively short lived. More importantly, looking at the discourse over the time line of campaigns clearly shows that there are peaks in general activity (though relatively lower peaks), in campaign information dissemination, in strategy framing, and in issue framing, that cannot be explained by debates and election days. Therefore, further research is needed to identify more clearly the types of events, aside from the types discussed here, that can influence candidates' discourse.

Looking at the various indicators, the eventual winner, Donald J. Trump, seem to have been a unique candidate among a large field of candidates. First, the volume of his activity on Twitter was significantly larger than any other candidate. Second, he was the candidate to use the least amount of issue-oriented framing and the largest rate of strategy-oriented framing. This question is beyond the scope of this study, and further research should be devoted to the question of whether this was a unique event or whether there is a clear advantage to usage of strategy framing in social media activity over more issue-oriented messages, though such argument does seem congruent with previous writing on the advantages of strategy framing in terms of attracting audiences (Iyengar et al., 2004).

Methodologically, this study used topic modeling as a mean for data reduction and as a way of scaling hand coding to the analysis of large textual databases. By first reducing our corpus of 22,064 tweets to a more manageable set of 60 topics (or 56 campaign-related topics), we were able to perform an analysis on the use of framing by candidates in a complete, rather than sampled, textual database that would be extremely costly to analyze in other ways. Topic modeling offers several advantages for those who wish to analyze framing in large and complex corpora, beyond improvement to cost efficiency. First, as the model considers each document (tweet) to be a mixture of topics, it allowed us to offer a more nuanced assessment of the content of messages, measuring the existence of strategy framing or issue framing on a continuous scale (0%–100%), rather than a binary measurement (issue or nonissue). Second, as topic modeling examines the co-occurrence of words over a large amount of texts, it can expose linguistic relationships that a human reader might not be able to uncover because of the complexity and size of the database (Soroka, 2014). Third, in contrast to approaches that use a dictionary for measuring whether a document consists of more issue or strategy words, our approach allowed words to have different meanings when appearing in different contexts.

However, there are several caveats about the interpretation of our findings. First, because of the scope of the study, we did not compare the Twitter data with communications by news media outlets during the campaign. Future studies may shed more light on the differences and commonalities between news media and social media. Second, this study focused on the Republican candidates in the 2016 presidential race only. This was done to maintain a more thematically coherent corpus for our analysis and to take advantage of the large number of participants in the Republican field. Thus, future exploration of the rhetoric in direct communication

via Twitter by presidential candidates from the Democratic party (as well as analyses of other political races) might offer different results from those found in this study. Third, as mentioned earlier, although the events we examined had a strong and statistically significant impact on campaign discourse, other extraneous events might be responsible for some of the unexplained changes and should be examined by future studies.

Nevertheless, our study points to a unique and highly unbalanced media environment, where one candidate, who is by far the most active online, employs framing in a highly distinguished way. Our data does not allow us to infer that Trump's extensive use of strategy framing won the primaries. However, the literature does show that it could increase cynicism and skepticism toward other candidates, the political process (that Trump repeatedly attacked as part of his "drain the swamp" rhetoric), and the political discourse (as evident in his unprecedented attack on truth, on evidence, and facts).³ Future studies should further inquire these potential effects. Our study cannot support the effect but does point to an unbalanced discourse during the campaign that does not correspond to findings from traditional news media that showed a relatively unified use of framing across channels. Further studies should look into the potential and actual effects of such imbalance between candidates.

References

- Aalberg, T., Strömbäck, J., & de Vreese, C. H. (2011). The framing of politics as strategy and game: A review of concepts, operationalizations and key findings. *Journalism, 13*, 162–178.
doi:10.1177/1464884911427799
- Allcott, H., & Gentzkow, M. (2017). *Social media and fake news in the 2016 election*. Retrieved from <http://www.nber.org/papers/w23089>
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research, 3*, 993–1022.
- Bode, L., Lassen, D. S., Kim, Y. M., Shah, D. V., Fowler, E. F., Ridout, T., & Franz, M. (2016). Coherent campaigns? Campaign broadcast and social messaging. *Online Information Review, 40*, 580–594.
doi:10.1108/OIR-11-2015-0348
- Bradner, E. (2016). Personal brawls dominate 2016 race. *CNN*. Retrieved from <http://www.cnn.com/2016/09/08/politics/trump-clinton-policy-free-2016-election/index.html>
- Cacciatore, M. A., Scheufele, D. A., & Iyengar, S. (2016). The end of framing as we know it . . . and the future of media effects. *Mass Communication and Society, 19*, 7–23.
doi:10.1080/15205436.2015.1068811

³ See <https://www.factcheck.org/person/donald-trump/>.

- Cappella, J. N., & Jamieson, K. H. (1997). *Spiral of cynicism: The press and the public good*. New York, NY: Oxford University Press.
- de Vreese, C. H. (2005). The spiral of cynicism reconsidered. *European Journal of Communication*, 20, 283–301. doi:10.1177/0267323105055259
- DiMaggio, P., Nag, M., & Blei, D. (2013). Exploiting affinities between topic modeling and the sociological perspective on culture: Application to newspaper coverage of U.S. government arts funding. *Poetics*, 41, 570–606. doi:10.1016/j.poetic.2013.08.004
- Entman, R. M. (1993). Framing: Toward clarification of a fractured paradigm. *Journal of Communication*, 43(4), 51–58.
- Evans, H. K., Cordova, V., & Sipole, S. (2014). Twitter style: An analysis of how House candidates used Twitter in their 2012 campaigns. *Political Science & Politics*, 47, 454–462. doi:10.1017/S1049096514000389
- Gamson, W. A., & Modigliani, A. (1989). Media discourse and public opinion on nuclear power: A constructionist approach. *American Journal of Sociology*, 95, 1–37. doi:10.2307/2780405
- Goffman, E. (1974). *Frame analysis: An essay on the organization of experience*. Boston, MA: Northeastern University Press.
- Gottfried, J., & Shearer, E. (2016). *News use across social media platforms 2016*. Retrieved from <http://www.journalism.org/2016/05/26/news-use-across-social-media-platforms-2016/>
- Grimmer, J., & Stewart, B. M. (2013). Text as data: The promise and pitfalls of automatic content analysis methods for political texts. *Political Analysis*, 21, 267–297. doi:10.1093/pan/mps028
- Hermans, L., & Vergeer, M. (2013). Personalization in e-campaigning: A cross-national comparison of personalization strategies used on candidate websites of 17 countries in EP elections 2009. *New Media & Society*, 15, 72–92. doi:10.1177/1461444812457333
- Hong, S., & Nadler, D. (2011). Does the early bird move the polls?: The use of the social media tool "Twitter" by U.S. politicians and its impact on public opinion. *Proceedings of the 12th Annual International Digital Government Research Conference: Digital Government Innovation in Challenging Times* (pp. 182–186). New York, NY: ACM. doi:10.1145/2037556.2037583
- Iyengar, S., Norpoth, H., & Hahn, K. S. (2004). Consumer demand for election news: The horserace sells. *Journal of Politics*, 66(1), 157–175. doi:10.1046/j.1468-2508.2004.00146.x

- Jackson, D. (2010). Strategic media, cynical public? Examining the contingent effects of strategic news frames on political cynicism in the United Kingdom. *The International Journal of Press/Politics*, 16, 75–101. doi:10.1177/1940161210381647
- Larsson, A. O., & Kalsnes, B. (2014). "Of course we are on Facebook": Use and non-use of social media among Swedish and Norwegian politicians. *European Journal of Communication*, 29, 653–667. doi:10.1177/0267323114531383
- Lee, E.-J., & Shin, S. Y. (2012). When the medium is the message: How transportability moderates the effects of politicians' Twitter communication. *Communication Research*, 41, 1088–1110. doi:10.1177/0093650212466407
- Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., . . . Adam, S. (2018). Applying LDA topic modeling in communication research: Toward a valid and reliable methodology. *Communication Methods and Measures*, 12, 93–118. doi:10.1080/19312458.2018.1430754
- Matthes, J. (2009). What's in a frame? A content analysis of media framing studies in the world's leading communication journals, 1990–2005. *Journalism & Mass Communication Quarterly*, 86, 349–367. doi:10.1177/107769900908600206
- McKinney, M. S., & Rill, L. A. (2009). Not your parents' presidential debates: Examining the effects of the CNN/YouTube debates on young citizens' civic engagement. *Communication Studies*, 60, 392–406. doi:10.1080/10510970903110001
- Ott, B. L. (2017). The age of Twitter: Donald J. Trump and the politics of debasement. *Critical Studies in Media Communication*, 34, 59–68. doi:10.1080/15295036.2016.1266686
- Patterson, T. E. (1994). *Out of order: An incisive and boldly original critique of the news media's domination of America's political process*. New York, NY: Vintage.
- Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., . . . Rand, D. G. (2014). Structural topic models for open-ended survey responses. *American Journal of Political Science*, 58, 1064–1082. doi:10.1111/ajps.12103
- Schwartz, H. A., & Ungar, L. H. (2015). Data-driven content analysis of social media: A systematic overview of automated methods. *The ANNALS of the American Academy of Political and Social Science*, 659, 78–94. doi:10.1177/0002716215569197
- Schweitzer, E. J. (2008). Innovation or normalization in E-campaigning?: A longitudinal content and structural analysis of German party websites in the 2002 and 2005 national elections. *European Journal of Communication*, 23, 449–470. doi:10.1177/0267323108096994

- Soroka, S. N. (2014). Reliability and validity in automated content analysis. In R. P. Hart (Ed.), *Communication and language analysis in the corporate world* (pp. 352–363). Hershey, PA: Information Science Reference.
- Strömbäck, J., & van Aelst, P. (2010). Exploring some antecedents of the media's framing of election news: A comparison of Swedish and Belgian election news. *The International Journal of Press/Politics*, *15*, 41–59. doi:10.1177/1940161209351004
- Sundar, S. S., Kalyanaraman, S., & Brown, J. (2003). Explicating web site interactivity: Impression formation effects in political campaign sites. *Communication Research*, *30*, 30–59. doi:10.1177/0093650202239025
- Tedesco, J. C. (2001). Issue and strategy agenda-setting in the 2000 presidential primaries. *American Behavioral Scientist*, *44*, 2048–2067. doi:10.1177/00027640121958483
- Trilling, D., Tolochko, P., & Burscher, B. (2016). From newsworthiness to shareworthiness: How to predict news sharing based on article characteristics. *Journalism & Mass Communication Quarterly*, *94*, 38–60. doi:10.1177/1077699016654682
- Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, *211*, 453–458. doi:10.1126/science.7455683
- Valentino, N. A., Beckmann, M. N., & Buhr, T. A. (2001). A spiral of cynicism for some: The contingent effects of campaign news frames on participation and confidence in government. *Political Communication*, *18*, 347–367. doi:10.1080/10584600152647083
- van Aelst, P., Sheafer, T., & Stanyer, J. (2012). The personalization of mediated political communication: A review of concepts, operationalizations and key findings. *Journalism*, *13*, 203–220. doi:10.1177/1464884911427802
- Vergeer, M., Hermans, L., & Sams, S. (2013). Online social networks and micro-blogging in political campaigning: The exploration of a new campaign tool and a new campaign style. *Party Politics*, *19*, 477–501. doi:10.1177/1354068811407580
- Verweij, P. (2012). Twitter links between politicians and journalists. *Journalism Practice*, *6*, 680–691. doi:10.1080/17512786.2012.667272
- Wallach, H. M., Murray, I., Salakhutdinov, R., & Mimno, D. (2009). Evaluation methods for topic models. *Proceedings of the 26th annual international conference on machine learning* (pp. 1105–1112). New York, NY: ACM. Retrieved from <http://dl.acm.org/citation.cfm?id=1553515>

Appendix 1

Table A1. Description of Topics Found in the Data and Their Main Frame Coding (Strategy, Issue, Campaign Information, Mixed) and Subframe.

#	Top FREX words	Main code	Subframe
1	people, nation, country, american, together, future, work, working, election, us	Mixed	
2	tune, tonight, @foxnews, pm, joining, @johnkasich, miss, @seanhannity, live	Campaign	
3	people, washington, back, american, power, political, take government, americans, country	Issue	
4	john, kasich, america, #gopdebate, ready, house, one, white, needs, experience	Strategy	Character
5	via, carson, ben, race, presidential, gop, gilmore, candidate, jim donald	Strategy	Mixed
6	jeb, @realdonaldtrump, bush, now, @jebbush, failed, got, romney, like, good	Strategy	Mixed
7	great, crowd, big, people, amazing, just, back, iowa, going, rally	Campaign	
8	get, questions, answers, ready, answer, important, #carlylive, getting, facebook, asked	Campaign	
9	last, night, debate, great, watch, night's, week, time, #gopdebate, see	Strategy	Mixed
10	@realdonaldtrump, trump, donald, vote, go, president, one, #makeamericagreatagain, love, want	Campaign	
11	read, @johnkasich, america, plan, case, #kasich4us, op-ed, missed, today, message	Mixed	
12	right, get, country, time, now, enough, refugees, tough, like, stop	Issue	
13	help, chip, can, keep, donate, us, now, momentum, tonight, campaign	Campaign	
14	debate, #standwithrand, paul, rand, #gopdebate, gt, retweet, read, vote, tonight's	Campaign	
15	book, america, read, signing, #festivus, now, new, order, crippled, great	Mixed	
16	#gopdebate, #imwithhuck, gt, agree, rt, watch, tonight's, name, #cnndebate, #cnbcgopdebate	Campaign	
17	hillary, clinton, trump, party, beat, republican, can, donald, crooked, run	Strategy	Character
18	get, campaign, today, now, order, gear, store, support, rand, sticker	Campaign	
19	special, money, campaign, just, people, ads, million, interest, spent, millions	Strategy	Strategy

20	isis, radical, islamic, terrorism, defeat, need, must, president, destroy, war	Issue	
21	vote, get, time, find, ballot, caucus, primary, today, still, polls	Campaign	
22	prayers, today, family, honor, thoughts, families, victims, god, attacks, life	Other	
23	state, stay, nj, please, #jonas, storm, city, today, hard, ac	Other	
24	jobs, economy, new, growth, taxes, tax, create, job, cut, state	Issue	
25	common, sense, problem, core, matter, addiction, people, must, drug, lives	Issue	
26	care, veterans, education, school, students, health, va, choice, college, vets	Issue	
27	us, join, #cruzcrew, help, #cruzcountry, #cruztovictory, campaign, america, thank, gt	Campaign	
28	thank, #makeamericagreatagain, support, #choosecruz, #votetrump, wisconsin, indiana, great, supporters, see	Campaign	
29	new, hampshire, #fitn, #nhpolitics, york, @johnkasich, ad, voters, today, #kasich4us	Campaign	
30	live, watch, now, debate, win, enter, #cruzcrew, listen, next, chance	Campaign	
31	@realdonaldtrump, trump, great, @foxnews, job, @cnn, nice, interview, #makeamericagreatagain, thank	Strategy	Media
32	@foxnews, really, debate, @megynkelly, failing, said, @nytimes, won, totally, @cnn	Strategy	Media
33	forward, looking, look, follow, tonight, sure, #gopdebate, campaign, trail, joining	Campaign	
34	rights, defend, liberty, amendment, 2nd, religious, bill, constitution, protect, president	Issue	
35	team, support, honored, proud, welcome, endorsement, state, excited, announce, leaders	Strategy	Mixed
36	nh, town, hall, #fitn, @johnkasich, #nhpolitics, gov, #kasich4us, live, today	Campaign	
37	#demdebate, @hillaryclinton, go, free, first, want, one, #gopdebate, @barackobama, @berniesanders	Strategy	Mixed
38	thanks, support, thank, words, glad, appreciate, great, work, team, much	Campaign	
39	south, carolina, sc, join, today, north, #scprimary, great, thank, greenville	Campaign	
40	happy, christmas, birthday, year, family, thanks, us, hope, wish, signed	Other	
41	great, good, best, friend, see, thank, congratulations, governor, honor, proud	Other	
42	cruz, ted, rubio, marco, just, senator, lvin, like, said, even	Strategy	Character

43	morning, interview, enjoy, interviewed, talking, a.m., watch, @foxandfriends, tune, good	Campaign	
44	security, national, border, social, medicare, #gopdebate, military, wall, protect, freedom	Issue	
45	know, can, people, one, say, want, many, get, like, think	Strategy	Mixed
46	kasich, john, gov, ohio, kasich's, see, @johnkasich, endorsement, #kasich4us, state	Strategy	Game/war
47	years, like, ago, time, still, never, two, made, four, past	Mixed	
48	thanks, great, everyone, morning, #standwithrand, came, today, time, speaking, nh	Campaign	
49	life, stand, fight, planned, parenthood, #defundplannedparenthood, senate, must, human, vote	Issue	
50	world, states, united, leadership, american, need, restore, military, america, president	Issue	
51	poll, trump, just, new, polls, carson, lead, big, iowa, cruz	Strategy	Game/war
52	join, tomorrow, see, rsvp, rally, hope, us, tonight, #cruzcountry, morning	Campaign	
53	tax, plan, immigration, #gopdebate, illegal, code, secure, simple, flat, border	Issue	
54	iran, deal, obama, president, israel, stop, #irandeal, nuclear, stand, must	Issue	
55	budget, government, spending, #standwithrand, federal, debt, congress, balance, time, plan	Issue	
56	conservative, record, #gopdebate, obamacare, president, need, repeal, proven, fight, can	Issue	
57	iowa, #iacaucus, today, join, caucus, ia, #caucusforcruz, des, moines, us	Campaign	
58	make, america, great, keep, safe, country, sure, president, need, can	Issue	
59	policy, foreign, obama, obama's, president, failed, @hillaryclinton, @potus, energy, policies	Issue	
60	first, day, president, every, reagan, office, one, elected, next, ronald	Issue	
