The Role of Slant and Message Consistency in Political Advertising Effectiveness: Evidence from the 2016 Presidential Election

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Abstract

We explore the relationship between the content of political advertising on television and ad effectiveness. Specifically, we investigate how slant – the extremeness of the message – and consistency with the candidate's primary campaign messaging in national ad buys relate to two measures of voter behavior: online word-of-mouth (WOM) and voter preference (captured through daily polls) for the candidates. Using data from the 2016 presidential election, we find that ad messages that are more (1) centrist and (2) consistent with a candidate's primary-election platform associate with increases in online WOM and voter preference for the candidate. We further find that consistency is more important in the early (pre-October) stages of the campaign. Our results suggest that while there may be a benefit to candidates moderating their message after winning the primary election, they need to be careful about shedding their messaging from the primary election during the early stages of the general election. Additionally, our results enrich our understanding of the use of extreme messaging in political advertising, a phenomenon that is on the rise, by showing that it may have a cost of decreased candidate-related WOM and voter preference for the candidate.

Keywords: political advertising, ad effectiveness, television advertising, word-of-mouth, social media

1. Introduction

Political advertising is typically the largest expense for political campaigns, with the vast majority of this spending going toward television advertising (Adgate 2019; Baer and Sinagoga 2018; OpenSecrets 2020). In the 2016 U.S. election, candidates, parties, and political action committees (PACs) spent $6 billion on television advertising, accounting for 8% of U.S. television ad revenue in 2016 (Kaye 2017). With many online sites like Twitter and Google restricting online political advertising (Conger 2019; Haggin 2019), political expenditures on television advertising rose to even higher levels – $8.5 billion – in the 2020 U.S. election (Passwaiter 2020). Numerous studies justify this heavy investment in political television advertising, which has significant impacts on election outcomes (e.g., Gordon and Hartmann 2013; Huber and Arceneaux 2007; Spenkuch and Toniatti 2018; Wang et al. 2018). Indeed, changes in political television ad spending strategies in 2000 could have resulted in a different U.S. president (Gordon and Hartmann 2013).

While there is a large literature that studies the effectiveness of political advertising, limited research has examined how the content of political advertisements (beyond tone) changes the effectiveness of these ads. Given recent advances in text analytic methods (see Berger et al. 2020), this offers an opportunity to further examine the way in which the content of political advertising shapes voter behavior. More broadly, text analytic methods offer a means of examining how messages from human brands (e.g., Thomson 2006) affect consumers' perceptions.

We apply text analysis to national political television ads from 2016 by the two main presidential candidates, Hillary Clinton and Donald Trump, to assess two key features of the advertising messages: slant and consistency. Slant refers to the extent to which each candidate's messages are extreme versus centrist, while consistency refers to how much the candidate's messages remain consistent between the primary and the general election.

We focus on these aspects of ad measures for two key reasons. First, politically there is a conventional wisdom that after candidates win their nominations, they should moderate their positions and become more centrist over the course of a campaign (e.g., Hummel 2010). However, changing one's positions and tone can demotivate the base of voters who supported the candidate in the primary election, and reduce the creation of brand associations that inform voters as to what the brand stands for. We aim to empirically investigate this tension between slant and consistency in our analyses. Second, both slant and consistency are two vital dimensions related to the branding of political candidates, with slant representing what the product (the candidate) stands for, and consistency representing the extent to which the candidate creates a clear and repeated message of what they represent.

Keller and Lehmann (2006) consider the importance of being consistent in the brand message, asking whether differing messages to distinct segments may cause confusion of what the brand stands for. Kotler and Keller (2016) similarly argue that message consistency is a fundamental element of the brand, playing a vital role in brand building and brand equity creation and reinforcement. As in the political domain, research on brand extensions links the branding dimensions of slant and consistency. Specifically, work on brand extensions has long studied how the similarity and dissimilarity of associations between a brand variant and the schema of that brand impacts the success of the brand variant and its ad effectiveness (e.g., Boush and Loken 1991; Broniarczyk and Alba 1994; Liu et al. 2017; Park et al. 1991). Overall, research on branding underscores the vital importance of slant and consistency in impacting the effectiveness of brand messages.

In our investigation, we examine how these two aspects of advertising content affect two distinct measures of voter engagement, online word-of-mouth (WOM) about the candidate (e.g.,

Bermingham and Smeaton 2011; Jahanbakhsh and Moon 2014) and voter preference captured through daily polling polls (e.g., Jennings and Wlezien 2018; Kennedy et al. 2018; Silver 2018), both of which have been shown to predict the candidate's vote share. Furthermore, online WOM and consumers' related online behaviors have been widely leveraged as a means to study the effectiveness of television advertising (e.g., Fossen and Schweidel 2017; Fossen et al. 2020; Joo et al. 2014; Lewis and Reiley 2013; Liaukonyte et al. 2015; Tirunillai and Tellis 2017).

Utilizing data on over 800 television ad airings during the 2016 U.S. presidential election, we find that ad messages that use language that is more (1) centrist and (2) consistent with a candidate's primary-election platform are associated with increases in online WOM volume and voter preference for the candidate. We also see some evidence that these attributes are more important early in the campaign. Overall, the results support that candidates should favor more moderate messaging for the general election as well as messaging that is consistent with their primary election communications in the early stages of the campaign. This pattern demonstrates a nuance to the conventional wisdom that candidates should move to more centrist messaging after winning their nomination. While this strategy is beneficial, consistency with the candidate's primary election messaging is particularly important early in the campaign. These results suggest that it would be advantageous for candidates to adhere close to their primary campaign messages in the early stage of the general election and emphasize moderate messages as the election further develops. Further, our results suggest that the rising use of extremist messages in political advertising (e.g., Bartels 2016; Wells and Seetharaman 2018) may be a flawed strategy for candidates that could decrease candidate-related WOM volume and voter preference for the candidate.

With this investigation, we acknowledge the challenge of establishing a causal relationship in a study using historical data. Our main results are based on using an event study in which we compare the volume of WOM on Twitter just before versus just after an advertisement. As we discuss later, while using such an approach removes most sources of coincident timing, there may remain some feasible confounds. For example, our measures of slant and consistency may be correlated to another attribute of the ad that is really the driver of our results. Further, an anonymous reviewer noted that an advertisement could prompt a viewer to tweet about the campaign at the time of the ad, when instead the viewer might have made the same tweet at a later time. In our analyses, we control for several observable ad attributes to reduce potential confounds. Ultimately, we discuss the assumptions under which the identified relationships are likely causal and allow the reader to decide whether these conditions are likely to be met. We also present confirmatory regression analysis using voter preference. This secondary analysis has more potential endogeneity concerns but is broadly consistent with the WOM analysis, presenting confirmatory correlational evidence of our key findings.

Our findings contribute to the political marketing literature by considering the role of message content in political advertising. Though prior research has examined the differential impact of tone (e.g., Lovett and Shachar 2011; Wang et al. 2018) and message source (Wang et al. 2018; Zhang and Chung 2020), we are among the first studies to consider other aspects of political ad content, namely the similarity of messaging over the course of the campaign with regards to the party (slant) and the candidate's earlier messaging (consistency). Our findings demonstrate that these dimensions of political advertising content affect voter behaviors beyond conventionally studied advertising dimensions in the political domain (e.g., tone, source, volume of advertising). Our results also contribute to the broader streams of research on advertising and text analysis.

While extant research has examined the role of different themes in advertising campaigns (e.g., Bass et al. 2007), to the best of our knowledge, our research is among the first in marketing to use automated text analysis to derive message-related metrics that are linked to the performance of television commercials. This has implications for brands as they develop and launch new marketing campaigns.

The remainder of this paper proceeds as follows. Section 2 describes the data and our key measures and presents descriptive evidence of our findings. Section 3 discusses our identification strategy and model specifications, and the results are reported in Section 4. Section 5 concludes with a discussion of the implications of our findings, both within the political domain and more broadly for marketers.

2. Data Description

We combine four data sources: national political television advertising, political communications from campaign speeches and congressional records, daily poll data on voter preferences, and online chatter about the candidates from Twitter. We detail each of these in turn.

2.1 *Television Advertising Data*

We collect data on political advertisements that aired on national primetime television during the 2016 presidential general election (June 30th to November 8th) from Kantar Media's Stradegy database. We utilize national television advertising because it is very challenging to obtain daily (or more granular) ad outcomes (i.e., polling and social media measures) at the DMA level. National ad buys typically account for more than 25% of a presidential candidate's television advertising spending (Miller 2015). This share is expected to increase, as the rising costs of local ad inventory in battleground markets during elections make national ad buys more economical

(Passwaiter 2018). Given that national ads have significantly higher reach and that our outcome measures of voter behavior are collected at the national level, we believe it is reasonable to focus on national ads in our investigation of how slant and consistency relate to their effectiveness.[5,6] The Stradegy data contains the date and time each ad airs, the program and network in which the ad airs, ad length, ad position, and the advertiser's name. We supplement the Stradegy data by collecting information on the number of viewers for each ad from Comscore's TV Essentials database (Comscore TV Essentials 2020). In total, our data include 824 ad airings for 60 unique ad creatives aired by 11 political advertisers, which include the campaigns for the two main candidates, two political party entities, and seven PACs.

We present descriptive information about the political ads in Table 1. Although the number of unique ad creatives are similar across the candidates, Clinton has more ad airings, while ads supporting Trump have larger audience sizes. Ads supporting the two candidates are comparable in tone, length, and ad position. Figure 1 illustrates the number of ad airings over time by candidate.

[Insert Table 1 and Figure 1 here]

2.2 *Using Text Analysis to Derive Measures of Slant and Message Consistency*

We define two dimensions of ad messaging for our analysis: political slant and message consistency. For *political slant*, we evaluate each ad in a purely political domain and measure the

[5] The WOM measures are available only nationally. While there are state-level polls, these tend to be conducted very irregularly, and by a number of different pollsters, making the creation of a high-quality state-specific panel very difficult (and nearly impossible to do so at the even more granular DMA level).

[6] We probe the overlap of national versus local primetime political ads in our data using the name of the TV creative and find significant overlap. This suggest that the content of national ads likely reflect the campaigns' overall message. Specifically, 100% of both Clinton and Trump's national primetime ad creatives in our data were also aired locally in primetime. That said, the candidates do employ more ad creatives for their primetime local ad airings. Yet, the majority of their local primetime airtime consists of ad creatives that are aired both locally and nationally. Specifically, only 3.1% (9.2%) of Clinton's (Trump's) primetime local ad airings consist of ad creatives that were only aired locally. Additionally, we find that Clinton and Trump's national primetime ads exhibit very similar airing patterns as their local primetime ads in terms of time, day of the week, and month aired (see Appendix G).

extent to which the ad message is extreme versus centrist. For *message consistency*, we evaluate each ad in the domain of semantic meanings and calculate the extent to which the ad message has similar content to the candidate's platform, which is derived from their speeches during the primary campaign. We detail each in turn.

Slant. We operationalize our slant measure using a technique introduced by Gentzkow and Shapiro (2010). For this, we utilize multiple datasets: the 114th Congressional Record, which includes all speeches and debates made on the congress floor during early 2015 to early 2017 (collected from Stanford Social Science Data and Software), public speech data during the primary elections (collected from American Presidency Project), ad creative transcriptions, and vote share data (collected from dailykos.com). We pre-process our texts – including punctuation, stop word and number removal, tokenization, and stemming – before constructing slant.

Following Gentzkow and Shapiro (2010), we first derive the mapping between a vector of word counts a politician used[7] and the political leanings of their district, as measured by the Republican vote share in their district.[8] Specifically, we estimate the extent to which each word is associated with the two parties. Table 2 presents a subset of the words that are most associated with a Democratic or Republican slant.[9] We observe that these words match the conventional wisdom of how they would map on to the conservative-liberal continuum, confirming the validity of the approach.

[7] Among the words in the congressional records that remain after pre-processing, we focus on words that appear at least 2 times and fewer than 100 times in the candidates' public speech documents and transcribed ad texts. We then select 1,000 words for analysis that are found to be most asymmetrically used by the parties. We conduct sensitivity analysis and find that our results are robust to the number of words in the analysis.

[8] We consider the Republican candidate's vote share in the 2012 presidential election in the state for senator and electoral district for representative.

[9] We consider unigrams for our implementation. Although higher-order n-grams capture richer information in general, this severely reduces both the total number and variety of n-grams that we can extract from ads due to their shortness.

[Insert Table 2 here]

After we estimate the slant of each word, we compute the slant of each television ad as the extent to which the words in the ad would be associated with being Republican (strongly Democratic messages have negative values). We then subtract 0.5, which corresponds to an even Democratic and Republican ideology. Finally, we multiply this score by –1 for Clinton's ads, so that a greater (lower) number corresponds to more extreme (more centrist) messages for both candidates compared with their party. We provide further technical details in Appendix A. Table 3 shows descriptive statistics for the slant measure. We observe that while most of the ads are fairly centrist, Trump's ads tend to be somewhat more centrist than Clinton's ads. Yet, we find that some ads from Trump appear to lean towards Democratic ideology, and some ads from Clinton appear to lean towards Republican ideology. We probe them and find that such ads from Trump highlight his promised support for gender equality, including equal pay and support for childcare. The Republican-leaning ads for Clinton discuss threats from nuclear weapons or the Islamic state. Therefore, these outliers seem to confirm the validity of our slant measure.

[Insert Table 3 here]

Message Consistency. We compute message consistency using doc2vec (Le and Mikolov 2014) to measure the semantic similarity between the contents in a candidate's ads and their platform as articulated in their speeches during the primary election (collected from American Presidency Project). To understand doc2vec, we first discuss its predecessor, word2vec (Mikolov et al. 2013). Word2vec is a word embedding methodology that projects each word into a low dimensional vector space such that words that frequently co-occur in similar contexts are closely located in the space. That is, word2vec considers co-occurrences of words – a given target word and its surrounding/context words – and then assigns those words coordinates that are close to each other.

Doc2vec extends this idea to allow the relationship to depend on the paragraph in which the words appear, allowing the context of the words to matter more broadly. Documents themselves are represented as high-dimensional vectors. In such a context, the cosine between the vectors for a pair of documents is the typical measure used to calculate textual similarities (e.g., Berman et al. 2019; Feng 2020), which we use here.

We train the model using 62 documents as inputs: the 60 ad creatives plus two documents, each consisting of the text of the aggregated primary campaign speeches given by one of the candidates. We use the primary election speeches as the benchmark against which their ads are compared because this is the time when the candidates define their campaign's message. After training, we compute the cosine similarity between each candidate's ads and their aggregated speech document to assess how similar the ad message is to the candidate's messaging during the primary. We note that, in addition to capturing similarity in political issues, the similarity measure also captures other dimensions, such as frequently used attack phrases by each candidate and other phrases that set the tenor of their campaign, which is confirmed by our validation checks.[10]

In our implementation, we first pre-process the corpus, including punctuation removal, tokenization, and stemming,[11] and then train the Distributed Bag of Words (DBOW) model using the *gensim* module in Python.[12] Our results under different dimensions of the vector space are reported in Appendix C. Table 3 shows descriptive statistics for our message consistency measure

[10] Similar to Wu et al. (2019), we conduct two types of validation checks. First, we treat the training documents (i.e., 62 documents that we use as inputs) as if they were new, and infer vectors for the documents using the trained model, and see whether the inferred documents are found to be most similar to themselves via cosine similarity. We find that all inferred documents are most similar to themselves. Second, in order to showcase the face validity of our approach to measuring consistency, we select a few documents and show documents that are most and least similar in terms of the cosine similarity, excluding the chosen document. See Appendix B.

[11] We do not remove stop words, because dov2vec deals with frequent word, which are akin to stop words, by randomly down-sampling high frequency words.

[12] For parameters, we use vector size = 200, epochs = 300, window = 5, sub-sampling = 10^{-2}, and negative = 5.

for the ads in our data. We observe that Clinton ads have a higher level of consistency than Trump, while both candidates have similar standard deviations.

Our analysis approach of using automated text analysis tools to extract measures of political advertising content (specifically, slant and consistency) offer advantages over commonly used survey-based measures of political ad content, such as those from the Wesleyan Media Project, which uses the same Kantar Media Stradegy raw data we use. For example, the Wesleyan Media Project codes tone (i.e., positive vs. negative), topic, and certain emotions (e.g., fear, anger, sadness, etc…), but not any measures of slant and consistency, nor do they code other linguistic measures that have been derived using automated text analysis such as language sophistication, concreteness and familiarity, arousal and dominance, and objectivity and subjectivity. The automated extraction and analysis of the ad transcript, in contrast, does not impose such restrictions and enables the identification of textual features of interest.[13] Additionally, through the use of an embedding space, our analysis takes into account the context in which words appear. This is particularly relevant in the case of political advertisements, as political campaigns may seek to link emotions with a particular topic. While there may be alternative methods of measuring these constructs, the use of automated text analysis offers an objective method to derive these variables that is both scalable and reproducible. Our research is among the first in marketing to use text analysis to derive message-related metrics that are linked to the performance of television commercials. Similar approaches could be used outside of political marketing, for example to assess the importance of message consistency (perhaps along specific dimensions) in messaging

[13] While our approach offers many benefits, one caveat is that the ad texts are very short. This may lead to some measurement error in our measures of slant and consistency. It is likely that any coding mechanism would also have some measurement error. Given that slant and consistency are independent variables, whatever measurement error does exist would be expected, on average, to lead to attenuation of coefficients.

used by product and service marketers. Overall, our analyses present an efficient, automated approach to construct measures of ad content.

2.3 *Outcome Measures of Political Ad Effectiveness*

Online WOM. We collect online WOM data from Twitter about Clinton and Trump during the 2016 general election from Crimson Hexagon (now Brandwatch), a certified Twitter partner. This data includes information on the volume of Tweets about the two candidates in one-second increments of time. We then examine the WOM activity about the candidates for the five minutes before and after the television ad airings. Table 4 presents summary statistics of the percentage change in WOM around the airings of the ads. On average, both candidates experience about a 30% average increase in WOM between the five-minute window before the ad is shown and the five-minute window after the ad is shown.

[Insert Table 4 here]

Figure 2 provides descriptive support for the idea that the changes in WOM may be correlated with political slant and message consistency of each ad. Panel A shows an overall negative relationship between the advertisement's slant and the average percentage change in WOM, indicating that extreme (centrist) messages may be associated with decreased (increased) WOM. Panel B suggests that message consistency is positively related with increases in the volume of WOM following the ads. These relationships are consistent with our empirical results.

[Insert Figure 2 here]

Voter preference data. Our voter preference data is inferred from daily polls from the USC Dornsife/Los Angeles Times Poll. This poll surveyed voter preferences from about 3,000

registered voters on a daily basis during the 2016 general election. We use the USC Dornsife/Los Angeles Times Poll data because this poll is one of the few daily tracking polls that surveyed a fixed set of voters, which has the advantage of revealing changes in respondents' preferences among the same panelists over time. We present summary statistics for the voter preference data in Table 4.

Figure 3 illustrates the relationship between the change in voter preferences, which is calculated as the difference between the two consecutive polling numbers, and different levels of slant and message consistency. Panel A shows that more extreme messages are correlated with decreased voter preferences, while Panel B shows that message consistency is positively related to changes in voter preference. These patterns match those of our empirical results.

[Insert Figure 3 here]

3. Model and Estimation

We model the impacts of political slant and message consistency on Twitter WOM in a manner consistent with prior literature on the effects of television advertising on online consumer behaviors (e.g., Liaukonyte et al. 2015; Fossen and Schweidel 2017). These approaches leverage granular time windows around an ad's airing to study the impact of the ad. Using short time windows makes it unlikely that outside variables will impact the outcome measure. As such, past work has argued that such identification strategies that analyze changes in behaviors in narrow time windows around television advertisements are effective at investigating the causal impact of television advertising and can produce results similar to a randomized experiment (e.g., Lewis and Reiley 2013; Joo et al. 2014; Liaukonyte et al. 2015; Fossen and Schweidel 2017).

An important element for such identification strategies is the exogenous nature of ad positioning (e.g., Wilbur et al. 2013; Fossen and Schweidel 2017; Deng and Mela 2018). Advertiser-network contracts rarely write-in the airing time of an ad or even state the specific show in which an ad will air (Liaukonyte et al. 2015). Television networks decide the sequence of ads and commonly use a random order within ad breaks, an assertion further verified in more recent data sets on television advertising (Deng and Mela 2018; Fossen et al. 2020; McGranaghan et al. 2019). If the selected time-slots deliver insufficient ratings, networks compensate the advertisers by rerunning the ad in a comparable spot on the same or a similar show to make up the remaining rating points (Katz 2013, p. 200). Consequently, advertisers currently have limited control over selecting a specific program, let alone the specific ad break, in which to air an ad to affect immediate online WOM.

The main threat to this identification strategy would occur if other campaign activities (e.g., social media positing) coincide with national TV ads, and these other activities drive changes in the outcome. Our use of granular time windows, and the random positioning of ads, make such coordination very unlikely. Nevertheless, to further probe this concern, we assessed Clinton and Trump's tweet activity in our data window. Clinton (Trump) tweeted 3,732 (2,688) times during our data window. Only 196 (60) of these were posted five minutes before or after the airing of one of their national ads. We test whether this is over-representative of what would be expected in a benchmark case without any coordination between advertising and social media. Specifically, we generate empirical probability distributions for ad airing and Twitter posting times for each candidate and draw randomized ad airing and posting times at the minute level, holding dates fixed. From the simulated data, we find that, on average, one would get 191 (69) tweets from Clinton (Trump) that would overlap the 5-minute pre- and post-ad windows if these were set in an

uncoordinated manner. Statistical tests on whether the coincident probabilities are different between the two conditions are rejected, suggesting that we do not see evidence for coordination. Additionally, we find that none of these coincident tweets in the observed data seem to be coordinated with the television advertising (e.g., mention the ad in order to amplify its impact). Thus, we don't see evidence that campaigns were coinciding their social media positing activities with their national television advertising activity to amplify their reach.

We measure the volume of online WOM mentioning the candidates using a five-minute window before and after the ad airs.[14] Specifically, for each ad airing i, we model the volume of post-ad WOM as follows:

$$\log\left(WOM_i^{post} + 1\right) = \beta_0 + \beta_1 \log\left(WOM_i^{pre} + 1\right) + \beta_2 Slant_i + \beta_3 Consistency_i + \beta_4 Attack_i + X_i'\rho + \varepsilon_i. \quad (1)$$

WOM_i^{post} is the online WOM volume about the candidate that occurs from the beginning of ad i until five minutes later. Similarly, WOM_i^{pre} is the volume of online WOM about the candidate that occurs from five minutes before an ad starts airing to the beginning of ad i. $Slant_i$ and $Consistency_i$ are the political slant and message consistency measures discussed in Section 2, respectively. $Attack_i$ is a dummy variable indicating that the ad is an attack ad or not. X_i is a vector of control variables that have been shown to impact political ad effectiveness and/or WOM activity following television ads (e.g., Fossen and Schweidel 2017; Wang et al. 2018). These variables include a dummy variable for which candidate the ad supports,[15] the log of audience size, a dummy

[14] For robustness, we also run the analysis using 2-minute and 3-minute time windows. See Appendix D.
[15] This is done through the inclusion of a Clinton dummy variable. We consider only whether the ad is pro-Clinton or pro-Trump, and not whether the ad was sponsored by the candidate or by a supporting PAC because the vast majority

variable of ad length (which is equal to 1 if the ad is greater than 30 seconds and 0 otherwise), the relative ad position in the ad break, program genre fixed effects, network fixed effects,[16] day of the week, time of the day, and week of the data window in which the ad airs.

Additionally, we test whether slant and message consistency have different effects on WOM across time as follows:

$$\begin{aligned}\log\left(WOM_i^{post}+1\right) &= \beta_0+\beta_1\log\left(WOM_i^{pre}+1\right)+\ \beta_2 PreOct1_i\cdot Slant_i+\beta_3 PostOct1_i\cdot Slant_i \\ &\quad +\beta_4 PreOct1_i\cdot Consistency_i+\beta_5 PostOct1_i\cdot Consistency_i \\ &\quad +\beta_6 PreOct1_i\cdot Attack_i+\beta_7 PostOct1_i\cdot Attack_i+X_i'\rho+\varepsilon_i,\end{aligned} \tag{2}$$

where, $PreOct1_i$ ($PostOct1_i$) are equal to 1 if ad *i* airs before Oct. 1st (on or after Oct. 1st) and 0 otherwise. We also interact tone ($Attack_i$), a vital component of political ad content, with the time division in order to test whether attack vs. non-attack ads differentially affects WOM activities over the course of the election campaign. We estimate Equation (1) and (2) with clustered standard errors at the candidate level[17].

To add credence to WOM analysis, we additionally run confirmatory regressions of voter preferences on political slant and message consistency. In modeling daily voter preferences, we

of Trump's ads were PAC ads while the vast majority of Clinton's ads were run by the campaign. Thus, the Clinton coefficient captures both the difference between Clinton and Trump as well as the difference between candidate ads and PAC ads.

[16] As there are many networks in the data, we group networks with fewer than 7 ad airings together as "Other Networks."

[17] We cluster at the candidate level to allow for the WOM residuals to correlate within candidates. However, we could instead cluster at the ad creative level, which is the level at which the slant and consistency measures vary. To guide our decision, we conduct statistical tests for the appropriate level of clustering (MacKinnon et al. 2020) and find support for clustering at the candidate level. This matches the recommendation of Cameron and Miller (2015) to cluster at a more aggregate level rather than a more disaggregate level. In Appendix E, we document the results of the statistical tests for clustering.

control for lagged voter preference and include a rich set of controls and fixed effects to help us isolate impacts of slant and consistency on voter preference. Nevertheless, it is impossible to control for all potential confounds. We model voter preference for candidate c at day t as:

$$VP_{c,t} = \alpha_c + \gamma_0 VP_{c,t-1} + \gamma_1 Slant_{c,t-1} + \gamma_2 Consistency_{c,t-1}$$
$$+\gamma_3 NoAds_{c,t-1} + X'_{c,t-1}\beta + T_{w_t} + \varepsilon_{ct}, \quad (3)$$

where $VP_{c,t}$ is voter preference of candidate c at day t (in %), α_c is a candidate fixed effect, and T_{w_t} is a weekly fixed effect. $Slant_{c,t-1}$ and $Consistency_{c,t-1}$ are the daily measures of slant and message consistency at $t-1$, respectively, which are measured as the weighted averages of these variables across all ads aired in a given day, where each ad is weighted by its audience size. $NoAds_{c,t-1}$ is a dummy variable equal to 1 if there are no ads supporting the candidate c on date t–1 and 0 otherwise. $X_{c,t-1}$ is a vector of control variables that includes the number of ads aired by the candidate, the audience size for the candidate as well as the rival's ads, the weighted average of attack tone, relative ad positions in breaks, ad length (as defined above), and the share of ads that aired on different program genres (for example, comedy, drama, news, etc…), and the share of ads that aired on major networks.[18] All of these control variables are calculated as the audience size weighted averages across all ads that aired in a given day, except for the number of ads aired and audience size.

Similar to Equation (2), we estimate a variation of equation (3) where we interact $Slant_{ct}$ and $Consistency_{ct}$ with $PreOct1_t$ and $PostOct1_t$, to see if the two variables of interest have

[18] As there are many small networks with only a few ad airings, we select the top 10 networks by the number of ad airings and group the rest as "Other Networks."

differing impacts on voter preference over the course of the election campaign. In both equations, we cluster standard errors at the candidate level.

4. Results

Table 5 presents the estimates for the WOM model.[19] Column 1 presents the results from Equation (1). We first observe that politically extreme messages decrease the volume of candidate-related WOM. In contrast, consistent messages increase the volume of WOM. We also see that attack ads decrease the volume of WOM. Column 2 reports the results from Equation (2), which includes the time interactions on the slant, consistency, and attack tone variables. We observe that the impact of slant appears to be larger in the early stages of the campaign, although the differences in the coefficients in each time period are not statistically significantly different. Next, we find that consistent messages are positively associated with WOM, although its impacts are much stronger and statistically significant early in the campaign. Attack ads have a slight positive impact on WOM in the early stages of the campaign, but the effects become negative in the later stage of the campaign. To summarize, our results show that politically centrist and consistent messages are beneficial for the candidates in terms of spurring a larger volume of online WOM.

[Insert Table 5 here]

While we interpret the impacts measured in Table 5 as being causal, it is worth clarifying the assumptions under which we consider this effect. First, as we note in Section 3, the impact of the advertisements on WOM could be affected by coincident events with the advertisements. The institutional details about how television advertisements are sold makes such coordination to the

[19] The estimation code can be found at https://github.com/political-advertising-replication/code-and-sample-data.

level of a 5-minute interval very difficult. We also note in Section 3 that we examined whether either candidate tweeted at times that coincided with the ads. We find that there were very few such tweets and that these numbers are not statistically different than those that one would expect with randomness. In appendix F, we probe the influence of outliers on the results. Specifically, we consider (1) winsorizing (i.e., replacing outliers with certain percentiles of the data) and (2) trimming the post-WOM volume at the 1% and 99%, and show that the results from these alternative analyses are very similar to our main analysis.

Another concern may be that these ads are not placed on random networks, but on optimal networks, some of which may match the audience with the message of the ad. While some readers may consider this to be a form of endogeneity, a more accurate interpretation of our results, given that we account for the network in which the ads airs, would be that our estimates reflect a causal effect of slant and consistency on WOM after accounting for the campaign's matching mechanism between the ad and the best media on which to place the ad. That is, our estimates account for the total effect consisting of both the direct effect of a change in slant or consistency, as well as the indirect effect of how slant and consistency would change the medium used to deliver such a message.[20]

While the results suggest that it is best for campaigns to present ad messages that are both politically centrist and consistent with their primary election messaging, these message characteristics may be at odds with each other. Thus, we consider whether slant or message consistency has a stronger impact on WOM behavior. Since the variables are on different scales, we compare the relative importance of these two measures using two different metrics. We first multiply the estimated coefficient with the difference between the 90th percentile and 10th

[20] As noted in the introduction, it is also possible that the ads prompt a flurry of tweets that would have been sent at a later time in the absence of the ad.

percentile values for slant and consistency, respectively. As a robustness check, we also multiply the coefficients with the standard deviation (SD) of each variable. The results in Table 6 show that consistency has a stronger impact on WOM than slant. Specifically, an increase from the 10th to 90th percentile values of consistency (one SD) is associated with an increase in WOM by about 4.4% (1.5%), while a similar change in slant is associated with a decrease in WOM by about 3.8% (1.3%). As was the case above, we find that both slant and consistency matter more in the early stages of the campaign, with the contrast being especially large for consistency. This seems to suggest that people may be more responsive to a candidate's messages in political ads early in the campaign.

[Insert Table 6 here]

While WOM is a means to generate attention and spread the candidate's message, which has been linked to increased vote share (e.g., Bermingham and Smeaton 2011; Jahanbakhsh and Moon 2014), voter preference offers a more direct measure of voting behavior that accurately predicts election results (e.g., Kennedy et al. 2018; Silver 2018). Thus, we examine the relationship between each candidate's voter preference and the slant and message consistency of the candidate's ads to lend further support to and confirm the relevance of the WOM analysis.

The results for our voter preference model appear in Table 7. Consistent with the WOM analysis, we observe from Column 1 that voter preference for a candidate is lower when the candidate's ads are more slanted, while it is higher when the candidate's ads are more consistent. The impact of whether the ad is an attack ad is very small. Column 2 reports the results when we interact slant, consistency, and tone with the time period (pre-Oct. 1 vs. post-Oct. 1). We find that more consistent messages are strongly and positively associated with increases in voter preferences in the early stages of the election, but its effects in the later stages of the election are much smaller

and not statistically significant. In contrast, the coefficients on slant are both negative and statistically significant. However, we again see that the impact of slant is stronger in the early stage of the general election. Additionally, the coefficient on attack ads in the late stage is negative, though only marginally significant. In sum, our analysis on voter preference suggests that a candidate would be better off by airing ads containing politically centrist and consistent messages, especially in the early stages of the campaign. While these results provide confirmatory evidence of the key findings from the WOM analysis, we note that we interpret these results as correlational, because it is possible that the strategy of ads being used (attack versus inconsistent new message versus slant) could be correlated with underlying trends or events not observed in our data that affect both the type of advertising and the voter preferences.

[Insert Table 7 here]

Many other papers that have sought to measure the impact of political advertising (e.g., Gordon and Hartmann 2013; Spenjuch and Toniatti 2016) have noted that measuring its impact is difficult because advertising intensity is often confounded with other campaign activities. However, the problem of measuring the impact on the quantity of advertising is somewhat different than the confounds we face in trying to understand how the message content of advertising affects voter preferences. In particular, if one is trying to calculate the impact of TV advertising spending on campaign outcomes, then one would over-estimate the impact of this advertising if one did not account for the fact that the TV advertising may coincide with non-TV advertising, campaign events, or earned media. However, our goal is not to measure the effectiveness of the advertising, per se, but of the impact of the messaging of the campaign as a whole.

Even with the set of fixed effects and controls we use, the key assumption we make is that the national campaign ads serve as central messaging devices used to amplify the same message

that the campaign is delivering in other activities it engages in. This assumption may be reasonable partially because we know that it is hard to create brands with multiple conflicting messages (Kotler and Keller 2016), so campaigns need to focus on the main message of the day. To support that national advertising campaigns reflect the message that the campaigns seek to get out, we note that all of Clinton's and Trump's national primetime TV ad creatives in our data were also aired as local TV ads in primetime, demonstrating the intended broad appeal of these messages. That said, the main purpose of this regression is to replicate the results of the WOM analysis. Also, as was the case with the WOM analysis, any estimated effects would have to be interpreted as being the effect of the message after the campaign's decision of how to match the message to the appropriate TV audience.

5. Conclusion

Using data on political advertising, online WOM, and daily polls for the 2016 Presidential Election, we find that ad messages that are politically centrist and consistent with the candidate's primary election messaging are associated with increases in online WOM. The voter preference analysis confirms these results. By comparing the relative impact of these two variables of interest, we find that consistent messages have a slightly larger impact on WOM. The result is somewhat reversed for the voter preference analysis, which may reflect significant differences or may reflect that the voter preference estimation is less able to control for confounds. Both measures are found to have greater impacts on voter preferences in the early stage of the campaign. Our results add nuance to the conventional wisdom that candidates should focus on taking stances that appeal to their party's primary electorate in the primary elections but then shift their message to be more centrist for the general election. While this strategy is beneficial, our results also show the value

of consistent political branding, especially in the early stages of a campaign. Our results further suggest that the rising use of extremist messages in political advertising (e.g., Bartels 2016; Wells and Seetharaman 2018) may be a flawed strategy for candidates as more extreme messages are associated with decreased candidate-related WOM volume and decreased voter preference for the candidate.

Our study is not without limitations. Our analysis is limited to one presidential election. Future research is needed to study whether our findings generalize to other presidential elections or other types of elections such as senatorial elections. Another limitation of the data we use is that we only focus on national television advertisements. This is done because it is very difficult to link local television advertising and online advertisements to our outcomes, as such ads are distributed widely throughout the day with a low density at any particular time. In contrast, national television advertising occurs at specific times, allowing us to detect the changes in our outcomes. Additionally, our consistency measure assumes that what would constitute a consistent message remains static. This reflects a natural breaking point that arises as candidates finish the primary season and enter the general election. However, a dynamic model that allows for additional break points throughout the campaign, or allows for a continuously updating measure of consistency, may prove to be fruitful. Finally, as noted in the introduction, there are several assumptions that are needed to make our findings causal. Unfortunately, we do not have exogenous data variation to exploit to further probe causal relationships. As such, it may be prudent to restrain the causal interpretations of the results until further studies confirm the results with other methods.

Beyond the political domain, our findings demonstrate the potential for marketers to make use of automated text analytic methods to evaluate their advertisements. We find that consumers react more favorably in terms of the volume of WOM and preference to advertising content that is

consistent with the established brand image of the political candidates. Future research may consider applying measures derived from text analysis to traditional brands. Evaluating the impact of ad campaigns on WOM and preferences may reveal insights for these traditional firms to increase the effectiveness of advertising. Such a relationship may vary across categories, potentially due to the nature of the products or the competitiveness of the category.

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Table 1. Descriptive Statistics for Candidates' Advertisements

Candidate	Unique ad creatives	Ad airings	% of attack ad airings	Ad length (in seconds)		Relative ad position in break		Break position in program		Audience (in thousands)	
				Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)
Clinton	28	634	71.50%	30.30	(4.12)	0.48	(0.21)	3.63	(3.02)	1,396.56	(3,181.85)
Trump	32	190	75.30%	31.70	(10.30)	0.48	(0.19)	3.96	(3.44)	2,430.335	(3,444.20)
Totals	60	824	73.33%	30.62	(6.16)	0.48	(0.20)	3.71	(3.12)	1,634.34	(3,271.20)

Note: Relative ad position is defined as ad's position in the break/number of ads in the break

Table 2. Words that are Highly Associated with Slant by Party

	Republican	Democratic
Words	senat, administr, regul, govern, rule, iran, law, spend, energi, busi, land, time, washington, balance, power, author, west, servic, move, obamecar, defens, north, life, obama, appreci, nuclear, deal, execut, plan, legisl, produc, materi, cost, debt, forc, process, account, dollar, appropri, manufactur, office, purpos, veteran, secretari, compani, provid, babi, illeg, price, suspend, defend, freedom, oil, pass, militari, south, sell, sponsor, alli, industri, entitl, islam, arm, bank, iranian, natur, document, radic, grow, control, enemi, innov, amend, faith, misson, alien, agreement, terror, missile	gun, act, vote, women, violence, hous, health, student, educ, commun, right, children, york, african, invest, citi, school, background, public, caucu, check, cut, live, climat, address, major, worker, prevent, justice, fund, water, child, civil, equal, pay, repress, afford, infrastructur, immigr, polic, colleg, action, homeland, girl, moment, progress, silenc, oppos, system, polit, kill, crisi, clean, access, democrat, care, wage, effort, discrimin, undermin, improv, corpor, secur, join, democraci, danger, shoot, crimin, famili, trade, incarcer, voter, fair, loan, kid, research, lgbt, inequ

Note: The words are stemmed (e.g., business and businesses are stemmed to busi).

Table 3. Descriptive Statistics for Political Slant and Message Consistency

	Political Slant						Message Consistency					
Candidate	Mean (SD)	Min	10th	50th	90th	Max	Mean (SD)	Min	10th	50th	90th	Max
Clinton	0.148 (0.514)	-0.625	-0.406	0.201	0.906	1.180	0.389 (0.067)	0.295	0.303	0.390	0.510	0.510
Trump	-0.084 (0.353)	-0.795	-0.626	0.002	0.294	0.539	0.353 (0.066)	0.209	0.217	0.359	0.407	0.452

Table 4. Descriptive Statistics for Percentage Change in WOM and Voter Preference

	Percent Change in WOM						Voter Preference					
Candidate	Mean (SD)	Min	25th	50th	75th	Max	Mean (SD)	Min	25th	50th	75th	Max
Clinton	35.5% (117)	-83.3%	-20.0%	6.1%	50.0%	930.0	43.1 (1.4)	40.0	42.3	43.3	44.2	46.3
Trump	28.3% (96.3)	-60.3%	-15.5%	6.8%	30.9%	643.0	45.0 (1.6)	41.6	43.8	44.8	46.3	48.2

Note: Percentage change in WOM is calculated as $\frac{(WOM^{post} - WOM^{pre})}{(WOM^{pre}+1)} \cdot 100$ at each ad each airing.

Table 5. Effects of Political Slant and Message Consistency on WOM

	Dependent Variable:	
	$\log(WOM^{post}+1)$	
	(1)	(2)
$\log(WOM^{pre}+1)$	0.649***	0.650***
	(0.002)	(0.0004)
Slant	-0.027***	
	(0.006)	
Consistency	0.214***	
	(0.039)	
Attack Ads	-0.065***	
	(0.014)	
Slant × Pre-Oct1		-0.078
		(0.098)
Slant × Post-Oct1		-0.002
		(0.098)
Consistency × Pre-Oct1		0.377***
		(0.053)
Consistency × Post-Oct1		0.167
		(0.338)
Attack Ads × Pre-Oct1		0.038*
		(0.021)
Attack Ads × Post-Oct1		-0.128**
		(0.057)
Pro-Clinton ads	-0.179**	-0.179**
	(0.091)	(0.084)
log(Audience Size)	0.127***	0.129***
	(0.048)	(0.048)
Ad length	0.319*	0.316**
	(0.170)	(0.157)
Ad position in break	-0.125**	-0.105***
	(0.054)	(0.027)
Week, Day, Hourly F.E.s	Yes	Yes
Program Genre and Network F.E.s	Yes	Yes
Observations	824	824
R^2	0.777	0.779

Note: S.E.s are clustered at the candidate level; *p < 0.1; **p < 0.05; ***p < 0.01

Table 6. Relative Importance of Slant and Consistency on WOM

Variable	WOM	
	90th vs 10th percentile	Standard Deviation
Slant	-0.038	-0.013
Consistency	0.044	0.015
Slant × Pre-Oct1	-0.132	-0.039
Consistency × Pre-Oct1	0.077	0.025
Slant × Post-Oct1	-0.002	-0.001
Consistency × Post-Oct1	0.023	0.011

Table 7. Effects of Political Slant and Message Consistency on Voter Preference

	Dependent Variable:	
	Voter preference (in %)	
	(1)	(2)
Lagged voter preference	0.865***	0.855***
	(0.012)	(0.015)
Slant	-0.294***	
	(0.022)	
Consistency	0.352***	
	(0.072)	
Attack Ads	-0.006	
	(0.082)	
Slant × Pre-Oct1		-0.323***
		(0.081)
Slant × Post-Oct1		-0.231***
		(0.017)
Consistency × Pre-Oct1		0.688**
		(0.339)
Consistency × Post-Oct1		0.130
		(0.087)
Attack Ads × Pre-Oct1		0.148
		(0.140)
Attack Ads × Post-Oct1		-0.326*
		(0.175)
No ads	-0.196	0.272
	(0.338)	(0.376)
log(Audience Size: Own Ads)	-0.039	-0.026
	(0.031)	(0.035)
log(Audience Size: Rival′s Ads)	0.001	0.005***
	(0.001)	(0.001)
Number of Ads	0.010	0.014
	(0.028)	(0.029)
Ad Position	-0.102	-0.085
	(0.291)	(0.321)
Ad Length	0.173	0.171
	(0.941)	(0.964)
Candidate and Week F.E.s	Yes	Yes
Program Genre and Network Controls	Yes	Yes
Observations	240	240
R^2	0.852	0.855

Note: S.E.s are clustered at the candidate level; *p < 0.1; **p < 0.05; ***p < 0.01

Figure 1. National Political Television Ads from June 30th to Election Day 2016

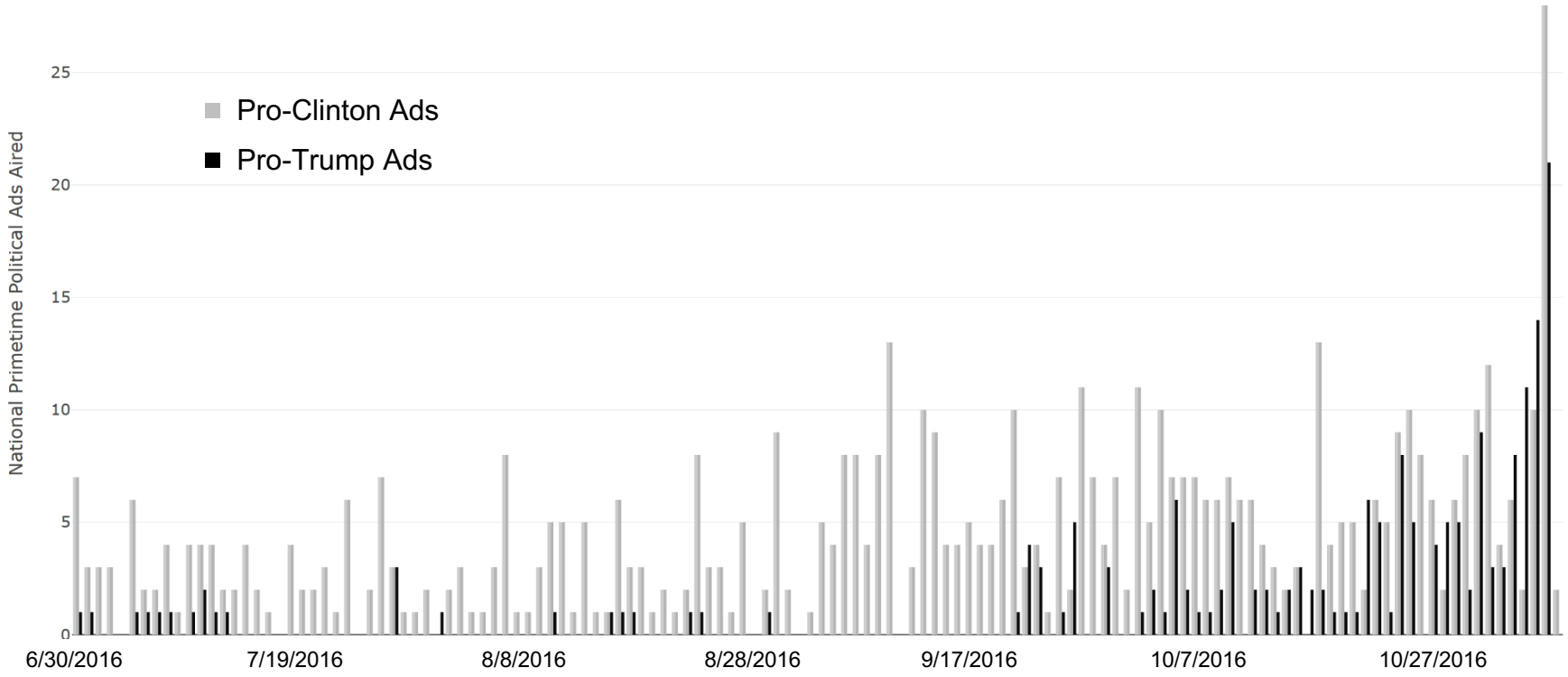
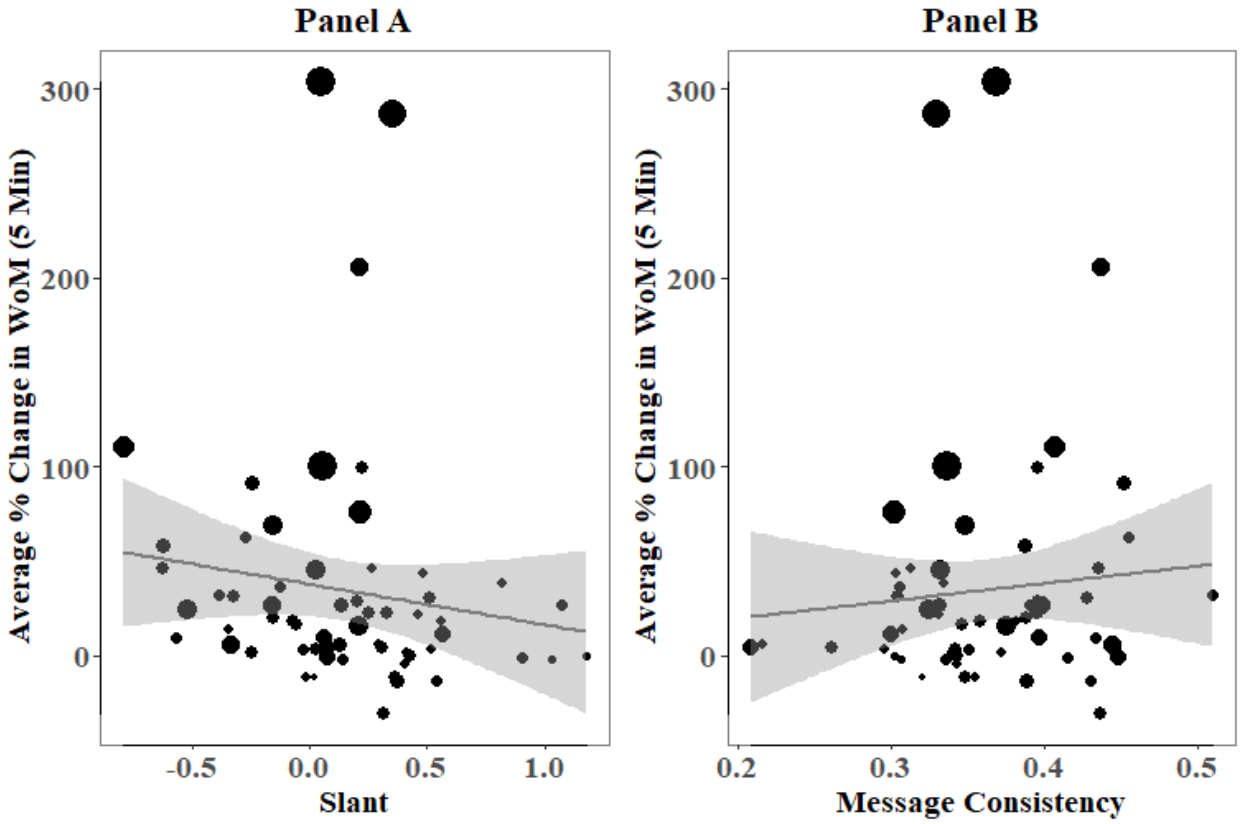
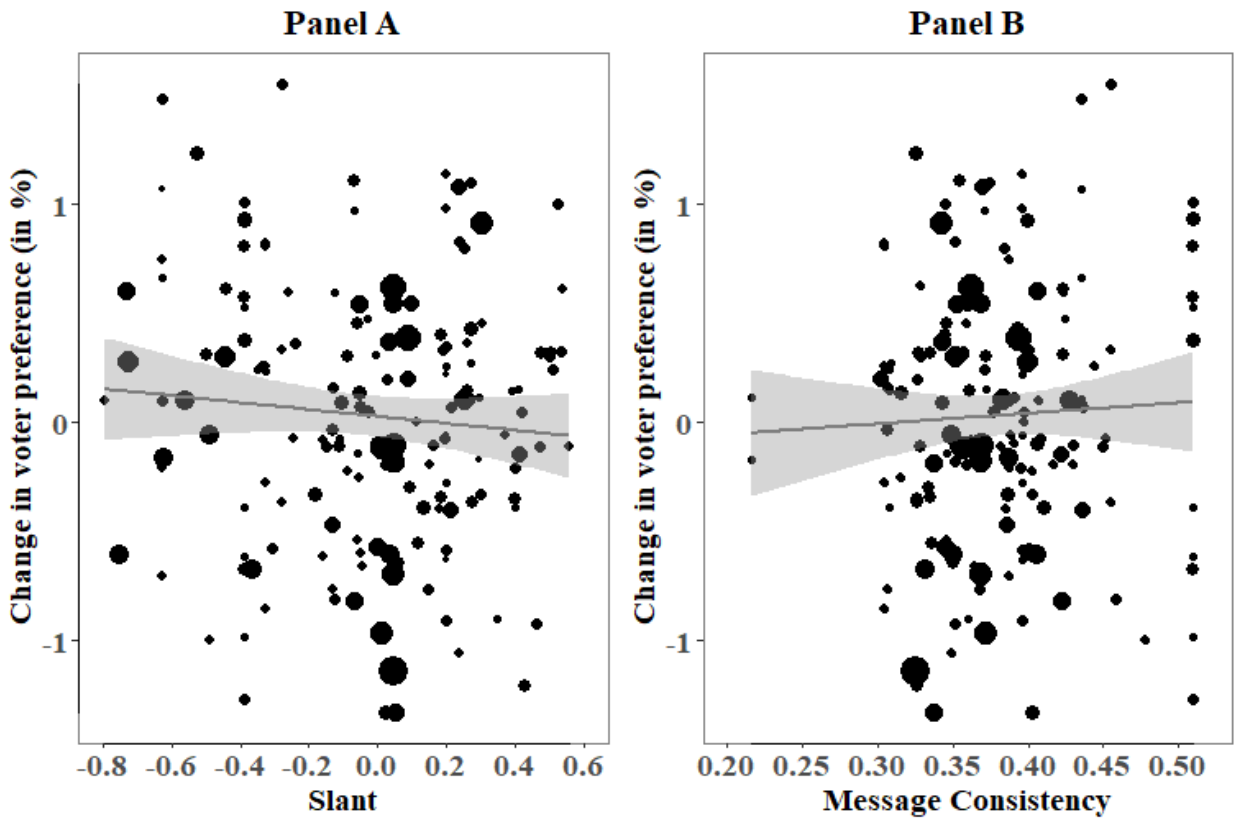


Figure 2. Relationship between Slant, Message Consistency, and Average Percentage Change in WOM



Note: The size of each dot represents the average ratings per each of the unique ad creatives (in millions).

Figure 3. Relationship between Slant, Message Consistency, and Change in Voter Preference



Note: The size of each dot represents the average ratings per each of the unique ad creatives (in millions).

Appendix A. Slant Variable Details

In this appendix, we present details on the calculations of the slant index.

Political Slant

We first pre-process texts using the NLKT module in Python: we make words lower case and remove stop words,[21] punctuations, and numbers. We then tokenize each of the texts and stem the words in the text.

Following Gentzkow and Shapiro (2010) and their notations for consistency, we first derive the mapping between a vector of word counts a congressperson used and the political leanings of their district. For each word p in the 114th Congressional Record, we count the number of times the word p is used by each of the two parties and calculate a chi-square statistic, x_p^2.[22] We restrict our focus to words that occur at least 2 times but fewer than 100 times in the candidates' public speeches and transcribed ad texts.[23] This removes some of the most common and least common words, which are not useful for the analysis. We then select the 1,000 words with the highest values of x_p^2.

Among the 1,000 selected words, we regress congressperson c's relative frequency of word p, $\tilde{f}_{pc}$, on their ideology, $ideology_c$, measured by the Republican vote share in the district[24] from the 2012 presidential election (collected from dailykos.com) and estimate an intercept parameter α_p and slope parameter β_p. A positive (negative) slope estimate suggests that the word p is associated with the Republican (Democratic) party.

We then compute the political slant for each of the ad creatives by applying the same mapping between the relative word frequencies and political slants of those words used in the ad. Specifically, the political slant of ad creative n is computed as $\tilde{y}_n = \frac{\sum_{p=1}^{p=1000} b_p(\tilde{f}_{pn} - a_p)}{\sum_{p=1}^{p=1000} b_p^2}$.[25]

Finally, we re-index the estimated political slant of ad creative n, $\tilde{y}_n$, to $\tilde{y}_{nc}$ to denote the candidate c that ad creative n supports. Our slant measure is then calculated as $\hat{y}_{cn} = -(\tilde{y}_{cn} - 0.5)$ if c is Clinton and $\hat{y}_{cn} = \tilde{y}_{cn} - 0.5$ if c is Trump. Thus, a greater (lower) slant measure always corresponds to a more politically extreme (centrist) message for both candidates.

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[21] We add a handful of words to the existing list of stop words from NLTK in Python, such as madam, speaker, and thank. These words appear frequently but are not informative of one's political ideology.

[22] The chi-square statistic measures the extent to which a given word is used with asymmetric frequencies by parties.

[23] Contrary to Gentzkow and Shapiro (2010) who used newspaper articles, ad texts are typically short. Therefore, in order to overcome the scarcity of words, we use both the candidates' speeches and ad texts to select words to consider.

[24] We consider the Republican candidate's vote share in the state for senators and congressional district for congresswomen and congressmen.

[25] This is equivalent to regressing $\tilde{f}_{pn} - \alpha_p$ on β_p.

Appendix B. Doc2Vec Validation

In this appendix, we provide additional evidence to confirm the validity of the performance of the doc2vec algorithm by presenting two ad creatives with the other ad creatives that are found to be the most similar, excluding the chosen ad creative in consideration, and the least similar.

Appendix B.1. Example of an Ad that supports Clinton

Selected Ad	Candidate (Tone)	Ad Content
Focal Ad	Clinton (negative)	I spent many years as a nuclear missile launch officer. If the president gave the order, we had to launch the missiles. That would be it. I prayed that call would never come. Self-control may be all that keeps these missiles from firing. [Trump speaking] *I would bomb the F out of them I want to be unpredictable. I love war*. The thought of Donald Trump with nuclear weapons scares me to death. Should scare everyone.
Most Similar Ad	Clinton (negative)	If he governs consistent with some of the things he said as a candidate, I would be very frightened. He's been talking about the option of using a nuclear weapon against our Western European allies. This is not somebody who should be handed the nuclear codes. You have to ask yourself, do I want a person of that temperament control the nuclear codes? And as of now, I have to say no.
Least Similar Ad	Trump (Positive)	The American moment is here, two choices, two Americans decided by you. Hillary Clinton will keep us on the road to stagnation. Fewer jobs, rising crime, America diminished at home and abroad. Donald Trump will bring the change we are waiting for. America better, stronger, more prosperous. For everyone, a plan for a future brighter than our past. The choice is yours.

Appendix B.2. Example of an Ad that supports Trump

Selected Ad	Candidate (Tone)	Ad Content
Focal Ad	Trump (Positive)	The most important job any woman can have is being a mother, and it shouldn't mean taking a pay cut. I'm Ivanka Trump, a mother, a wife and an entrepreneur. Donald Trump understands the needs of the modern work force. My father will change outdated labor laws so that they support women and American families. He will provide tax credits for childcare, paid maternity leave and dependent care savings accounts. This will allow women to support their families and further their careers.
Most Similar Ad	Clinton (Positive)	Far too many families today don't earn what they need and don't have the opportunities they deserve. I believe families deserve quality education for their kids. Childcare they can trust and afford. Equal pay for women and jobs they can really live on. People ask me what'll be different if I'm president? Well, kids and families have been the passion of my life, and they will be the heart of my presidency.
Least Similar Ad	Clinton (Positive)	What does showing up when it's time to vote actually mean? You care about protecting his legacy and our progress. You care about moving forward, united as one, because when we show up in full force and when we refuse to stand by quietly, we show what it means to be stronger together.

Appendix C. Sensitivity to Size of Vector Space in dov2vec

In this appendix, we demonstrate that our results in the main text are robust to the dimension of the vector space, one of the most important hyper-parameters, by providing results for different vector sizes. In all cases, standard errors are clustered at the candidate level.

Table C.1. Effects of Political Slant and Message Consistency on WOM (*vector = 150*)

	Dependent Variable:	
	$\log(WOM^{post}+1)$	
	(1)	(2)
$\log(WOM^{pre}+1)$	0.649***	0.650***
	(0.001)	(0.0004)
Slant	-0.030***	
	(0.009)	
Consistency	0.173**	
	(0.076)	
Attack Ads	-0.064***	
	(0.015)	
Slant × Pre-Oct1		-0.082
		(0.098)
Slant × Post-Oct1		-0.007
		(0.018)
Consistency × Pre-Oct1		0.208***
		(0.036)
Consistency × Post-Oct1		0.162
		(0.389)
Attack Ads × Pre-Oct1		0.045*
		(0.024)
Attack Ads × Post-Oct1		-0.131**
		(0.059)
Pro-Clinton ads	-0.178*	-0.183**
	(0.093)	(0.088)
log(Audience Size)	0.128***	0.129***
	(0.048)	(0.048)
Ad length	0.317*	0.316**
	(0.168)	(0.154)
Ad position in break	-0.125**	-0.107***
	(0.054)	(0.028)
Week, Day, Hourly F.E.s	Yes	Yes
Program Genre and Network F.E.s	Yes	Yes
Observations	824	824
R^2	0.777	0.779

Note: S.E.s are clustered at the candidate level; *p < 0.1; **p < 0.05; ***p < 0.01

Table C.2. Effects of Political Slant and Message Consistency on WOM (*vector = 300*)

	Dependent Variable:	
	$\log(WOM^{post}+1)$	
	(1)	(2)
$\log(WOM^{pre}+1)$	0.649***	0.650***
	(0.001)	(0.0001)
Slant	-0.030***	
	(0.008)	
Consistency	0.186***	
	(0.072)	
Attack Ads	-0.065***	
	(0.014)	
Slant × Pre-Oct1		-0.083
		(0.096)
Slant × Post-Oct1		-0.005
		(0.017)
Consistency × Pre-Oct1		0.305***
		(0.035)
Consistency × Post-Oct1		0.151
		(0.349)
Attack Ads × Pre-Oct1		0.039
		(0.026)
Attack Ads × Post-Oct1		-0.129**
		(0.060)
Pro-Clinton ads	-0.177*	-0.179**
	(0.092)	(0.082)
log(Audience Size)	0.127***	0.129***
	(0.048)	(0.048)
Ad length	0.319*	0.316**
	(0.169)	(0.156)
Ad position in break	-0.125**	-0.106***
	(0.054)	(0.028)
Week, Day, Hourly F.E.s	Yes	Yes
Program Genre and Network F.E.s	Yes	Yes
Observations	824	824
R^2	0.777	0.779

Note: S.E.s are clustered at the candidate level; *p < 0.1; **p < 0.05; ***p < 0.01

Table C.3. Effect of Slant and Message Consistency on Voter Preference (*vector = 150*)

	Dependent Variable:	
	Voter preference (in %)	
	(1)	(2)
Lagged voter preference	0.865***	0.855***
	(0.012)	(0.015)
Slant	-0.299***	
	(0.023)	
Consistency	0.279***	
	(0.046)	
Attack Ads	-0.005	
	(0.079)	
Slant × Pre-Oct1		-0.343***
		(0.084)
Slant × Post-Oct1		-0.228***
		(0.010)
Consistency × Pre-Oct1		0.521
		(0.317)
Consistency × Post-Oct1		-0.233**
		(0.105)
Attack Ads × Pre-Oct1		0.129
		(0.140)
Attack Ads × Post-Oct1		-0.290*
		(0.174)
No ads	-0.189	0.300
	(0.341)	(0.367)
log(Audience Size: Own Ads)	-0.037	-0.019
	(0.031)	(0.034)
log(Audience Size: Rival′s Ads)	0.001	0.005***
	(0.001)	(0.0004)
Number of Ads	0.010	0.012
	(0.028)	(0.029)
Ad Position	-0.103	-0.094
	(0.291)	(0.320)
Ad Length	0.173	0.136
	(0.946)	(0.965)
Candidate and Week F.E.s	Yes	Yes
Program Genre and Network Controls	Yes	Yes
Observations	240	240
R^2	0.852	0.855

Note: S.E.s are clustered at the candidate level; *p < 0.1; **p < 0.05; ***p < 0.01

Table C.4. Effect of Slant and Message Consistency on Voter Preference (*vector = 300*)

	Dependent Variable:	
	Voter preference (in %)	
	(1)	(2)
Lagged voter preference	0.866***	0.856***
	(0.011)	(0.015)
Slant	-0.299***	
	(0.023)	
Consistency	0.279***	
	(0.046)	
Attack Ads	-0.005	
	(0.079)	
Slant × Pre-Oct1		-0.340***
		(0.083)
Slant × Post-Oct1		-0.226***
		(0.012)
Consistency × Pre-Oct1		0.615
		(0.435)
Consistency × Post-Oct1		-0.159
		(0.234)
Attack Ads × Pre-Oct1		0.132
		(0.142)
Attack Ads × Post-Oct1		-0.286*
		(0.166)
No ads	-0.193	0.305
	(0.337)	(0.362)
log(Audience Size: Own Ads)	-0.037	-0.020
	(0.028)	(0.032)
log(Audience Size: Rival′s Ads)	0.001	0.005***
	(0.001)	(0.0004)
Number of Ads	0.010	0.012
	(0.027)	(0.028)
Ad Position	-0.103	-0.096
	(0.294)	(0.320)
Ad Length	0.171	0.141
	(0.936)	(0.951)
Candidate and Week F.E.s	Yes	Yes
Program Genre and Network Controls	Yes	Yes
Observations	240	240
R^2	0.852	0.855

Note: S.E.s are clustered at the candidate level; *p < 0.1; **p < 0.05; ***p < 0.01

Appendix D. Sensitivity of the WOM Results to the Time Window Used

In this appendix, we show that our results in the main text are robust to different time windows by providing results for two- and three-minute windows.

Table D.1. Effects on WOM (*time window = 2 minutes*)

	Dependent Variable:	
	$\log(WOM^{post}+1)$	
	(1)	(2)
$\log(WOM^{pre}+1)$	0.529***	0.530***
	(0.002)	(0.004)
Slant	-0.032	
	(0.039)	
Consistency	0.446***	
	(0.079)	
Attack Ads	-0.059	
	(0.041)	
Slant × Pre-Oct1		0.027
		(0.077)
Slant × Post-Oct1		-0.068**
		(0.028)
Consistency × Pre-Oct1		0.135
		(0.092)
Consistency × Post-Oct1		0.632*
		(0.347)
Attack Ads × Pre-Oct1		0.196***
		(0.045)
Attack Ads × Post-Oct1		-0.209*
		(0.126)
Pro-Clinton ads	-0.270***	-0.282***
	(0.061)	(0.056)
log(Audience Size)	0.176***	0.172***
	(0.046)	(0.040)
Ad length	0.131	0.148
	(0.176)	(0.170)
Ad position in break	-0.131**	-0.116
	(0.199)	(0.162)
Week, Day, Hourly F.E.s	Yes	Yes
Program Genre and Network F.E.s	Yes	Yes
Observations	824	824
R^2	0.675	0.680

Note: S.E.s are clustered at the candidate level; *p < 0.1; **p < 0.05; ***p < 0.01

Table D.2. Effects on WOM (*time window = 3 minutes*)

	Dependent Variable:	
	$\log(WOM^{post}+1)$	
	(1)	(2)
$\log(WOM^{pre}+1)$	0.603***	0.603***
	(0.002)	(0.001)
Slant	-0.084***	
	(0.027)	
Consistency	0.158	
	(0.118)	
Attack Ads	-0.085***	
	(0.021)	
Slant × Pre-Oct1		-0.062
		(0.075)
Slant × Post-Oct1		-0.099***
		(0.008)
Consistency × Pre-Oct1		0.072
		(0.068)
Consistency × Post-Oct1		0.227
		(0.444)
Attack Ads × Pre-Oct1		0.106**
		(0.047)
Attack Ads × Post-Oct1		-0.196**
		(0.093)
Pro-Clinton ads	-0.205***	-0.209***
	(0.074)	(0.068)
log(Audience Size)	0.180***	0.178***
	(0.042)	(0.039)
Ad length	0.220	0.228
	(0.175)	(0.167)
Ad position in break	-0.178	-0.161
	(0.140)	(0.167)
Week, Day, Hourly F.E.s	Yes	Yes
Program Genre and Network F.E.s	Yes	Yes
Observations	824	824
R^2	0.731	0.734

Note: S.E.s are clustered at the candidate level; *p < 0.1; **p < 0.05; ***p < 0.01

Appendix E. Tests on the Level of Clustering

In this appendix, we conduct the statistical test for the appropriate level of clustering proposed by MacKinnon et al. (2020). MacKinnon et al. (2020) test the null hypothesis of a finer clustering level against the alternative hypothesis of a coarser clustering level. In our context, we can test whether clustering at the ad creative level (null hypothesis) against clustering at the candidate level (alternative hypothesis). The results, shown below, reveal that the no clustering case (the finest case) is rejected for both the ad creative level and the candidate level, but clustering at the ad creative level is rejected against the candidate level. Taken together, these results suggest that we cluster standard errors at the candidate level.

	Estimated Model: Equation (2)	
Test	Statistic	Bootstrapped *p*-value
N vs *A*	76.63	0.000
N vs *C*	29.35	0.014
A vs *C*	19.08	0.031

Note: *N* denotes no clustering; *A* denotes clustering at the ad creative; *C* denotes clustering at the candidate level.

Appendix F. Influence of Outliers on the WOM analysis

In this appendix, we show that our results remain very similar to removal of outliers. Specifically, we run our WOM analysis after both winsorizing and trimming the post-WOM volume at the 1 and 99% level.

Table F.1. Effects on WOM (*winsorized Post-WOM at the 1 and 99% level*)

	Dependent Variable:	
	$\log(WOM^{post}+1)$	
	(1)	(2)
$\log(WOM^{pre}+1)$	0.633***	0.634***
	(0.006)	(0.008)
Slant	-0.095***	
	(0.007)	
Consistency	0.215***	
	(0.079)	
Attack Ads	-0.068***	
	(0.017)	
Slant × Pre-Oct1		-0.073
		(0.100)
Slant × Post-Oct1		0.005
		(0.014)
Consistency × Pre-Oct1		0.361***
		(0.013)
Consistency × Post-Oct1		0.173
		(0.359)
Attack Ads × Pre-Oct1		0.031**
		(0.015)
Attack Ads × Post-Oct1		-0.130**
		(0.057)
Pro-Clinton ads	-0.193**	-0.196**
	(0.086)	(0.079)
log(Audience Size)	0.117**	0.118**
	(0.053)	(0.052)
Ad length	0.247***	0.245***
	(0.079)	(0.067)
Ad position in break	-0.148***	-0.129***
	(0.065)	(0.040)
Week, Day, Hourly F.E.s	Yes	Yes
Program Genre and Network F.E.s	Yes	Yes
Observations	824	824
R^2	0.779	0.781

Note: S.E.s are clustered at the candidate level; *p < 0.1; **p < 0.05; ***p < 0.01

Table F.2. Effects on WOM (*trimmed Post-WOM at the 1 and 99% level*)

	Dependent Variable:	
	$\log(WOM^{post}+1)$	
	(1)	(2)
$\log(WOM^{pre}+1)$	0.629***	0.629***
	(0.013)	(0.015)
Slant	-0.029***	
	(0.005)	
Consistency	0.140***	
	(0.044)	
Attack Ads	-0.063***	
	(0.002)	
Slant × Pre-Oct1		-0.074
		(0.109)
Slant × Post-Oct1		-0.015***
		(0.002)
Consistency × Pre-Oct1		0.393***
		(0.066)
Consistency × Post-Oct1		-0.018
		(0.278)
Attack Ads × Pre-Oct1		0.010
		(0.010)
Attack Ads × Post-Oct1		-0.133***
		(0.037)
Pro-Clinton ads	-0.178**	-0.176**
	(0.080)	(0.073)
log(Audience Size)	0.106*	0.107*
	(0.056)	(0.073)
Ad length	0.239***	0.237***
	(0.058)	(0.044)
Ad position in break	-0.150***	-0.133***
	(0.043)	(0.022)
Week, Day, Hourly F.E.s	Yes	Yes
Program Genre and Network F.E.s	Yes	Yes
Observations	809	809
R^2	0.769	0.771

Note: S.E.s are clustered at the candidate level; *p < 0.1; **p < 0.05; ***p < 0.01

Appendix G. Comparison of National Primetime Ads versus Local Primetime Ads

In this appendix, we show that Clinton and Trump's national primetime ads exhibit very similar airing patterns as their local primetime ads in terms of time, day of the week, and month aired. Note that the summary statistics for the local prime ads are generated from the raw Stradegy data on the candidate's primetime advertising and have not been cleaned for data errors.

Table G.1. National versus Local Primetime Ad Airings by Time

	Clinton				Trump			
	Local Ad Airings		National Ad Airings		Local Ad Airings		National Ad Airings	
7:00-7:59 PM	12522	4.2%	10	1.6%	2576	6.9%	5	2.6%
8:00-8:59 PM	108931	36.8%	178	28.1%	13808	37.1%	57	30.0%
9:00-9:59 PM	99866	33.7%	232	36.6%	11930	32.0%	81	42.6%
10:00-10:59 PM	74887	25.3%	214	33.8%	8928	24.0%	47	24.7%

Table G.2. National versus Local Primetime Ad Airings by Day of the Week

	Clinton				Trump			
	Local Ad Airings		National Ad Airings		Local Ad Airings		National Ad Airings	
Sun	50782	17.1%	104	15.4%	8195	22.0%	32	16.8%
Mon	33262	11.2%	75	11.1%	6061	16.3%	42	22.1%
Tue	42763	14.4%	120	17.8%	4011	10.8%	25	13.2%
Wed	44725	15.1%	121	17.9%	4468	12.0%	22	11.6%
Thu	41944	14.2%	77	11.4%	5388	14.5%	23	12.1%
Fri	44247	14.9%	78	11.5%	4420	11.9%	21	11.1%
Sat	38483	13.0%	59	8.7%	4699	12.6%	25	13.2%

Table G.3. National versus Local Primetime Ad Airings by Month

	Clinton				Trump			
	Local Ad Airings		National Ad Airings		Local Ad Airings		National Ad Airings	
Jun	3679	1.2%	9	1.4%	0	0.0%	1	0.5%
Jul	52326	17.7%	92	14.5%	206	0.6%	13	6.8%
Aug	35314	11.9%	99	15.6%	172	0.5%	8	4.2%
Sep	85014	28.7%	178	28.1%	2275	6.1%	17	8.9%
Oct	87039	29.4%	181	28.5%	23618	63.4%	81	42.6%
Nov	32834	11.1%	75	11.8%	10971	29.5%	70	36.8%