How Social Media drove the 2016 US Presidential Election:

a longitudinal topic and platform analysis

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Abstract

To what extent did external events and news versus the candidates' own actions drive the 2016 election outcome? And were candidates misled if they focused on traditional market research versus the newer probabilistics polls? Based on the dynamic political will formation framework, the authors address these questions with a national daily dataset combining polling, donations and TV advertising data with social media interactions to all candidates' posts of the two candidates on Twitter, Facebook, and Instagram. Persistence modeling reveals that donations followed rather than drove the candidates' polls. The probabilistic polls show a different impact of candidate ads and statements, news coverage and fake news than do the traditional polls. TV ads on the economy or gun control, and on terror threats were most effective for respectively Hillary Clinton and Donald Trump. Topics matter, as fake news about a candidate hurtsher chances on one topic, but benefits her on another topic. Moreover, platforms matter: Clinton's chances benefitted from promoting women issues on Instagram, but declined from doing so on Twitter. Her moral language on Fairness Vice and social media users' on Authority Virtue made voters less likely to vote for her, but more likely to share fake news about her and to talk positively about Trump. While news coverage had minimal impact, fake news on Clinton's emails, shared on her Facebook page, greatly damaged her election chances. This fake news impact was most pronounced for seniors, Hispanics and high earners – demographics who moved towards Trump in the last weeks before the election. The authors draw lessons from the past election to advise where, when and how to drive the political conversation.

Keywords: politics, marketing, social media, time series, probabilistic polls, election

‘Every 4 years, the country stages a large-scale experiment in political propaganda and public opinion.’ (Lazarsfeld, Berelson, and Gaudet 1944)

„It's funny if you go to trumps page you see trump supporters, and then you check out Hilary's page and you see trump supporters.“ *(Facebook User Nick M.’ comments on Hillary Clinton’s Facebook page on July 23, 2016)*

The 2016 US presidential election outcome was perceived by many as a surprise, and has been the topic of much speculation and research. Journalistic coverage, surprise events, social media and fake news are all believed to have played a role (Allcott and Gentzkow 2017; Kennedy et al. 2018; Persily 2017). From a marketing perspective though, a key under-researched area is the impact of the candidates’ own actions, from official statements and TV ad topics to owned and earned social media (Gordon et al. 2012; Shachar 2009; Silver 2017a). While the specific events will differ in future elections, and news coverage is changing, the differential effects from e.g. promoting women issues on Instagram vs. Twitter or TV ads on the economy vs. terror threats may be insightful for future campaigns. To what extent did these actions drive the election outcome? Moreover, the value of traditional polls as a market research instrument (Gordon et al. 2012; Hillygus 2011) was questioned in 2016 (Coppock 2017; Kennedy et al. 2018; Klar, Weber, and Krupnikov 2016), and may have given candidates inaccurate information to base their decisions on. Did candidate actions have different effects on the traditional market research versus the newer probabilistic polls?

Current research provides only partial answers to the above research questions. Economists have shown that factually false news on social media did not sway the election (Allcott and Gentzkow 2017), but did not analyze the biased rumors and shared opinions (hereafter ‘fake news’), nor did they distinguish between the topics. Political scientists have developed and tested probabilistic polling as an alternative to traditonal polls (Delavande and Manski 2010; Gutsche et al. 2014), but have not analyzed how candidate’s actions and events influenced those differently. As to temporal causality (what drives what?), Sides and Vavreck (2013) were the first to show that news coverage is driven by polls close to the (2012) election, but did not analyze donations and voter reactions in the same way. Finally, research in marketing has focused on money spent on traditional as well as digital ads and both on the topics and the origin of those ads (Fowler, Ridout, and Franz 2016; Francia 2018; Tedesco and Dunn 2019), but not differentiated their impact from TV ads, nor from the candidate statements on owned social media such as Instagram and Twitter. Table 1 summarizes previous research on the topic and positions our paper.

<Table 1 about here>

Inspired by the dynamic political will formation framework in political science (Tucker et al. 2018) and branding research in marketing science, we combine rich daily data on the candidates' owned media (statements and social media posts), TV advertising and donations with almost 100 million Twitter, Facebook and Instagram social media reactions, news coverage of events and both traditional and probabilistic polls by demographic. We perform natural language processing of the candidates' owned media to identify both linguistic and moral foundations and organize advertising according to topics obtained from Latent Dirichlet Allocation (LDA) topic models. Persistence modeling shows whether and to what extent each variable drove the traditional and the probabilistic polls of different demographic segments, allowing us to quantify their relative importance in the 2016 US presidential election.

Our research contributes to political science, marketing and social media/fake news literatures. First, political science has focused on the foundational context (e.g. state of the economy and incumbent party) and the identity of the candidates (e.g. gender, race) and their followers (Sides and Vavreck 2013), while we uncover the candidates' *actions* in statements and topic/media combinations that matter most. As to empirical analysis, political science has been 'dominated by cross-sectional analyses of survey data' (Chanley, Rudolph, and Rahn 2000, p. 241), and longitudinal analyses suffer from temporal aggregation which can undermine the efficiency of least squares estimation, alter the fit of regression models, and mask the nature of underlying causal relationships (Freeman 1989). In contrast, social media interactions occur fast and are typically available and analyzed at a daily level (Barberá et al. 2019; Hennig-Thurau et al. 2020; Ilhan, Kübler, and Pauwels 2018). Commenting on the 2016 election, Newman (2016) notes that “the events that unfold on a day-to-day basis may create the need to resort to the use of new technological tools” (p. 792). Answering calls for a more granular dynamic political will formation analysis (Tucker et al. 2018), we compile a *daily* data set of social media interactions, fake news sharing, news coverage, TV ads and candidate statements to reveal that their polling effects occur within days, and typically have vanished within a week. Most importantly, our findings yield specific recommendations on which topics candidates should focus on in which media. Second, marketing literature has focused on the study of company brands, while we answer calls for analysis of individuals as brands (e.g. Oh et al. 2020) and to demonstrate the societal impact of marketing strategies (Moorman et al. 2018). Marketing modeling applications in politics have been mostly concerned with exploiting zip-code or media market level differences in the candidate’s marketing spending to estimate structural models of marketing elasticities (Gordon and Hartmann 2013; Shachar 2009; Spenkuch and Toniatti 2018). In contrast, we select leading poll drivers with Granger Causality tests among hundreds of variables, estimate their complex and dynamic interactions in a flexible model, and reveal which ones mattered most. Third, recent papers have demonstrated that fake news travels faster and further than real news on social media (Vosoughi, Roy, and Aral 2018) but it is unclear about whether or not it affected voter behavior, with economists finding factually false news had no decisive impact (e.g. Allcott and Gentzkow 2017) while others find a correlation between partisan news (‘disinformation’ in Tucker et al. 2018) and polls (e.g. Guess, Nyhan, and Reifler 2020; Gunther, Beck, and Nisbet 2019), but without controlling for other potential drivers. We distinguish fake news and real news topics to show their different impact on different polls (traditional versus probabilitistic) and on demographics.

Key findings include that donations followed rather than drove the candidates' polls. The probabilistic polls, which predicted the 2012 election outcome well (Gutsche et al. 2014) and implied a close race with Trump ahead for most of the 2016 campaign (see data section), show a different impact of candidate statements and events than do the traditional polls, TV ads on the economy and on terror threats were most effective for respectively Hillary Clinton and Donald Trump. Interestingly, Clinton's chances benefited from promoting women issues on Instagram, but dropped from promoting these topics on Twitter. The moral language of candidate statements affected the traditional polls and the probabilistic poll differently. Key events include Trump's 'Grab Them' tape, Clinton's 'Basket of Deplorables' statement and the FBI email investigation against the Democratic campaign (Gambino and Pankhania 2016; Stracqualursi 2016), which also changed the nature of the fake news posted on the candidates' Facebook pages. Finally, the single most important driver of the probabilistic poll gap was fake news on Clinton's emails, posted on Facebook. This fake news impact was most pronounced for high earners (over $75K annual income), seniors, and Hispanics. Interestingly, black voters were more affected by Fake News on Clinton and Muslims. We find substantial demographic differences in the effects of other drivers as well. As to gender, women were more affected by TV ads on gun control, Clinton's moral language and News coverage on Clinton's emails and Democratic Party division, while men were by Clinton's 'Basket of Deplorables' statement and her tweets on women issues, and the expressed Joy for Trump on Twitter and sentiment for Clinton on Facebook. Thus, social media in general appears more important in driving men's voting intentions. As to income, low-earners were more affected by Clinton ads about the economy, mid-earners were most affected by Trump TV ads on Terror, Clinton tweets and Instagram posts on Women, and high earners more by Clinton's moral language and news coverage on Democratic Party division. As to race, black voters were more driven by Clinton Economy TV ads and her Instagram posts on women issues and Facebook sentiment, white voters by Joy sentiment for Trump shared on Twitter, Hispanics by Trump's 'Grab Them' tape and the New York Times' story of no Russia interference, and other races by Clinton's Instagram posts on women issues. From these 2016 findings, we make specific recommendations for upcoming elections and draw general conclusions for the theory and practice of political marketing.

Research background

We base our literature discussion and conceptual model development on three streams of research: (1) research that focuses on the intersection between political and marketing research, (2) research that focuses specifically on false and fake news during the 2016 US presidential elections and (3) research on other factors driving the outcome of the 2016 presidential election.

Research on political marketing

Starting with Lazarsfeld (1944), political marketing literature has investigated the roll of mass media and interpersonal interactions for different demographics. In their review and theory of individual choice behavior, Newman and Sheth (1987) discuss both 'rational' drivers, such as the candidates' stance of political issues, and 'emotional' drivers, such as the candidates' social imagery and feelings evoked by their personality. As to 'future trends', Newman and Sheth (1987) point to the increased importance of TV advertising and call for research to assess the voter effectiveness of different advertising appeals. If voters are mostly driven by the candidates' stand on issues, information is key – but persuasion is when they vote for a candidate if perceived as 'a strong and charismatic leader who will be innovative in implementing policies' (p. 147).

Political science has a rich history of analyzing survey data to understand what matters to voters (Chanley et al. 2000; Hillygus 2011). The economy typically comes out as the most important topic. For instance, in May 2012, 52% of voters said the economy and jobs were the single most important issue in their choice for president. To not discuss those matters makes the candidate appear inattentive or uncaring (Sides and Vavreck 2013). In contrast, the extent of news coverage is only important in driving candidate fortunes during the primaries – in the 2012 election, it follows rather than drives poll numbers (ibid). Likewise, perceived 'blunders' by candidates (e.g. Romney's '47% of Americans pay no taxes' leaked statement) have less impact than pundits think, as most Americans have not heard blunders or misattribute, and the people who have heard are least likely 'to change their minds' (p. 115).

Much of political science focuses on 'the fundamentals' (e.g. the state of the economy, which party is currently in power) and the candidates' identities (e.g. race, past record), none of which can be addressed by candidates in the months from nomination till election. Only a handful of studies specifically discuss how marketing activities shape political outcomes, focusing on either marketing spending or on the framing of political messages.

On the impact of marketing spending, the four major empirical studies by marketing scholars (Shachar 2009; Gordon and Hartmann 2013; Wang, Lewis, and Schweidel 2018; Zhang and Chung 2020) rely on county level advertising and voting data to show the impact of TV advertising and grass roots campaigning. While political advertising increased voter turnout by more than 15 million in the 2004 election, political marketing activities explain only 1% of the variance of political preferences and voting behavior (Shachar 2009). Applying different endogeneity controls for county level ad allocation strategies, Gordon and Hartmann (2013) similarly find that TV ads have a party preference elasticity of 0.033 (Republican) and 0.036 (Democratic), both below the typical TV ad elasticities for consumer good sales (0.05). Likewise, Zhang and Chung (2020) show that field operations and political advertising from outside groups were more effective in countries with more partisans, while a candidate's advertising was more effective in counties with less partisans in the 2004 to 2012 elections. They report elasticities of 0.034 for candidate advertising, 0.026 for PAC advertising and 0.078 for field operations. Finally, Wang et al. (2018) find that negative advertising sponsored by PACs is significantly less effective than that sponsored by candidates, with a 0.015 elasticity on the candidate's unconditional vote shares in the 2010 and 2012 senate races. They specifically call for future research to go beyond the tone and analyze the issues discussed in the ads via content analysis.

Political scientists recently generated results similar to these results on marketing effectiveness. In an online experiment, Haenschen and Jennings (2019) show that micro-targeted social media ads can increase turnout for younger voter groups in case of municipality elections. Based on a 3-cycle longitudinal panel model estimated on county level data for the 2004 to 2012 presidential elections, Spenkuch and Toniatti (2018) find that a one standard deviation increase of TV ad spent raises the partisan difference by 0.5%.

Framing political messages is mainly discussed conceptually in early work with a focus on manipulation (Lippmann 1922; Herman and Chomsky 1988) versus information (Bernays 1928; Downs 1957). Content wise insights are rather limited, with Stewart and Schubert (2006) failing to find a significant impact of hidden cues in advertisements on behavioral intentions. In contrast, several authors find the moral foundations of candidate statements have important political consequences. Moral foundations theory was developed to study the underlying structures that form individuals' morality. Defined by Haidt (2008), moral systems are "interlocking sets of values, practices, institutions, and evolved psychological mechanisms that work together to suppress or regulate selfishness and make social life possible" (p. 70). Based on extensive research across contexts, moral foundations theory advances five moral foundations: care/harm, fairness/cheating, loyalty/betrayal, authority/subversion, and sanctity/degradation (Graham et al. 2013). These moral foundations have been categorized into individualizing and binding foundations (Hadarics and Kende 2017; Weber and Federico 2013). Individualizing foundations, including care/harm and fairness/ cheating, are based in considerations of individual rights. Binding foundations, including loyalty/betrayal, authority/subversion, and sanctity/degradation, are based in the efforts made to support group cohesion. Research on these moral foundations has revealed that liberal individuals are more likely to focus on individualizing foundations. Conservatives, on the other hand, are more likely to form judgments based on binding foundations (Weber and Federico 2013). Clifford and Jerit (2013) conclude that elite individuals' usage of moral language helps citizens in connecting their own moral foundations with political attitudes. This implies that the right moral framing of political messages in different media channels with varying target audiences may help to gain support (see e.g. Clifford and Jerit 2013; Clifford et al. 2015; Nelson and Oxley 1999) or increase fundraising (see Winterich, Zhang, and Mittal 2012 for the relationship between moral, donations and political orientation). However, insights into how to best frame moral foundations and which moral topics may work best for a specific candidate are underdeveloped (Gordon et al. 2012). Our study therefore aims at bridging this research gap by taking advantage of our rich social media data set and investigating how moral statements within a candidate's social media activities affected political attitudes and resonated again in moral statements from social media users.

Finally, studies on the intersection between politics and (social) media find a strong positive relation between (social) media usage and political participation (see e.g. Knoll, Matthes, and Heiss 2018; Boulianne 2015; Dimitrova and Bystrom 2013). To the best of our knowledge though, none of these studies takes specific content or actions of politicians into account when it comes to explaining political participation or political will formation and preferences.

In sum, empirical insights into marketing effects in politics are mainly limited to two marketing instruments: advertising and grass-root campaigning, which can be understood as the political equivalent of direct sales activities (Gordon et al. 2012; Zhang and Chung 2020). Even though a large body of literature investigates the impact of classic and social media use on political participation, the vast majority of these studies does not include topics and message framing into their analyses. To our best knowledge, this empirical study is hence amongst the first ones to investigate the impact of paid and earned social media as well as advertising content on political will formation.

Research on Fake News in the Wake of the 2016 elections

Fake news is commonly defined as '*information fabricated to mimic news media content with the intention to undermine public opinion, and the credibility of the political system as well as traditional media*' (Lazer et al. 2018). However, opinions differ about the exact criteria (Tandoc, Lim, and Ling 2018). Economists such as Allcott and Gentzkow (2017) only consider factually incorrect information, while others include highly partisan or 'slanted' news in the fake news category (e.g. Tandoc et al. 2018; Zimdars and McLeod 2020). In their comprehensive review of the scientific literature, Tucker et al. (2018) define online "disinformation" as "a broad category describing the types of information that one could encounter online that could possibly lead to misperceptions about the actual state of the world" (p. 3). We agree with this definition, consistent with several recent papers examing the exposure to and spread of such disinformation in the election (Guess et al. 2020; Gunther et al. 2019; Vosoughi et al. 2018). Contributing to that literature, we focus on the *topic* of fake news (e.g. sharia law, email scandals) as an under-researched area.

The *presence, spread and impact* of fake news have seen the lion share of research attention. Allcott and Gentzkow (2017) find that the average American citizen was exposed to at least one to three out of the 156 different fake news stories they tracked during the 2016 election. As to the type of misinformation, most studies conclude that fake news spread during the 2016 election favored extreme right-wing positions (Bovet and Makse 2019; Guess, Nagler, and Tucker 2019; Vosoughi et al. 2018). However, empirical findings are mixed as to the impact of fake news on the election (Allcott and Gentzkow 2017; Guess et al. 2020; Gunther et al. 2019).

On the one hand, most academic studies conclude that fake news played only a minimal role in the election outcome. Allen et al. (2020) find that that the share of daily fake news exposure is only 0.15% and blame general media avoidance or bad journalistic practices instead of fake news exposure for public misinformation. Likewise, Guess et al. (2020) find that fake news content on Facebook contributed only 5.9% to the overall media exposure of an average American during the 2016 elections. Grinberg et al. (2019) find similar numbers about fake news on Twitter, with approximately 5% of tweets referring to political websites in an average user's Twitter feed being related to fake news.

On the other hand, Bovet and Makse (2019) find 'fake news or extremely biased news' in a quarter of tweets with links to political news websites during the 2016 elections. Moreover, fake news exposure grew in 2016 with a peak in the last two weeks prior to the election, when the average user was exposed to 204 potential fake news items on Twitter (Grinberg et al. 2019). Vosoughi et al. (2018) find that false information related to political topics diffuses 'farther, faster, deeper, and more broadly than the truth' (p. 1150).

When it comes to the question of what *drives fake news exposure and spread*, insights are again mixed. Grinberg et al. (2019) and Guess et al. (2019) find a substantially higher fake news exposure for right-wing than for left-wing supporters. Both studies similarly identify an impact of age and race, with elderly white people being most vulnerable to be exposed to, and share false information. However, the lion share of fake news spread has been attributed to anonymous, non-verified social media accounts, many of which were deleted after election day or have been inactive since (Bovet and Makse 2019). This is in line with prior research showing high levels of bot activities surrounding the 2016 elections (Azzimonti and Fernandes 2018; Badawy et al. 2019; Shao et al. 2018).

Evaluations of the medium-to-long–run impact on political behavior of exposure to fake news 'are essentially nonexistent in the literature' (Lazer et al. 2018). Only a few studies have answered this call for research, and their scope differs from ours. Bovet and Makse

(2019) show that social media activity Granger-causes right-wing news spread, indicating that fake news does not drive voter's behavior. Looking into how subjects react on social media to fake news exposure, Vosoughi et al. (2018) find that false news information triggers fear, disgust, and surprise, whereas exposure to true stories is more likely to trigger reactions such as anticipation, sadness, joy and trust.

In sum, while the literature provides clear and decisive information into the level of fake news exposure and spreading behavior, insights into how fake news spread affected political will formation and how strong this effect was compared to other factors, are underdeveloped. Closing this research gap is important to give better recommendations to publishers as well as policy makers (Lazer et al. 2018; Persily 2017), in the context of the other potential drivers of the candidates' election fortunes. Our study is the first to combine fake news volume and topics directly with political preference data such as polls, donations, and social media emotions.

Research on the 2016 US presidential election

Much has been written about the 2016 US presidential election, from a wide spectrum of research disciplines such as political research, media research, gender research, and communications research. The main focus of these studies lies on understanding and disentangling the factors that lead to the victory of Donald Trump (Abramowitz and McCoy 2019; Francia 2018; Persily 2017).

The main body of this research stream looks at the *positioning of the two candidates* and tries to understand which specific topics appealed to which type of voter sub-groups. Abramowitz and McCoy (2019) rely on survey-based information from the American National Election Studies, which indicates that Trump's victory was largely due to his ability to mobilize white working-class voters in the swing states of the Northeast and Midwest.

Kahane's (2020) county level analysis of election results shows that Trump profited in non-metro, metro-adjacent and main line protestant counties.

Within this demographic, Trump benefitted from factors such as the strong identification with the Republican party, racial resentment, economic conservatism, anti-gay rights and anti-free trade (Abramowitz and McCoy 2019). Similarly, Green (2020) finds that Trumps success is largely due to floating voters who changed sides or did not attend the election due to changes in the specific positioning of the two parties and their respective candidates. Public opinion for topics like foreign trade issues and unemployment, as well as racial resentments shifted since 2012 more towards classic republican positions, which again favored Trump (ibid). Meanwhile Clinton's campaign emphasized more personal traits than policy issues, which did not resonate well with the white working-class segment in many of the swing states. This together with the shift of topic importance towards racism, sexism, and immigration further put Trump into advantage, as black minority voters were not mobilized as strongly as other parts of society that were in favor of Trump. These findings are consistent with research by Abramowitz and McCoy (2019) and Gunther et al. (2019) who attribute shifts in public opinion to high rates of political polarization and disenchantment. Some Obama 2012 voters abstained from voting for Clinton in the 2016 election, and believing in fake news against the candidate may have amplified this behavior (Gunther et al. 2019).

The second stream of research related to the 2016 elections focuses on the *candidates advertising behavior*. Franz et al. (2020) find that both candidates did not take advantage of the opportunity of online micro-targeting and adapting positioning strategies to the different preference structures of voters. Their results indicate that, compared to online advertising, TV ads covered mostly the same topics, with a slightly stronger focus (5%) on gun control, budget deficit, crime and abortion. In turn, terrorism, the environment, race relations and the economy were more prevalent on TV than in online advertisements. Tedesco and Dunn (2019) point out that both candidates heavily polarized advertising topics with Trump favoring an ad hominem strategy that focused on attacking his opponent by trying to diminish her perceived competence. Rhodes and Vayo (2019) demonstrate this behavior is typical, as speeches from all elections between 1952 to 2016 show that Republican candidates are more likely to attack the opponent than their democratic counterparts. However, they find that 2016 saw the highest number of negative words used by a Republican candidate while talking about his rival even though that 2016 also saw the least public speeches delivered by both candidates.

Beyond this paid media, *earned media* may have played an important role. Reuning and Dietrich (2018) find that Trump profited from higher levels of media coverage. Their Vector Autoregressive model indicates that 1% increase in media reporting lead to a significant increase of public interest, with effects being significant for more than 3 days post media coverage. Likewise, Francia (2018) shows that Trump generated more free media coverage through provocative Tweets and social media use, increasing the gap with Clinton throughout the election period, cumulating with free media coverage worth \$ 3.2 billion for Clinton and almost \$ 5 billion for Trump – substantially more than the \$1.15 billion of free media coverage Obama attracted in the 2012 election.

Our study builds on these insights and is the first one to simultaneously combine the social media behavior of the two candidates with the respective advertising strategies on the one hand and political preferences on the other hand to investigate which marketing strategy lead to more and or less favorable reactions on voter’s side, accounting for different racial, educational, and income classes within the US population. By doing so we are also the first study to measure direct responses within the electorate and to quantify the different effect sizes of the taken measures.

Conceptual development

We start from recent political science, in particular the dynamic political will formation framework (Tucker et al. 2018), and add key insights from applying marketing concepts to politics, which has a long history in conceptual literature. Kotler (1982) distinguishes three marketing activities for the political candidate: (1) marketing research, (2) candidate concept and strategy, and (3) communication and distribution strategy (pp. 462-463). Likewise, Newman and Sheth (1987)'s framework consists of 3 stages: (1) identifying one's own and the competitor's target segments, (2) create a position by focusing on values that distinguish the candidate from the opposition, and (3) develop a marketing strategy.

In their review of the scientific literature, Tucker et al. (2018) discuss how social media and online disinformation (1) have a complex dual relationship with traditional media, (2) may help to mobilize supporters and demobilize opponents, and (3) may be encouraged by the actions of the candidates themselves. First, social media can both drive traditional news coverage and, through both human users and bots, help ensure that some traditional media news stories are viewed more than others (Hennig-Thurau et al. 2010; Sanovich, Stukal, and Tucker 2018). Second, the candidate can intentionally sow distrust in traditional media to help boost less credible sources (Ladd 2012). As a result, Tucker et al. (2018) propose their dynamic political will formation framework depicted in Figure 1.

<Figure1 about here>

Based on their systematic review, Tucker et al. (2018) call for more research on the consequences of disinformation and for cross- and multi-platform research, which we address in our study. However, our dependent variable is not the quality of public policy/democracy, but 'Political Outcome', i.e. the relative election chances of the presidential candidates, captured in both the traditional and the probabilistic polls. Moreover, we distinguish platforms and topics in the 'disinformation' box, 'TV Advertising' from 'Traditional Media Coverage' (in 'Traditional Media Use' Figure 1 box), social media posts, topics and moral language (in the 'Politicians' Behavior Figure 1 box) and social media following and emotions (in the 'Social Media Use' Box). Hence, we propose Figure 2 as a useful conceptual framework to understand the candidates' fortunes in the months leading up to the election.

<Figure 2 about here>

The left-hand side of Figure 2 shows our focus on the candidates' actions, from owned social media and the topic and sentiment of their statements to paid media such as mass media (TV) advertising. Our framework is thus consistent with Kotler (1982) and Newman and Sheth (1987)'s emphasis on marketing research, target segments and the candidates' (campaign) actions. Candidates can and do assess how these actions resonate with likely voters in the response of political engagement (earned media and donations) and the polls to changes in candidates' actions (Gordon et al. 2012). In the words of Newman (2016), organizations 'are now in a position to understand the interaction taking place between its' customers and the various social media sites that reflect on the chatter and tone of the conversation' (p. 786). Figure 2 also expands previous frameworks for political marketing. First, Lazarsfeld et al. (1944) emphasize demographics, mass media, and the processes of interpersonal behavior. Fast forward to 2016, and we study demographics, mass media and interpersonal influence on social media, including the size of the following, the emotions and the fake news they share. Second, in Newman and Sheth (1987)'s theory, political choice behavior is driven by political issues (the voter's beliefs on the candidate's stand on economic, social and foreign policy issues), the candidate's social image (based the association with specific demographic (age, sex), socioeconomic (income, occupation) and cultural-ethnic (education, race) groups), the candidate's personality (emotional feelings such as hope, anger, patriotism and pessimism), situational consistency (external events) and epistemic (change of pace) value. Our framework captures these elements, but our empirical study uses voter online expressions in the aggregate to operationalize most variables, instead of relying on individual surveys.

For insights on which topics and media to emphasize when aiming to drive behavior, we turn to branding literature. As to *topics,* people choose among alternatives which share 'points of parity' (held by all considered alternatives) but are distinguished by their 'points of difference' (Keller, Sternthal, and Tybout 2002). For instance, mobile carriers could offer similar coverage (point of parity) but differ in low rates vs. customer service. The inexpensive mobile carrier can increase choice either by emphasizing its low rates (point of difference) and/or by persuading consumers that customer service is a point of parity shared with its competitor. In political branding, this means a focus on topics which are relevant to voters and for which the candidate has positive associations (Keller 1993). Likewise, Newman and Sheth (1987) distinguish the political marketing strategy to either reinforce positive attitudes with information (e.g. about the candidate's record or family) or confront negative attitudes with persuasion (e.g. attacking the competitor's record). For instance in the 1980s, Reagan created and reinforced a tough-on-foreign policy position, consistently speaking out on defense issues, stressing his intention to build up every part of the military (p. 137). At the same time, he criticized the handling of the Iran hostage situation by the Carter adminstration, which ″helped create the entire situation that made their kidnap possible″ (Haas 1985). In the 2016 election, Trump may have focused on the economy and terror threats, as both issues have been shown to be important to US voters for decades, and as he could establish points of difference with Clinton. At the same time, he could advertise on foreign policy and the military to negate his competitor's experience as a point of difference. Likewise, Clinton may focus on women, civil rights and gun control issues to establish points of difference that are not easily imitated, and thus negated, by her opponent. Economy would be her point of parity.

As to *media*, marketing literature shows that the social media platform matters (Schweidel and Moe 2014). In their general classification of social media platforms, Zu and

Chen (2015) distinguish *relationship* platforms that are profile based and consist mostly of customized messages (e.g. Facebook), (2) s*elf-media* platforms allowing users to manage their own communication channels (e.g. Twitter), and (3) *creative outlet* platforms that are content based and allow users to share their interests and creativity (e.g. Instagram). Specifically, relevant for information exchange, Instagram is typically used to share visual information and its user base skews young and female (Schmidbauer, Rösch, and Stieler 2018), while Twitter is suitable for broadcasting short texts to many – lesser known – followers, and Facebook for social interaction and sharing longer texts with fans and friends, about which much information is known. Negative content-related emotions are more often experienced on Twitter and Facebook than on Instagram, while Instagram and Facebook scored higher than Twitter as a way to pass the time (Voorveld et al. 2018). The platforms also differ in the ease of sharing links to stories: while Facebook and Twitter allow direct links outside the platform, Instagram does not automatically convert links inside posts and comments to be clickable, so users need to copy and paste links into their browsers if they want to access the content (Bossetta 2018; Kreiss, Lawrence, and McGregor 2018).

The topics, sentiment and (moral) language used by the candidates should help them to build ingroups and to drive people's emotions enough to take action, e.g. by inducing them to donate and vote for the candidate (Clifford et al. 2015; Gordon et al. 2012; Simas, Clifford, and Kirkland 2020). We measure the ingroup building by social media reaction: *volume* of followers on Facebook, the dominant source of online news for Americans (Shearer and Gottfried 2017; Lazer et al. 2018), and follower engagement on the three main social media platforms, the *sentiment* expressed by these followers and the topics they discuss (O'Connor et al. 2010; Tumasjan et al. 2011; You, Vadakkepatt, and Joshi 2015). These are in turn influenced (on the bottom of Figure 2) by both news coverage and fake news topics shared by followers (Allen et al. 2020; Vargo, Guo, and Amazeen 2017). Note the bidirectional arrows, as journalists may report on social media discussions, and social media may react to journalists (Francia 2018; Kreiss et al. 2018) and all of these potential poll drivers can also be driven by the polls (Gordon et al. 2012; Hennig-Thurau et al. 2010; Hillygus 2011). The only exogenous variables, in the bottom right of Figure 2, are external events (Gordon et al. 2012), which include leaked candidate statements (e.g. Clinton's 'Basket of Deplorables' statement and Trump's 'Grab them' tape), leaked documents (e.g. Wikileaks) and stakeholder actions, such as FBI announcements (Gambino and Pankhania 2016; Stracqualursi 2016). Finally, all these effects could materialize with some time delay, requiring a longitudinal dataset and analysis.

Given the many mixed findings and divergent opinions discussed in the research background, we don't formulate explicit hypotheses on the importance of these factors. Instead, this importance emerges from the flexible long-term modeling approach to our comprehensive dataset, to which we turn next.

Data Description

We combine for each candidate polling data, donation data, as well as traditional TV advertising data and a set of event-specific control variables. In addition, we enrich our data set with a unique set of social media interactions, including all posts of the two candidates on the leading social media platforms Twitter, Facebook, and Instagram. Our data set furthermore includes user reactions on social media for each candidate. For Twitter, we collected in total 80,443,809 Tweets, with 10,364,939 Tweets mentioning only Clinton, 17,090,616 tweets mentioning only Trump, and the remaining 52,988,254 tweets mentioning both candidates together. For Instagram, we extracted 2,770,714 and 2,228,289 user comments from respectively Trump's and Clinton's official Instagram accounts. For Facebook, we collected 4,531,431 and 2,522,112 user comments from respectively Trump's and Clinton's official Facebook pages. Table 2 gives a summary of all variables, their operationalization, as well as the different data sources.

Voter political action

To measure political will formation, we follow political science and political marketing literature and rely on a set of polls for the two candidates and their respective parties (see e.g. Converse and Traugott 1986; Gordon et al. 2012; Hillygus 2011). Longitudinal polls are better than cross-sectional snapshots as they track changes over a period of time and allow us to analyze the impact of our explanatory variables, which themselves change over time. Longitudinal polls are typically conducted in a panel (instead of changing participants) to observe the prospective behavior of a fixed group of people over a period of time (Delavande and Manski 2010; Gutsche et al. 2014). Using daily polls since both presidential candidates were known (July 11th, when Bernie Sanders endorsed Hillary Clinton), we have 119 daily datapoints till November 7th, 2016; the day before the election.

The nature of the questions asked is crucial to poll accuracy (Delavande and Manski 2010; Hillygus 2011; Kennedy et al. 2018). Traditional polls ask respondents to (1) rate their probability of turnout from a limited number of predefined response categories (e.g. scales from "by no means" to "certain" or dichotomous options such as "unlikely"/"likely") and (2) give their candidate choice. A key issue with the first question is that the candidate choice of "more unlikely than likely" voters is typically discarded, even though in reality, some will end up casting their ballot. A key caveat with the second question is that it does not capture the conclusiveness (strength of will formation) of candidate choice (Delavande and Manski 2010; Gutsche et al. 2014; Hillygus 2011).

To improve upon these issues, probabilistic polling was first used in the 2008 US presidential election and has shown to predict election outcomes well (Delavande and Manski 2010; Gutsche et al. 2014). Probabilistic polling estimates the candidate voting outcome as the respondent's probability of planning to appear at the polling station multiplied by the likelihood of prospective voting for the candidate. Respondents are asked about all candidates running and scales ranging from 0 to 100 % capture the respective likelihoods (Delavande and

Manski 2010). Directly relevant to our study, the 2016 USC Dornsife Presidential Election Poll in collaboration with LA Times (for more details see https://cesrusc.org/election) applied probabilistic polling to a representative sample of 3,000 members of an online panel. Preferences are measured by asking questions on a regular basis, usually by surveying one-seventh of all panel participants per day (Gutsche et al. 2014). An additional question (not used in our analysis) is the voters' prediction of who would become president. Right before the election, 'the average voter gave Clinton only a 53 % chance of winning and gave Trump a 43 %' (Silver 2017b); a much closer race than traditional polls predicted.

Figure 3 depicts the daily probabilistic poll from July to election day in November. Face validity does not only come from showing a tight race, with Trump in the lead for almost all days from mid September until election day, but also for the changes at the same time as events believed to be influential, such as the "*Basket of Deplorables*" interview (leaked September 12th) and the FBI announcement to further investigate in Clinton's handling of emails for Clinton (October 28th) and Trump's suggestion to kill his opponent (during an August 10th rally) and his "*grab them by the…*" video (leaked October 10th) (see Gambino and Pankhania 2016 and Stracqualursi 2016 for a list of campaign events mentioned in this paper).

<Figure 3 about here>

While Figure 3 represents the national probabilistic poll, data are also available for specific subgroups of society, allowing an in-depth analysis for different levels of income, education, gender and ethnicity. Empirically, this distinction is important as the Figure 3 pollgap was negatively correlated between some demographics, as shown in Table 3.

<Table3 about here>

In particular, black and white voters went opposite ways during the election period (correlation of -0.55), while low income and middle-income voters (-0.10) as well as women and men (-0.02) also showed negative correlations. In contrast, we observe high correlations between the men poll gap and that of No College education (0.89) and high income (0.77) and several other demographics, thus indicating the need to analyze them in distinct models.

Substantively, the demographic distinction is important as sociologists and pundits disagree (Gunther et al. 2019; Kennedy et al. 2018) on whether the key to the eventual election outcome was 'the white vote' or the 'non-white vote': 'were it not for Republican gains (and Democratic losses) among blacks, Hispanics and Asians – Trump likely would have lost, given that he actually won a smaller share of the white vote than Mitt Romney' (al Gharbi 2018, pp. 511-512). Figure 4a demonstrates that the probabilistic poll gap between Clinton and Trump drops for Hispanics and 'Other Races' (which included Asians) 2 weeks before the election, while African Americans and white Americans consistently preferred respectively Clinton and Trump:

<Figures 4a and 4b about here>

Other demographic breakdowns also echo substantial movement over our period of analysis. As plotted in Figure 4b, Clinton consistently carried the low-income voters (below \$35 K annually) and Trump the middle-income voters (between \$35 K and \$75 K annually) but the high earners (over \$75 K) switched sides around September 12th. While other groups also saw a dip around that time, Clinton's standing among high earners never recovered, and took a further hit about 2 weeks before the election.

Other demographic groups for which Clinton lost ground in the last 2 weeks include seniors (over 65 years old), and women. Thus, the election outcome was not pre-determined based on the identity or party-affiliation of the candidates, leaving a potential role for marketing strategies, events, news coverage and social media sharing over our period of analysis.

Traditional polls in our sample are represented by Real Clear Politics PollTracker (2016), which summarizes all available daily consensus numbers among US citizens. Beyond the above noted theoretical issues, these polls also failed to predict the 2016 election outcome as they favored Hillary Clinton till the last week (Francia 2018; Kennedy et al. 2018; Klar et al. 2016). Studies point to three key sources: social desirability bias in not professing towards the controversially discussed candidate Trump (Coppock 2017; Kennedy et al. 2018; Klar et al. 2016), the mobilization of previously non-voting voters and people not voting, despite voicing a political preference in the polls (Converse and Traugott 1986; Gunther et al. 2019; Hillygus 2011). Figure 5 shows the traditional polls for the same time period.

---- Insert Figure 5 about here ----

Citizens do not only support candidates by voting, but also by donating money (Ansolabehere, de Figueiredo, and Snyder 2003; Gordon et al. 2012). We collected all publicly available donation data linked to the two candidates as provided by the Federal Election Committee (FEC) for which there is a compulsory obligation to notify, that represents individual donations and is thus more representative for stated political preferences than the PAC donations, which include both large corporate as well as private member's donations (Ansolabehere et al. 2003). For our model, we aggregated donations for each candidate on a daily level. Daily donations were much higher for Clinton (over 2.7 M donations total) than for Trump (over 470,000 donations total), and grew over the election period. An interesting empirical question is whether donations drove the polls and/or were driven by the polls (Ansolabehere et al. 2003; Converse and Traugott 1986; Gordon et al. 2012). The same holds true for the candidate's campaign strategies and media coverage: While a candidate's behavior can influence the polls and vice versa, news reporting may drive donations but (spectacular) donations may also capture the attention of journalists, hence leading to subsequent media reporting (Bossetta 2018; Francia 2018; Hillygus 2011).

Voter Engagement on Social Media: volume, emotion, moral language & fake news topics

Consistent with our conceptual framework in Figure 2, we go beyond donations and polls and measure public support for a candidate by social media activity generated by the platform's users (for a political science rationale, see Tumasjan et al. 2011). Just as for brands (Colicev, Malshe, and Pauwels 2018), three major components include (1) the size of a candidate's following, (2) the volume of user generated content (UGC), and (3) the sentiment of UGC (emotion valence and arousal level). We add (4) the moral foundations of the UGC text, which may be especially relevant in political discourse, and (5) the topics discussed, which have been shown to matter for brand-related actions (Pauwels and Joshi 2016).

First, we collected he daily number of followers of the largest social media platform, Facebook, via Facebook's API from the candidates' official Facebook pages. Trump maintained a substantial lead over Clinton, growing from 6,251,209 followers in July 2016 to 8,446,741 followers before election day (respectively 2,237,908 and 3,837,510 for Clinton). Trump also had more followers on Instagram (Graham 2016) and had over 2 million more Twitter followers in September 2016 (Day 2016, Statista 2016). However, following a candidate does not necessarily mean endorsing them, as our opening quote, and our sentiment analysis of user generated content demonstrate.

Second, to collect all related user generated content, we extracted all posts, tweets, and comments mentioning one of the two candidates with the help of various Python and Java based crawlers as well as API-access tools. We collected data from the three largest social media platforms at the time: Twitter, Facebook and Instagram. Our data crawling respected the specific privacy requirements of each platform, e.g. Facebook's API allows tracking of all comments on the candidate's public page, but not conversations in e.g. closed groups, private messages, and on private walls. Similar to the size difference in followers, the Trump page's 4.5 M user comments showed higher UGC volume (often used as a measure of 'engagement', see Kupfer et al. 2018) than the Clinton page's user comments (over 2.5 M users comments).

Third, we apply a sentiment analysis to all user posts and user comments (for a political science application, see O'Connor et al. 2010). Specifically, we conducted several 'top-down' sentiment analyses in the terminology of Humphreys and Wang (2018). To measure general sentiment, we applied the *Valence Aware Dictionary and sEntiment Reasoner* (VADER) dictionary developed by Hutto and Gilbert (2014) to each post or comment we collected[1]. VADER provides three different measures: a score for the share of positive words, the share of negative words and a compound score that accounts for *total net sentiment*. Moreover, different types of emotions are captured using the dictionary of Mohammad and Turney (2013) that measures different aspects of emotions in texts. The eight emotions included (fear, anger, sadness, joy, trust, surprise, anticipation and disgust) cover the established dimensions of valence (e.g. anger and sadness are negative) as well as arousal (e.g. anger is high arousal, while sadness is low arousal) and have been successfully applied in different marketing, political science and information system studies (Humphreys and Wang 2018; Mohammad et al. 2015).

Fourth, we measure morality as in Kübler et al. (2020) with the moral foundation theory dictionary developed by Graham, Haidt and Nosek (2009). The dictionary provides word lists for eight different moral dimensions, as well as an overall dictionary that measures any type of morality. For instance, Clinton expresses 'Fairness Vice' moral language in these statements: '*It's not complicated: We need our economy to work for everyone, not just the rich or the well-connected'* and '*Imagine Trump sitting in the Oval Office the next time America faces a crisis. Imagine him in charge, with your job and savings at stake'*. Likewise, her Facebook Page users express Authority Virtue moral language in comments such as "*Hillary Rodham Clinton is Ineligible to be POTUS. You can not take America Back and Make*

[1] VADER has been developed for social media posts and is known to be especially suited for the detection of valence within short texts. The dictionary further accounts for specific social media slang, as well as the co-occurrence of words, negations and the use of symbols like emojis and emoticons. VADER has been successfully applied to different marketing and management information studies as demonstrated e.g. in Ferrara and Yang (2015).

America Great again if you do not recognize the Law which has been stolen from you. The very law which says Hillary Rodham Clinton is Ineligible to hold ANY public office of trust or profit. Wake Up America!!!"

Fifth, we identify the topics discussed on social media's fake news sharing. For all the user posts and comments, we count the number of links that relate to any known source of fake news based a set of pre-classified URLs for websites known to publish different types of fake news (Zimdars and McLeod 2020)[2]. We combined available fake news website lists from sources such as Zimdars (2016), Pennycook and Rand (2019), and Vosoughi, Roy, and Aral 2018). In total, we identified 29,359 links referring to fake news stories: 18,119 were shared on Clinton's Facebook page and 11,240 on Trump's Facebook page. To identify the topic of the shared fake news stories, we rely on a specific feature of the links. Given that fake news sites imitate journalistic media outlets and want stories to spread fast (Allcott and Gentzkow 2017; Lazer et al. 2018; Tandoc et al. 2018), they optimize their content as well as their URLs for search engine retrieval (Dick 2011; Giomelakis and Veglis 2016). As a result, the vast majority (over 99% of the fake news links captured) uses the title of the related fake news story as part of the URL (see also Giomelakis and Veglis 2016). Examples of such titles include *'breaking fbi agent wife found deceased suspected leaking emails from clinton'*, *'bombshell hillary linked to child rape network emails suggest'* and '*politics hillary clinton deleted 33000 emails'*. On Clinton and Muslims, fake news headlined '*hillary clinton oks introduction of sharia law in us'* and '*what the media and others arent telling you about khans muslim brotherhood connections'*.

For a more detailed example of how fake news article URLs is composed see Web Appendix WA1. We follow the approach by Bovet and Makse (2019) and use this

[2] However, we did not gather links from Instagram, since the platform does not automatically convert posted links into a clickable format (except for a link in the user's profile info box), and users stumbling upon links would hence have to transfer them into their browsers manually (Bossetta 2018; Kreiss et al. 2018).

phenomenon to “harvest” all fake news titles from all fake news URLs. Next, we apply a Latent Dirichlet Allocation (LDA) model to classify the fake news titles into topics. We further followed the approach of Silge and Robinson (2017) and used the 15 words with the highest TF-IDF score per topic to interpret the topic’s main focus (see Web Appendix WA1).

Candidates’ Marketing: TV ad topics, social media topic and sentiment

We account for a candidate’s marketing activities in two different ways. First, we obtained the airing times for each of the two candidates’ TV advertisements via a political marketing research company. The same research company provided us for each advertisement with a list of the topics the respective advertisements addressed. We use this topic list and the airing time information to create a daily time series for each TV ad topic. To do so we divide the airing time of each advertisement by the number of the respective topics and assign the resulting timeshares to each topic. We then aggregate the airing time of each topic for each day and candidate.

We match the TV advertising data with social media data from the three major social media platforms Twitter, Facebook, and Instagram. From each platform, we extracted all posts a candidate shared between July 2016 and election day via the platforms’ app programming interfaces (APIs) or with the help of a self-coded crawler. Our data set contains 1,309 Facebook posts, 284 Instagram posts, and 2,527 Tweets from Hillary Clinton. Similarly, for Trump, we gathered 1,265 Facebook posts, 390 Instagram posts, and 1,289 Tweets.

The content of the candidate’s statements is uncovered by several text mining techniques. First, to match the topic information of the TV advertisements, we apply an LDA model to all posts a candidate published on the different social media channels. Second, we applied the same sentiment analyses as we did for UCG, to gain further insights about a candidate’s posting style (Kupfer et al. 2018; Tumasjan et al. 2011). We expect these analyses to yield several practical implications for future political campaigning. Web Appendix WA2 presents all details related to the respective LDA analyses.

News Media Coverage

News media agency AllSides (see www.allsides.com) provides classifications for 56 major US news media from various channels such as print newspapers, TV, and online magazines and news websites. Their classification relies on user surveys to classify news outlets into 5 political orientations: left (e.g. Huffington Post), lean-left (e.g. The Washington Post), center (e.g. USA Today, Reuters), lean-right (e.g. the Washington Times) and right (e.g. New York Post) media. To track coverage, we rely on our own social media dat set by examining all official Twitter accounts of the 56 news oulets listed in the AllSides database. For each account, we track all tweets[3] mentioning one of the two candidates. Mentioning only Hillary Clinton, we identify in total 17,688 tweets of articles, 2,646 from left media, 6,807 from lean-left media, 1,917 articles from center media, 4,473 from lean-right media, and 1,825 from right media. Mentioning only Donald Trump, we observe a total of 29,788 tweets referring to unique articles: 6,805 from left media, 13,243 from lean-left media, 2,717 from center media, 5,182 from lean-right media, and 1,841 from right media. Thus, Trump got higher media coverage, especially from left and lean-left media.

As to topics, we apply an LDA analysis to the Twitter texts featuring each article. For each candidate, we again identify 5 latent topics. For Clinton, they include her polling numbers, Clinton and the Demoratic Party, Clinton vs. Bernie Sanders, the email investigation, and alleged accusations against the Clinton Foundation, Podesta and Wikileaks. As examples of Clinton vs. Bernie Sanders, the New York Times headlined 'Bernie Sanders

[3] Even though this does not guaruantee full coverage, news outlets are motivated to attract users to their websites and use social network sites as an advertising tool for promoting their content. Thus, we assume their tweets represent their topics (Edy, Althaus, and Phalen 2005; Halbheer et al. 2014; Sismeiro and Mahmood 2018).

Backers March Against Hillary Clinton in Philadelphia' (July 24th) and Fox News headlined 'WikiLeaks' Podesta email release reveals massive Clinton 'hits' file on Sanders' (October 10th).

For Donald Trump, news topics include his polling numbers, his role in the Republican Party, his career and tax reports, general coverage about his personality, and reports related to alleged accusations of sexual misconduct against women. As an example of the latter, the Washington Post headlined "'Public slut-shaming' and Donald Trump's attack on a former Miss Universe's alleged sex history" (September 30th). Web Appendix WA3 features all details of the respective LDA.

Longitudinal analysis

Our longitudinal data allow an analysis of the *dynamic* relationships among the conceptually motivated metrics, which helps to "identify when shifts in behavior are most likely to occur, and estimate the direction, magnitude and duration of these shifts" (Marketing Science Institute 2018). This requires a methodology that allows for dynamic effects and is flexible in terms of the temporal hierarchy and complicated relationships among metrics (Gordon et al. 2012; Hennig-Thurau et al. 2010; Kreiss et al. 2018). For instance, donations may, as intended, influence poll numbers and/or the candidate's actions (e.g. more marketing spending on specific topics) and ultimately the election outcome (Alexander 2005; Ansolabehere et al. 2003; Gordon et al. 2012). However, donations may also be driven by the polls or by negative social media sentiment against a candidate, as donators fear their favorite may lose out (Ansolabehere et al. 2003; Gordon et al. 2012; Francia et al. 2003). Such endogeneity has been acknowledged in previous literature as important (Ansolabehere et al. 2003; Gordon et al. 2012; Hillygus 2011). Moreover, as it may take several days for these effects to materialize, a flexible treatment of lags in the model is important (Pauwels 2014): to the best of our knowledge, no theory in marketing or politics prescribes effect timing. Thus, our methodology needs to allow for recursive effects among polls, candidate actions (statements, advertising, social media posts), media coverage, and the public's social media reaction, with multiple paths and alternative hierarchies.

To satisfy these requirements, we apply the persistence modeling approach (Chanley et al. 2000; Dekimpe and Hanssens 1999; Freeman, Williams, and Lin 1989), which selects variables that are leading performance indicators (Granger Causality tests), quantifies dynamic relations in a Vector Autoregressive (VAR) model and derives the relative importance of each variable in driving the outcome with Forecast Error Variance Decomposition (FEVD). Given the possibility of simultaneity between several of our endogenous variables, using vector autoregression (VAR) is a particularly appropriate for two reasons (Freeman et al. 1989): VAR 'does not impose a priori structural relations between potentially endogenous variables, reducing the risk of omitted variables bias' and is 'flexible enough to allow us to specify variables that are distinctly exogenous' (Chanley et al. 2000, p. 248). Table 4 summarizes the steps in this approach.

<Table 4 about here>

In the first step, we verify that each variable has a finite variance with augmented Dickey–Fuller unit-root tests, the most popular test in economics and business applications (Colicev et al. 2018; Enders 2004; Dekimpe and Hanssens 1999). In the second step, we conduct Granger Causality tests on each pair of a brand's attitude survey metrics and online behavior metrics (Granger 1969). Granger Causality of a variable Y by a variable X means that we can predict Y substantially better by knowing the history of X than by only knowing the history of Y. We perform a series of Granger Causality tests on each pair of variables, paying special attention to the leading indicators of poll numbers. As in previous marketing applications, we guard against lag misspecification by running the test for daily lags from 1 up to 30 (i.e. a month) and report the results for the lag that has the lowest *p*-value for Granger Causality (Trusov, Bucklin, and Pauwels 2009).

In the third step, we capture the dynamic interactions, cross-metric influence, and feedback effects from Figure 1 in Vector Autoregressive (VAR) models, in which a vector of variables is regressed on its past (Dekimpe and Hanssens 1999). By treating all variables with 'incoming arrows' in Figure 2 as endogenous (explained by the model), we capture the dynamic relationships among them without imposing a priori restrictions (Sims 1980). At the same time, strictly exogenous events can be added to each equation to quantify their impact on each endogenous variable (Chanley et al. 2000). Equation 1 displays the structure of the VAR model in matrix form:

$$Y_t = \mathrm{A} + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \Psi X_t + \Sigma_t, \quad t = 1, 2, \ldots, T, \qquad (1)$$

where Y_t is the vector of the endogenous variables, A is the vector of intercepts, p is the number of autoregressive lags, and X_t is a vector of exogenous control variables. The full residual variance–covariance matrix Σ contains the contemporaneous (same-day) effect of each endogenous variable on the others. We estimate the VAR model for the following outcome variables, each calculated as the gap between Clinton and Trump according to:

1) the national probabilistic poll gap (our main outcome variable);
2) the traditional consensus poll gap (to demonstrate the differential effects with (1));
3) the demographic sets of the probabilistic poll gap (to analyze segment differences).

The models' in-sample fit is evaluated by (1) the information criteria for the full model (which also determine the optimal lag length, balancing forecasting accuracy with model parsimony) and (2) the (adjusted R^2) of the separate equations, where we expect a higher explained variance for our performance variable (the poll gap) than for the candidate actions (e.g. moral statements), as observed in the branding literature (e.g. Srinivasan, Vanhuele, and Pauwels 2010).

In the fourth step, we assess the models' out-of-sample forecasting performance at 3 days, 1 week, 2 weeks, 4 weeks, 8 weeks and 12 weeks before the election. Based on the remaining estimation sample, we use the resulting estimated coefficients to make a one-step-ahead forecast of the pollgap in the holdout sample. To compare models on out-of-sample forecasting accuracy, we report the typical metrics of Mean Absolute Error (MAE, wich gives equal weight to positive and negative errors), the Root Mean Squared Error (RMSE, which punishes large errors more), and Mean Absolute Percentage Error (MAPE, which is scale invariant). We also calculate Theil (1966)'s inequality coefficient (TIC), which normalizes the forecast error to be between 0 (perfect forecast) and 1 (if the model forecasts only as well as the naive model, which is operationalized as a random walk). Moreover, we have a benchmark: Lindberg (1982, p. 369) considers TIC values around .55 and below "very good".

In the final steps, we show the VAR model *substantive results* in three ways. First, for the exogenous variables (the events in Figure 2), we directly show the estimated coefficients on the performance variable of interest. Second, for the endogenous variables (receiving an arrow in Figure 2), we calculate the Impulse Reponse Function (IRF), i.e. the net daily effect combining all estimated dynamic coefficients in equation 1 relevant to the Impulse variable (e.g. the TV ad on the Economy) and the Response variable (e.g. the poll gap). We obtain the same-day (immediate) effect by calculating the expected contemporaneous shock in the residual variance-covariance matrix (Evans and Wells 1983; Pesaran and Shin 1998). This allows computing the generalized impulse response functions (GIRFs), which do not depend on a pre-specified causal ordering. Following best practice, we apply a one-standard-error band to each GIRFs in each period (Sims and Zha 1999) and sum up the significant effects to come up with the total effect under the curve, often called the 'cumulative effect' of a 1 standard deviation *change* in the impulse variable on the response variable (Slotegraaf and Pauwels 2008; Trusov et al. 2009). Third, forecast error variance decomposition (FEVD) reveals the *relative importance* of each variable in having contributed to the variation in the outcome variable, analogous to a 'dynamic R^2' (Srinivasan et al. 2010). While e.g. each news coverage may have had less of an impact than each candidate statement, the much higher occurrence of the news coverage can still result in a higher overall importance than candidate statements in driving the poll gap. Techinically, FEVD calculates (from the VAR coefficients) how the forecast error variance in the outcome variable can be explained by its own past shocks and all the past shocks of the other endogenous variables (Hanssens 1998). FEVDs always sum up to 100%, and the standard errors obtained with Monte Carlo simulations allow us to evaluate statistical significance (Srinivasan et al. 2010).

VAR Model Variable Selection

From the 210 variables summarized in Table 2, we narrow down the number of variables before including them into our Vector Autoregressive model using two criteria typically used in such time series models:

1. The variable should significantly Granger-cause the key outcome variable for at least one time lag (Pauwels and Joshi 2016).
2. The variable should be less than 0.80 correlated with another qualifying variable (Leeflang et al. 2015).

For the first criterion, we run the Granger Causality test for lag 1, lags 2, … till 14 daily lags, and classify a variable as Granger-causing the key outcome variable if it Granger-causes it at the 5% significance level for any of these lags (Trusov et al. 2009). For the second criterion, to choose among variables that are highly correlated with each other, we select the variable that explains most forecast error variance in the outcome variable (Pauwels and Joshi 2016) of probabilistic polls.

Findings

Candidate marketing strategies and voter reaction

The first set of results involve our classification and dynamics of (1) TV ad topics, (2) news coverage topics (3) social media post topics, and (4) social media sentiment and the social media reaction in (1) sentiment and (2) fake news postings.

Figures 6a and 6b show the shares of *TV advertising topics* for Hillary Clinton and Donald Trump, respectively.

<Figures 6a and 6b about here>

Candidate biography was the topic of about a quarter of both Trump's and Clinton's total TV ad time. The remaining 11 topics for Clinton show a shift from the Economy in the Summer to Civil Rights, Family and Terror in the Fall. Beyond Clinton's topics, Trump TV ads also discussed foreign policy and the military. In summer, the Trump TV campaign focus is on the economy, immigration and the military. In the Fall, terror becomes more important, while family and women are more popular topics in the final stretch, similar to Clinton.

Social media posting behavior of the two candidates across all three networks for the four months before the election is shown in Web Appendix WA2. Clinton shows rather heterogeneous communication behavior, with e.g. Instagram focusing more on women issues, Facebook on rallying support, and Twitter on the Democratic Party. Over time, we observe a decrease of posts that directly confront Clinton's rival and of all posts overall. Trump's social media mostly involved his election rallies and attacks the opposite candidate and her party. We also observe changes over time: while Instagram focusing on attacking Democrats in Fall but switching in the final stretch to Trump's key topics such as Obama Care, Muslims and Islamic Terror.

Candidates express emotions and moral language through their statements, as detailed per platform and time period in Web Appendix WA 2 Figures WA2.4 and WA2.5. We observe substantial differences in wording style and tone across the candidates as well as across platforms. While Trump is using more fear and anger words than Clinton in general, he does less so on Instagram. For Clinton, we observe marked changes in her use of Authority Virtue moral language, with peaks in July and the end of September as shown in Figure 7. The largest peak starts 2 weeks before the election, consistent with the candidate's own account that she and her campaign felt the need to change course in the light of FBI Director Comey's Letter to Congress on Clinton's email (October 28th) and that they would focus on moral issues of Clinton's virtue and experience versus her opponent (Clinton 2017).

<Figure 7 about here>

How did social media users change in emotional expression? Not much, as shown in Web Appendix WA2. More common than Disgust were Anger and Fear for Clinton, and Fear and Sadness for Trump as negative emotions, while Trust, Anticipation, Surprise and Joy were the most common positive emotions, and Morality expressed the least for either candidate. However, social media users expressed more positive emotions in total for Trump (about 48% of all emotions) than for Clinton (about 40%) throughout the campaign period. Moreover, user comments on the Clinton Facebook Page ramped up the Authority Virtue moral language in the last 2 weeks before the election (at the time of Comey's Letter to Congress on October 28th), as shown in Figure 7.

<Figure 7 about here>

Fake news topics vary substantially over time (Figures 9a-9b). On both candidates' sites, the majority of fake news stories targets Hillary Clinton. Five key topics represent the links shared on Donald Trump's social media domain: (1) Clinton's emails and those of her campaign manager John Podesta, (2) Wikileaks, (3) the Clinton foundation, (4) rumors on Muslims (e.g. imposition of Sharia law), and (5) Russia and ISIS. Figure 8a shows the topic shares of false news links shared on Trump's social media pages for the 4 months prior to the elections. While most fake news initially focused on Clinton foundation allegations[4], later stages focused on Clinton and Muslims, Clinton's emails, Wikileaks, and ISIS.

<Figures 8a and 8b about here>

On Clinton's own social media accounts, we see a fake news focus on her emails in the first and the last month, with the remaining months showing more attention to Wikileaks and ISIS, Benghazi and a secret Black movement, and Muslims. The dynamic pattern of fake news on Clinton's Emails (on Clinton's page) and on Clinton and Muslims (on Trump's page) is particularly interesting, as visualized in Figure 9.

<Figure 9 about here>

Fake News on Clinton and Muslims peaked in early August, when Trump criticized the parents of a slain Muslim US soldier in an ABC News interview, and saw his poll numbers decline (Figure 3). Muslim topics were also popular in Fake News in October, but then dropped to almost zero after Comey's Congress letter on Clinton's emails. In contrast, Fake News on Clinton's emails peaked in July and mid September, and grew tenfold after Comey's letter of October 28th. Finally, the news coverage of media by political ideology is detailed in Figures 10a and 10b.

<Figures 10a and 10b about here>

While the left leaning media focused more on Trump's alleged sexual scandals and refusal to publish his tax records, center media mostly focused on polls and the Republican Party. In addition, the right (leaning) media focused more on Trump's biography at the start, they increasingly focused on poll results throughout the campaign. For Clinton, left media focused on discussing the divide between Clinton and Sanders and mostly covers news related to Clinton's relation with the Democratic Party, while center media largely covered the polling results throughout the campaign. In contrast, the right (leaning) press focused more on

[4] Such as its alleged connection to a pedophile ring, which resulted in an assault of an associated pizza delivery store in December 2016 (Persily 2017; Tandoc et al. 2018).

Clinton's scandals such as the allegations regarding her email investigation and to the Clinton foundation.

Granger Causality tests

Now that we understand changes to key candidate actions as well as social media and fake news reaction to them, were any of these variables leading indicators of Clinton's relative standing in the traditional poll and each of the probabilistic polls? The full Granger Causality tests are shown in Web Appendix WA4, while Table 5 shows the main insights by gender, income and race demographics.

<Table 5 about here>

First, donations only Granger-cause the traditional poll gap, while they follow the probabilistic poll gap. For instance, at lag 2, the national probabilistic poll gap Granger-causes Clinton's donations (F-stat 3.95, p = 0.02), but Clinton's donations do not Granger-cause the poll gap (F-stat 0.08, p = 0.93). In contrast, many other variables Granger-cause at least one probabilistic poll gap. First, the probabilistic poll gap for both black and white demographics is Granger-caused by Clinton's TV ads on the Economy, and Trump's TV ads on Terror. Second, Fake News Topics Granger-cause several polls – with Fake News on Clinton's Emails standing out as driving all polls. Third, Social Media Sentiment Granger-causes the poll gap for black and Hispanic demographics. Fourth, Clinton's moral language on Fairness Vice, and her Facebook page's user comments on Authority Virtue, are other important drivers – but not for high earners, whose gap is Granger-caused by Clinton's posting regarding women issues on Instagram (consistent with the user profile of that platform, see e.g. Schmidbauer et al. 2018). Fifth, *News Coverage* only Granger-causes the poll gap for Hispanics (Clinton's emails stories), African Americans (Trump's sex stories) and low-income voters (Clinton vs. Sanders stories). All three demographics were affected by Tweets expressing joy or positive sentiment about Trump, with the latter also affecting women and middle-income voters. As to *events*, Clinton's '*Basket of Deplorables'* statement Granger-caused the probabilistic poll for men, while Comey's Letter on Clinton Emails did so for Hispanics. Trump's 'Grab Them' video Granger-caused the traditional poll gap and the probabilistic poll gap for high earners.

Variables who failed to Granger-cause the probabilistic poll gaps include the growth in Facebook followers of either Trump or Clinton, and most external events, including Wikileaks statements, the three debates, Clinton accepting the nomination, Clinton's New York Times endorsement and Trump's tax evasion revelations. As a result, we don't include those in our VAR models. Among the 22 continuous variables Granger-causing the probabilistic poll, 8 were highly correlated with another variable that correlates more strongly with the probabilistic poll, and thus eliminated from the model variable selection. Our VAR model therefore includes 14 explanatory variables and 1 outcome variable for a total of 15 endogenous variables, and this procedure yields 15 continuous variables, and 3 events for a total of 18 variables (= 8% of the total), which is similar to the reduction of 99 to 17 variables in a marketing applications (Pauwels and Joshi 2016). We include the 15 continuous variables as endogenous in our model (allowing them to both drive and be driven by the other variables), and the 3 events as exogenous variables. Table 6 shows the descriptive statistics and correlations of traditional and probabilistic polls with each of the leading variables.

<Table 6 about here>

The first observation from Table 6 is the modest (0.48) correlation between the traditional poll gap, which stayed in favor of Clinton for the full election period, and the probabilistic poll gap, which took both signs but with a negative median and mean, indicating a Trump advantage. As highlighted in bold, the strongest correlation with the traditional poll gap was News Coverage of Trump's sex allegations, while for the probabilistic poll gap it was Clinton's TV ads on the Economy. The moral language on Authority Virtue (in comments on Clinton's Facebook Page) was most negatively associated with both poll gaps (respectively -0.38 and -0.50) and highest with Fake News on Clinton's emails (0.70). This 'model-free evidence' suggests a complex web of interesting relations amongst the 2016 election drivers – but of course is limited to same-day movements of each variable pair in isolation. Hence, we turn to our dynamic model.

VAR model order and fit statistics

The VAR order (lag number) of 1 was selected for all outcome variables (traditional and probabilistic poll and the 15 probabilistic poll demographics), based on the modified likelihood ratio tests and all four information criteria (BIC, AIC, FPE and Hannan-Quin). Analysis of the residuals detected neither serial correlation nor autoregressive conditional heteroskedasticity (ARCH) in any of the equations. Balancing model parsimony and comprehensiveness (many endogenous variables), VAR-models of lag order 1 are typical in both political science (e.g. Chanley et al. 2000) and marketing science (e.g. Pauwels, Aksehirli, and Lackman 2016) and do not preclude effects to last for many days (as demonstrated in the impulse response functions in the next figures). As a robustness check, we also estimated a VAR(2) model and found the same substantive conclusions.

As demonstrated by Hamilton (1994), model estimation by least squares *equation-by-equation* is efficient because the right-hand-side variables are identical across equations and disturbances are reduced to white noise by appropriate lag length (Chanley et al. 2000). Hence, we need to estimate 20 parameters (16 lagged endogenous variables, 3 exogenous events and 1 intercept) from 177 observations. This observation-to-parameter ratio of 6.16 is above the 5 recommended by Leeflang et al. (2015), and estimation converged immediately for each model.

Our outcome dependent variable, the relative probabilistic poll standing (probpollgap) is significantly explained by the VAR(1) model, with an R^2 of 0.87 (adjusted R^2 = 0.82). Interestingly, the model explains the traditional poll tracker even better (R^2 = 0.95, adjusted R^2 = 0.92), suggesting that our variable inclusion criterion (Granger-causing at least 1 probabilistic poll) was not substantially 'unfair' to the traditional poll. Separate demographic probabilistic pollgap models yielded R^2 of 0.79 on average, with the range between 0.70 (Hispanics) and 0.87 (African Americans). The other endogenous variables were, as expected, less explained by the VAR model, with an average R^2 of 0.61. Least explained are Clinton's Instagram posts on women issues (R^2 = 0.15), most explained are Fake News posts on Clinton's emails and her website's comments with the moral language of Authority Virtue (each R^2 = 0.86), which both increased more than tenfold after Comey's Letter to Congress about Clinton's emails (October 28th), the last weeks before the election (see Figures 7 and 9).

Out-of sample forecasting accuracy also indicates turmoil in October, with the forecast error peaking 2-4 weeks before the election (Figure 11).

<Figure 11 about here>

Consistent with the in-sample fit, our model is even better able to forecast the traditional poll than the probabilistic poll. Three days before the election, the TIC is 0.0132 and 0.0139 for respectively the traditional and the probabilistic poll gap, with similar excellent forecasting accuracy shown by RMSE (0.1556 and 0.0781), MAE (also 0.1556 and 0.0781), and MAPE (2.7348 and 2.6713). A week before the election, forecast errors are higher, with a TIC (MAPE) of 0.0425 (7.4821) for the traditional poll and 0.1052 (20.1488) for the probabilistic poll. As expected, forecast errors increase when we go back further, but even 8 and 12 weeks show an acceptable forecasting accuracy, with the TIC staying below 0.25 for the traditional poll and the TIC for the probabilistic poll staying below Lindberg's (1982) 0.55 benchmark for a 'very good' forecast. However, the forecasting accuracy for both polls shows a notable issue at 2 weeks before the election, supporting the notion that our knowledge till October 25th (before Comey's Letter) did not quite prepare us for what happened next (Silver 2017a).

In sum, our models show satisfactory in-sample fit and out-of-sample forecasting accuracy for both the traditional and probabilistic polls.

The impact of external events

Our first main result is the effect of external events on each of the endogenous variables, as directly represented by the estimated coefficients. First, Comey's Congress Letter significantly increased Joy for Trump on Twitter (0.057, t = 2.739) and News Coverage on Clinton and Emails (58.269, t = 2.347) and lowered Fake News on Clinton and Muslims (-18.104, t = -2.236) and the Clinton-Trump probabilistic poll gap (-2.687, t = -2.365). Our analysis is consistent with Silver's (2017a) result of 2.5 points and that 'the Comey Letter probably cost Clinton the Election'. Second, Clinton's 'Basket of Deplorables' statement increased Joy for Trump on Twitter (0.044, t = 2.045) and Trump Ads on Terror (2977.394, t = 4.063), and lowered the Clinton-Trump probabilistic poll gap (-3.629, t = -3.127) by 3.6 points – the highest effect for any event. Interestingly, these effects are substantially smaller and not significant on the traditional poll gap (-0.854, t = -1.374 for Comey and -0.586, t = -0.937 for Deplorables). In contrast, Trump's 'Grab Them' tape increased the traditional poll gap (1.506, t = 1.967) but did not significantly affect the probabilistic poll gap (-0.116, t = -0.083) nor any other endogenous variable at the 95% significance level. This finding is consistent with the survey literature arguments that traditional polling induces social desirability bias ('I should be offended and reflect this in my voting preferences') and may produce misleading results when voters don't act on such survey responses (Coppock 2017; Kennedy et al. 2018; Klar et al. 2016).

Demographic voter segments differed in their reaction to external events. First, Comey's letter to Congress significantly hurt Clinton's probabilistic poll gap with female and Hispanic voters, voters below 35 and over 65 years old, voters with annual income over $75K and voters without a college degree. Other demographics did not show an effect of the event itself (but – as we will discuss next – of exposure to event-related stories). Second, Clinton's '*Basket of Deplorables'* statement, hurt her polls significantly for young voters, bachelor degree voters, rich voters and African Americans. This suggests that the statement offended a wide range of demographics. Finally, Trump's 'Grab Them' tape did not significantly affect the poll gap at the 95% level for any demographic.

Dynamic effects of each poll gap driver (impulse response functions)

The dynamic effects of the endogenous variables are captured in the impulse response functions, as depicted in Figures 12a and 12b for Clinton's Women topics posted on respectively Instagram and Twitter.

<Figures 12a and 12b about here>

When Clinton posts on women topics on Instagram, we observe an increase in her probabilistic poll gap over the next few days. In contrast, her posting on Twitter on women issues reduces her probabilistic poll standing immediately, with a peak at day 3. Within 10 days, both impulse response functions have reverted back to 0 (baseline). We calculate these IRFs for every pair of endogenous variables, respectively as the impulse and as the response variable. Our main interest is in the cumulative poll gap impact for each driver, captured as the 'area under the curve' in above figures, or more formally as the sum of all significant impulse response function coefficients. Table 7 and Figure 13 show this cumulative impact from increasing every driver by 1 standard deviation.

<Table 7 about here>

<Figure 13 about here>

We observe the highest probabilistic poll gap effect of a one standard deviation change in Fake news on Clinton Emails, followed by Authority Virtue comments on her Facebook page and her tweets on women issues, together with the events of the Deplorables statement and the FBI Emails investigation. All harmed Clinton's probabilistic poll standing, while her TV Ads on the Economy benefitted her most. In contrast, the traditional poll gap shows the highest effect of Trump's TV ads on Terror, pro-Trump sentiment on Twitter and Clinton's statements on Fairness and Vice. While both polls agree that Fake News on Muslims benefitted Clinton, they dramatically differ on Trump's 'Grab Them' event (only benefitting Clinton in the traditional poll), News Coverage on Clinton vs. Sanders and Fake News on Clinton Emails (benefitting her in the traditional polls, but harming her chances in the probabilitistic poll).

Interesting demographic differences in reaction to candidate actios, shown in Table 7b, demonstrate the importance of audience targeting across topics and platforms. Clinton's Twitter posts on women issues help her chances with women, but hurt her chances with men. Interestingly, her Instagram's posts on women issues help her with men. Clinton's TV ads work especially well for low earners, but not at all for mid earners, who are instead affected by Trump's Terror ads. As to race, black and Hispanic voters often show opposite signed effects, e.g. to Clinton's Instagram posts and TV ads about the Economy. Age differences show intuitive patterns, with only young voters being affected by Clinton's Instagram posts, and being most affected by her Twitter posts, followed by the middle aged and then by seniors.

Voter reaction in social media sentiment and moral language also shows demographic differences. While net positive sentiment for Clinton helps her with women and seniors, it hurts her with men and young voters – possibly as a contrarian reaction to such sentiment. Likewise, Clinton's moral language on Fairness Vice help her with Hispanics and voters without college, but hurts her with voters with a bachelor degree. In contrast, the Authority Virtue moral language in comments on Clinton's Facebook page, hurt her chances across demographics, with large impact for women, high earners, seniors, Hispanics and voters without college degree. News Coverage on Clinton also hurts her chances across the board, with especially large effects for women, Hispanics and ‘other races’, and young voters. In contrast, news coverage of Trump’s sex scandals only hurts his chances for seniors, women and ‘other races’, and even benefitted him for middle income earners and for Hispanics.

Fake News on Clinton’s emails, posted on her Facebook page, was much more impactful on high earners (-20.23) than on middle (-0.24) and low income (0) groups, consistent with the high earners’ drop in Clinton polls over the campaign period. It was also significantly more impactful for women (-13.06) versus men (-0.42). As to race, Hispanics (-45.49) were affected, not black or white voters (0). Both young (-14.38) and senior (-20.98) voters showed higher impact than middle aged voters (-0.39), while voters with no college (-19.93) were more affected than voters with some college (0) or bachelor degrees (-2.71). In contrast, Fake News on Clinton and Muslims, posted on Trump’s Facebook page, did not affect the demographic poll gaps much, even substantially increasing Clinton’s lead among black voters (7.99). This strengthens our inference that such Fake News topic failed to convince voters, and may have been seen as a sign of the Trump campaign’s weakness, benefitting Clinton. Finally, positive Trump sentiment on Twitter had rather small effects, with low income voters and other races more affected than others.

In sum, our IRF analysis shows that, against common wisdom, Fake News had substantial and diverse effects on the probabilistic poll gap in the 2016 US presidential election. An increase in Fake News targeting Clinton connection to Muslims benefitted instead of harmed the candidate’s election changes. Examing the Response of Fake News to and Impulse in the poll gap (the reverse arrow in Figure 2) shows that such fake news posts surged when Clinton was further ahead in the traditional polls, in an apparent – and unsuccessful attempt to halt her poll rise. The one topic of Fake News that did hurt Clinton’s election chances concerned her emails, together with the related Comey Letter and their mainstream news coverage. But how important is each of these drivers in explaining the poll gap?

Relative importance of each driver in explaining the poll gap

Figure 14 shows the Forecast Error Variance decomposition (FEVD) of the probabilistic poll gap – for ease of exposition we omitted the poll gap's own past (which drops from 81% on day 1 to 9% on day 30) and any driver explaining less than 5% for the full 30-day period.

<Figure 14 about here>

Initially, Hillary Clinton's TV ads on the economy have the largest poll gap importance on the positive side (see the IRF results), and News Coverage on her divide with Sanders on the negative side (see the IRF results). Over time, the importance of the Economy Ads first increases, and then starts decreasing after 6 days, to end up explaining only 2% of the probabilitistic poll gap after 30 days. In contrast, other drivers become more important over time, including Clinton TV ads on Gun Control, Trump TV ads on Terror, and especially Clinton's Facebook moral language on Fairness Vice (7%) and the Authority Virtue comments on her page (17%). However, by far the most important driver of the probabilitistic poll gap is Fake News about Clinton's emails, becoming the dominant driver after 4 days and accounting for 37% of the full poll gap variance. To compare with other poll gaps, we evaluate each FEVD at day 30.

Figure 15 contrast the FEVD of the probabilistic poll gap with that of the traditional poll gap.

<Figure 15 about here>

Taken together, the endogenous variables in our model explain 54.43% of the variance in the traditional poll gap and 90.54% of the variance in the probabilistic poll gap (the remainder is explained by the past of poll gap itself). While the traditional poll gap is mainly driven by Trump's TV ads on Terror (12%), Twitter positive mentions of Trump (8%), fake news on Clinton's emails (8%) and news coverage on Clinton's rivalry with Sanders (7%), the probabilistic poll is driven by fake news on Clinton's emails (37%) and Clinton's Facebook comments on Authority Virtue (17%) as well as Fairness Vice (7%). Strategies informed by traditional polls would have underestimated the impact of Gun Control (5%) and Economy TV ads (2%), and overestimated the impact of women issues on Instagram and news coverage of Trump's sex scandals.

Differences across demographics:

As the main analysis identified the key drivers of the probabilistic polls, we discuss the demographic differences in order of their importance.

<Table 8 about here>

Most variables have similar effects across most demographics, showing the robustness of our general results. However, a few differences stand out. As to gender, we find a higher importance of moral language and News Coverage on Clinton's emails and Democratic Party division for Women, versus Trump's Twitter Joy and Clinton Facebook sentiment for men. Thus, social media in general appears more important in driving men's voting intention. The one exception is Fake News shared on Facebook on Clinton's emails, which had a higher importance for women than for men. Future research is needed to investigate whether women were more exposed to such fake news, or whether it affected their voting preferences more than it did men's, and why.

As to income, low-earners were more affected by Clinton ads about the economy, mid-earners were most affected by Trump TV ads on Terror, Clinton tweets and Instagram posts on women, and high earners more by Clinton's moral language and news coverage on the Democratic Party division and especially Fake News on Clinton's emails. To the best of our knowledge, these findigns are new to the literature and need further research to uncover the mechanisms.

As to race, black voters were more driven by Clinton Economy TV ads and her Instagram posts on women issues, Facebook sentiment and Fake News on Clinton and Muslims. Hispanics showed a higher importance of Fake News on emails, Whites on Trump

Twitter Joy, and other races on Clinton's Instagram posts on women issues. While the economic focus of black voters is well established (Gurin, Hatchett, and Jackson 1989; Rosenstone and Hansen 1993), our other findings are new to the literature.

On age and education, seniors (65+), and voters without college degree, were more driven by Fake news on Clinton's emails. Both findings are consistent with recent literature that low information literacy forms an obstacle to identifying fake news (Jones-Jang, Mortensen, and Liu 2019). As shown by Grinberg et al. (2019) and Guess et al. (2019), seniors are most vulnerable in general to fake content. Information literacy focuses on peoples' abilities to navigate and find information *online* that is verified and reliable. To identify fake news stories, individuals need the skills and competencies to sustain and update their access to rapidly changing information systems, such as fact-checking websites and compare and evaluate multiple sources (Jones-Jang et al. 2019; Mihailidis and Viotty 2017).

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6. Discussion: key findings and marketing lessons for future elections

The key research questions of this paper are (1) to what extent did candidate actions, moral language, events, news coverage, social media and fake news drive the 2016 presidential candidates' polls and (2) does it substantially between the traditional and the probabilitistic poll gap (did market research matter?). Figure 16 visualizes our answer to these questions.

<Figure 16 about here>

Earned social media (the sentiment and moral language in social media user comments) are important drivers for both polls, explaining the Clinton-Trump gap by respectively 13% for the traditional and 23% of the probabilistic polls. This social media influence outshines the effect of news coverage (about 9% in either poll). However, insights on the effects of candidate actions starkly differ between the polls. Judging from the traditional poll gap, candidates may have concluded that Trump's TV ads were most influential and *six times more powerful* than Clinton's TV ads. Clinton's coverage in News and Fake News come next and are about equally important. In contrast, the probabilistic poll gap is over a third explained by *Fake News about Clinton*, and shows a 9% (versus 5% for Trump) impact of Clinton's own moral language. Clinton's TV ads explain more than Trump's TV ads, demonstrating the power of Clinton's ad themes on the Economy and Gun Control to improve her election chances.

Two key contributions of our research concern the importance of topic and platform. We find that *topics matter a lot,* even reversing the sign of voter impact of fake news about a candidate (Clinton's email versus Muslim associations). Moreover, we find starkly different effectiveness for topics pushed by the campaigns. We recommend campaigns focus most on topics that are a necessary condition to voters (point of parity, such as the economy) and that represent the candidate's point of difference (such as terror for Trump and gun control and women's issues for Clinton). However, *platforms matter,* and they interact with topics in new ways. The 'creative outlet' platform Instagram works for showing support for women issues, but 'self media' platform Twitter does not and is better used to stir sentiment. At the same time, *offline marketing* (in our study, TV ads) remains a powerful vehicle to get the candidate's message across, especially on topics voters care most about: the *economy, terror and gun control*. Finally, mainstream news mostly matters for its coverage of scandals, and the general understanding it provides for interpreting fake news on the same topics. Which lessons can we draw from these 2016 findings for future occasions?

The first key lesson is that *quality market research* matters to put the customer first, also in politics. Commenting on the apparent overconfidence of at least some media and campaigners in the traditional poll gap, Silver (2017c) asks: 'Could this misreading of the polls — and polling-based forecasts — actually have affected the election's outcome?' While political science has focused on the prediction accuracy of different polls (Gutsche et al. 2014; Kennedy et al. 2018; Jennings and Wlezien 2018), we show that this choice of poll matters for the size and even the sign of campaign actions on voter preferences. Future research should dive deeper into the conditions and explanations for these differences, and use these insights to better design and/or combine polls. Meanwhile, we recommend candidates to leverage probabilistic polls and their breakdowns to observe voter reactions and adapt tactics based on this information. In an April 2020 Politico interview, Sean McElwee blamed the failure of candidates, despite well-crafted and executed messages, on the lack of polling and focus groups to ensure their voter reception: “I’m a college-educated 18-to-34-year-old urban professional, so I’m a tiny percentage of the electorate. I’d be pretty surprised if what appealed to me appealed to the modal American voter. The modal American voter is non-college and over 50. People like me have to stop trusting our instincts. We should make ads that non-political voters want to see, not ads that we want to see” (Grunwald 2020). In other words, campaign managers should take the heart the marketing 101 insight that the target audience differs from the (political) marketer (Gordon et al. 2012; Haenschen and Jennings 2019; Hillygus 2011). In this regard, it is striking that Clinton’s TV ads switched attention from gun control and the economy, the 2 topics that increased her probabilistic polls most in our analysis, to family, crime, and justice as well as terror threats. However, our analysis showed it was ineffective: none of these themes moved the probabilistic polls. In Silver’s (2017a)’s words, Clinton’s campaign ‘went off script in the final 10 days’. Clinton (2017) acknowledges the campaign pivot (seen as necessary after the Comey Letter), but also shows a chart of how many times she mentioned “jobs” to support the claim she continued to pay attention to the economy. Our data show the Clinton campaign indeed continued Economy TV ads, but that this message likely did not come across due to the heavy spending on other issues. Marketing literature has consistently demonstrated the importance of brand messaging over time to build and maintain the clarity and strength of the brand’s position (Braun-LaTour and LaTour 2004; Erdem and Swait 2004). In sum, fundamental marketing concepts appear important to political strategies as well.

Second, *consistency in messaging* is key: external events matter, but not as much as how they resonate in the candidates' strategies and people's social media interactions and fake news sharing. Of the 18 events we analyzed, only 3 had a significant impact on daily poll numbers: Comey's Letter to Congress, Clinton's '*Basket of Deplorables*' statement and Trump's 'Grab them' tape (only on the traditional poll gap). This reflects Sides and Vavrek's (2013) insight on the 2012 election, for which '68 moments were described as 'gamechangers' by pundits, but most weren't' and even Mitt Romney's '47% of Americans pay no income tax' video was 'not as important as some reporters suggested'. Thus, while 'a presidential campaign is in a constant state of crisis from the moment it begins, with forces that are often unknown until they hit the news' (Newman 2016), we agree with Silver (2017a) that *'if I were advising a future candidate on what to learn from 2016, I'd tell him or her to mostly forget about the Comey letter and focus on the factors that were within the control of Clinton and Trump'.* Indeed, how candidates and their fans/opponents react to events can be very impactful. While Trump succeeded in diverting attention from poor debate performance with a tweet about a 'big announcement' (Newman 2016, p. 789), Clinton's lower relative emphasis on the economy in TV ads in reaction to the FBI email investigation (Clinton 2017) hurt her in the polls. Marketing theory recommends that, while a brand can ride an opportunistic wave (such as denouncing an opponent's ethical lapses) or defend against attacks by denouncing them, it should return to its few core points of difference (Erdem and Swait 2004; Keller 1993). In this respect, Trump showed a long-term adherence to the principles of authentic branding, being perceived relatively similar in the 2016 primaries to his persona on 'The Apprentice' (Dholakia 2016). Likewise in his presidential campaign, Trump's consistent slogan of 'Make America Great Again' was a call-to-arms that evoked passion, purpose and sizzle, while Clinton's 'Stronger Together' evoked process and policy experience (Quelch 2016). Moreover, Trump matched his message with himself in public and in advertising, 'ranting and raving if he chooses, thereby creating the image of a macho politician who is stronger and bolder than any of his opponents' (Newman 2016, p. 790). When Trump did publicly experiment with messages and taglines (such as crowdsourcing how to call his opponent at a rally), he then consistently used the result (#CrookedHillary) in later messaging, making it easy for his fans to repeat it. In contrast, none of the negative hashtags for Trump became dominant, and the 'Grab them' tape only lowered his chances in the traditional polls, not in any demographic segment for the probabilistic polls.

Third, the main long-term driver of Clinton's polls in our analysis were *fake news* posting related to her emails on her Facebook page[5]. Our finding is consistent with the argument that 'the mediation of much fake news via social media might accentuate its effect because of the implicit endorsement that comes with sharing' (Lazer et al. 2018). Mainstream news coverage also mattered, but was ten times less important in our analysis. Again, this is consistent with Sides and Vavreck (2013)'s finding of a limited impact of news coverage on polls. The mainstream topic most hurting Clinton's chances was the continued discussion of her Primary rival Bernie Sanders, focusing on the lack of unity within the Democratic Party. Meanwhile, fake news stories shared on Facebook were most effective for seniors, who have also been shown to be more active sharing such stories on social media (Grinberg et al. 2019; Guess et al. 2019; Guess et al. 2020). However, a completely new finding is that the impact of Fake News depends on the topic, to the extent Clinton's alledged connections with Muslims actually helped her in the polls. It could be that such connections were seen as positive by certain demographics. However, assimilation-contrast theory (Sherif, Taub, and Hovland 1958) offers an alternative explanation: while exaggerated claims about Clinton's email

[5] In turn, these fake news stories were mostly driven by the traditional poll new numbers, such that fake news on Clinton increased when the traditiona polls gave her a higher chance of winning the election. This is consistent the Office of the Director of National Intelligence (2017) report that Russia's disinformation strategy evolved over the course of the campaign based on its assessment of Clinton and Trump's electoral prospects: "When Moscow became convinced that Secretary Clinton was likely to win the election, the Russian influence started to focus more on undermining her future presidency. They find that this strategy combined covert intelligence operations—such as cyber activity—with overt efforts by Russian Government agencies, state-funded media outlets like RT, third-party intermediaries, and internet trolls." (Tucker et al. 2018, p. 3).

scandal hurt her chances as voters perceived them as 'having a ground in truth' (assimilation), exaggerated claims about Clinton's Muslim connections were too outlandish to be believed (contrast). Future research should investigate this theory-derived explanation explicitly, as it has important implications on which fake news topics would matter for future elections (e.g which topics would be more versus less believable about Joe Biden?). We recommend candidates to carefully monitor not only polls but also social media interactions as well as fake news sharing and its impact on polls for different demographics. Appropriate action to fake news depends on whether it helps or hurt the candidate, similar to how negative comments on a brand's social media page may actually benefit its standing (e.g. Ilhan et al. 2018). Unfortunately, platform and regulatory interventions to fake news have seen little success, whether aimed at either empowering individuals to evaluate the fake news they encounter, or at preventing their fake news exposure in the first place (Lazer et al. 2018). For the foreseeable future, fake news is thus here to stay and counteracting its negative influence will remain the responsibility mostly of the targets themselves.

Fourth, *place matters*: Clinton got a boost from discussing women's issues on Instagram but not on Twitter. Moreover, her own Facebook page was full of negative comments using Authority Virtue language, which substantially hurt her in the polls. This reflects recent research that different social media platforms attract different people and see different dynamic interactions (Kreiss et al. 2018; Schmidbauer et al. 2018). While Instagram focuses on sharing beautiful images and supportive words among the like-minded, Twitter and Facebook interactions are often angry discussions among followers – which can be lovers or haters (Ilhan et al. 2018). In contrast, Trump benefitted from Twitter as a direct broadcasting to likely voters, bypassing the typical gate-keepers of media and party apparatus (Newman 2016). Already in the Obama campaigns, urging followers to post, share, and get involved in any way they could, enabled them to effectively create their own campaign (ibid).

However, such open sharing also allows ‘haters’ to directly address the candidate’s fans, as illustrated in the Facebook user’s opening quote. In contrast to the findings that allowing such negative comments is good for commercial brands as it ‘rallies the troops’ (Ilhan et al. 2018), the substantial harm (from Authority Virtue comments on Clinton’s own Facebook page) indicates different considerations for political brands. The widely acknowledged *differences* between commercial and political branding battles are a likely explanation for this discrepancy. Political battles are winner-takes-all and, with freedom-not-to-vote in most countries and a defacto two-party system in the US, can be won on the margin by simply discouraging citizens to vote for a candidate they mildly prefer over the other candidate (e.g. Bump 2018). Such Clinton-negative comments on her own Facebook page (as captured in our data section example) often referred to her alleged lack of Authority and Virtue, which are typical Republican talking points in moral foundations research (Graham et al. 2009). Thus, our new findings show an important caveat to the advice to ‘use virtually all possible social media platforms’ (Newman 2016).

We recommend candidates to carefully match their messages with the best platform, and monitor the moral language in negative comments posted on their owned media. In contrast to recent findings in marketing science for commercial brands, action should be taken by political brands to mitigate the harm of such social media discourse. Importantly, if such negative comments only get a weak push-back from the candidate’s fans, this may indicate a deeper issue that should be addressed. Our cross-platform analysis also contributes to political science, as Tucker et al. (2018) specifically called for research on platforms different than Twitter, the most commonly studied platform for political discourse and fake news: “While there are very good reasons to justify using Twitter data to study politics, especially in the United States, it is, of course, not the most popular social media platform either in the United States or globally: that distinction belongs to Facebook. Simply put, if we want a better understanding of how social media usage is affecting U.S. politics along all the lines discussed in this report, analysis of the effects of Facebook usage needs to play a larger role in scientific studies."

Limitations and future research suggestions

We acknowledge several limitations of our research. First, our data are on the aggregate (national) level and do neither speak to the candidates' fortunes nor to their actions in specific states. Hence, we highly recommend future research at the state, and even the county level, both due its importance in the US political system and its potential to study geographic differences in the observed effects. However, we note that several of the most influential drivers (such as fake news and moral language on social media) occur across counties/states and that explaining the national polls is of key importance, given that a national advantage exceeding 2 points yields electoral victory in the US (Silver 2017a). Second, our findings for the studied variables may be partially due to omitted variables they correlate with. For one, social media conversations are often used as a proxy for voter or consumer conversations in general, but they may represent only the 'tip of the iceberg', with offline word-of-mouth actually playing a large role. Third, several variables studied in previous literature are missing from our data, such as field operations (Wang et al. 2018). While Silver (2017b) found these did not explain the 2016 election outcome, future research should include field operations, to the extent they don't correlate highly with the many other candidate variables in our analysis. Fourth, our methodology excells in a flexible treatment of time lags and allows complex interactions amongst endogenous variables. This is appropriate when the literature's body of knowledge is unclear on the lag structure and/or on unidirectional causality, but makes it harder to precisely test specific hypotheses (Freeman et al. 1989). Building on our insights, future research can build causal models and isolate incremental effects through counterfactuals (Gordon et al. 2012). Most importantly, we only empirically study 1 election and thus require future research to investigate whether the results hold up for other election and in other conditions. For one, Deighton (2016) argues that the same branding strategies that helped win an election, may backfire when it comes to retention, and thus re-election: ‘If you’ve been promising jobs in demolished steel mills or shuttered coal mines, better health insurance with lower taxes, remember the essence of a brand is promise, large promise. Pin your brand to a dream, yes, but have a plan or today’s happy buyers will become tomorrow’s angry owners.’

Coming back to our opening quotes, we have shown the relative importance of several factors believed to have driven election results, from external events and social media interactions to especially the topics, channels and moral language chosen by the candidates. The results demonstrate a blend between old-school insights and newer developments as a result of both new market research tools and new ways for candidates and citizens to express themselves through social media. While we were limited to influencing a few people we knew personally, now we can influence ‘hundreds, maybe thousands, and maybe even millions of people who follow a person’s thinking’ (Newman 2016, p. 794). Capturing this rich information and analyzing it for actionable insights is a key challenge and opportunity. We hope that our longitudinal analysis of the 2016 US presidential election will inspire researchers, politicians and citizens to act, refine and improve on what we learned.

Tables and Figures

Table 1: Literature Overview and Positioning

Study	Owned Media	Paid Media	Earned Media	Traditional Media	Fake News	Donations	Polls	Sentiment Analysis	Topic Analysis	Morality	Study Design	Directionality	Methodology
Alexander (2005)						x					Longitudinal	Unidirectional	OLS
Allcott and Gentzkow (2017)					x						Cross-sectional	Unidirectional	OLS
Bovet and Makse (2019)	x			x	x						Longitudinal	Multidirectional	Network Analysis
Clifford et al. (2015)										x	Cross-sectional	Unidirectional	Description
Francia (2018)	x	x	x	x							Longitudinal	Unidirectional	Description
Gordon and Hartmann (2013)		x									Longitudinal	Unidirectional	2SLS/OLS
Gordon et al. (2012)	x	x	x	x		x	Traditional				Longitudinal	Multidirectional	Conceptual
Guess et al. (2020)				x	x						Cross-sectional	Unidirectional	OLS
Gunther et al. (2019)					x						Cross-sectional	Unidirectional	Logistic Regression
Gutsche et al. (2014)							Traditional and Probabilistic				Longitudinal	Multidirectional	OLS
Kennedy et al. (2018)							Traditional				Longitudinal	-	Description
Kreiss et al. (2018)	x	x	x	x		x					Longitudinal	Multidirectional	Qualitative
Mohammad et al. (2015)	x		x	x	x			x	x		Cross-sectional	-	Description
O'Connor et al. (2010)			x				Traditional				Longitudinal	Multidirectional	Correlations
Ohme (2019)	x	x	x	x							Longitudinal	Unidirectional	OLS
Reuning and Dietrich (2018)				x			Traditional				Longitudinal	Multidirectional	Vector Autoregressive model
Schmidbauer et al. (2018)			x					x			Longitudinal	Multidirectional	Wavelet Transformation
Shachar (2009)		x		x			Traditional				Longitudinal	Unidirectional	OLS
Spenkuch and Toniatti (2018)		x		x							Longitudinal	Unidirectional	OLS
Tedesco and Dunn (2018)		x						x	x		Longitudinal	Unidirectional	Manual content analysis
Tumasjan et al. (2010)	x		x				Traditional	x			Cross-sectional	Unidirectional	Correlations / Difference scores
Vosoughi et al. (2018)			x		x			x	x		Longitudinal	Unidirectional	Kolmogorov-Smirnov tests
Wang et al. (2018)		x						x	x		Longitudinal	Unidirectional	OLS (Diff-in-Diff)
Winterich et al. (2012)						x				x	Cross-sectional	Unidirectional	OLS / t-Tests
Zhang and Chung (2020)		x						x			Longitudinal	Unidirectional	OLS
This study	**x**	**x**	**x**	**x**	**x**	**x**	**Traditional and Probabilistic**	**x**	**x**	**x**	**Longitudinal**	**Multidirectional**	**Vector Autoregressive model**

Table 2: Variables used in the analysis

Category	Variable	Description	Source
Performance Variables	Probabilistic Polls Clinton	Daily Poll Clinton, weighted by intention to vote	USC Dornsife Polls
	Probabilistic Polls Trump	Daily Poll Trump, weighted by intention to vote	USC Dornsife Polls
	Donations Clinton	Daily sum of donations (in USD) to Hillary Clinton made by private US citizens	Federal Election Commission (FEC)
	Donations Trump	Daily sum of donations (in USD) to Donald Trump made by private US citizens	Federal Election Commission (FEC)
	Followers Clinton	Daily number of US based followers of Clinton's official Facebook page	Facebook API
	Followers Trump	Daily Number of US based followers of Trump's official Facebook page	Facebook API
	Aggregated Daily Traditional Polls Clinton	Daily Poll Clinton (averaged over all major US polls)	Polltracker
	Aggregated Daily Traditional Polls Trump	Daily Poll Trump (averaged over all major US polls)	Polltracker
	TV Advertising Time Clinton	12 variables indicating daily sum of seconds of ad time related to candidate's biography, civil rights, crime and justice, economy, education, environment, family, gun control, healthcare, immigration, terror, and women	AdSpend Database
TV Advertising	TV Advertising Time Trump	14 variables indicating daily sum of seconds of ad time related to candidate's biography, civil rights, crime and justice, economy, education, environment, family, foreign policy, gun control, healthcare, immigration, military, terror, and women	AdSpend Database
	Topics of Social Media Posts from Clinton on Facebook, Instagram, and Twitter	Individual LDA analysis for each social media channel with 8 topics per channel: Attack Trump, Clinton Personal, Democratic Party, Family, Rally Support, USA and Unity, Women, and other mixed topics (in total 24 variables)	Separate LDA analyses of Clinton's posts in each social media channel
Content Marketing by candidates on social media	Topics of Social Media Posts from Trump on Facebook, Instagram, and Twitter	Individual LDA analysis for each social media channel with 6 topics per channel: Attack Clinton, Attack Democratic Party, MAGA, Rally Support, Trump Movement, and other mixed topics (in total 18 variables)	Separate LDA analyses of Trump's posts in each social media channel
	Valence for Clinton's and Trump's posts on Facebook, Instagram and Twitter	VADER Compound Score (daily number of positive words – number of negative words) divided by total daily number of words of a candidate in a social media channel	Python 3.63 VaderSentiment module
Social Media Post Valence per Candidate	Emotions for Clinton's and Trump's posts on Facebook, Instagram and Twitter	NRC based count of daily words associated to the 8 emotions: Anger, Disgust, Fear, Sadness, Anticipation, Joy, Surprise, and Trust. For each dimension, candidate, and social media channel one daily count variable is calculated (48 variables in total)	NRC emotion dictionary provided by R package syuzhet
	Morality for Clinton's and Trump's posts on Facebook, Instagram and Twitter	Moral Foundation Theory Dictionary based daily sum of all words associated with moral emotions. For each candidate and social media channel one variable is generated (6 variables in total)	MFT dictionary as provided by Graham et al. (2009)
	Valence for user generated comments on Clinton's and Trump's own Facebook and Instagram pages, and from all Tweets mentioning Trump or Clinton	VADER Compound Score (daily number of positive words – number of negative words) divided by total daily number of words in comments on the official Facebook page of a candidate (2 variables in total)	Python 3.63 VaderSentiment module
Sentiment and Emotions of user reactions in Social Media	Emotions for user generated comments on Clinton's and Trump's own Facebook and Instagram pages, and from all Tweets mentioning Trump or Clinton	NRC based count of daily words associated to the 8 emotions: Anger, Disgust, Fear, Sadness, Anticipation, Joy, Surprise, and Trust. For each dimension and candidate, one daily count variable is calculated (16 variables in total)	NRC emotion dictionary provided by R package syuzhet
	Morality for user generated comments on Clinton's and Trump's own Facebook and Instagram pages, and from all Tweets mentioning Trump or Clinton	Moral Foundation Theory Dictionary based daily sum of all words associated with moral emotions. For each candidate one variable is generated (2 variables in total)	MFT dictionary as provided by Graham et al. (2009)
	False News Topics Clinton	4 variables with daily number of links associated to 4 false news topics resulting from LDA analysis: Emails, Assange & ISIS, Benghazi & Secret Black Movement, Muslims & Tax Issues	LDA analysis of all False News links posted by users on Clinton's Facebook page referring to any Website listed in MIT, Harvard and Zimdars

Category	Variable	Description	Source
False News	False News Topics Trump	5 variables with daily number of links associated to 4 false news topics resulting from LDA analysis: Emails, Assange & Wikileaks, Clinton Foundation & PedoRing, Muslims & Sharia, Russia & ISIS	LDA analysis of all False News links posted by users on Trumps's Facebook page referring to any Website listed in MIT (2016), Harvard (2017) and Zimdars (2016)
	Media Coverage Clinton	25 topic variables with daily number of links for each of the 5 topics and each of the 5 media categories Topics: • Clinton Polls vs. Trump Polls • Clinton and Democratic Party • Clinton vs. Sanders • Email Investigations • Clinton Foundation, Podesta and Wikileaks	LDA Analysis of all Tweets from Center, Lean Left, Left, Lean Right and Right media outlets referring to a news article on their own website
Media Coverage	Media Coverage Trump	25 topic variables with daily number of links for each of the 5 topics and each of the 5 media categories Topics: • Trump Polls vs. Clinton Polls • Trump General Coverage • Women Accusations • Republican Party • Trump Taxes and Career	LDA Analysis of all Tweets from Center, Lean Left, Left, Lean Right and Right media outlets referring to a news article on their own website

Table 3: Correlations between Poll-Gap and Demographics*

	women	men	bachelor	college	no college	Black	Hispanic	Other race	White	middle income	high income	low income	young	middle-aged	old
women		**-0.02**	**0.71**	0.37	0.13	0.28	**0.65**	0.45	0.02	0.11	0.30	**0.62**	0.28	0.41	0.58
men	**-0.02**		0.13	0.33	**0.89**	0.13	0.06	0.38	0.67	0.62	**0.77**	0.13	0.76	0.67	0.40
bachelor	**0.71**	0.13		0.10	0.06	**0.55**	0.56	0.23	-0.13	0.00	0.40	0.52	0.44	0.32	0.38
college	0.37	0.33	0.10		0.13	-0.24	0.09	0.32	0.57	0.39	0.26	0.27	0.21	0.40	0.55
no college	0.13	**0.89**	0.06	0.13		0.16	0.16	0.47	0.59	0.60	0.73	0.21	0.72	**0.69**	0.40
Black	0.28	0.13	0.55	**-0.24**	0.16		0.26	**-0.09**	**-0.55**	**-0.18**	0.19	0.47	0.44	0.23	**-0.19**
Hispanic	0.65	0.06	0.56	0.09	0.16	0.26		0.19	-0.13	0.11	0.41	0.22	0.32	0.28	0.33
other race	0.45	0.38	0.23	0.32	0.47	-0.09	0.19		0.37	0.25	0.43	0.39	0.27	0.54	0.53
White	0.02	0.67	**-0.13**	**0.57**	0.59	**-0.55**	**-0.13**	0.37		**0.67**	0.48	-0.06	0.34	0.43	**0.60**
middle income	0.11	0.62	0.00	0.39	0.60	-0.18	0.11	0.25	**0.67**		0.32	**-0.10**	0.42	0.47	0.45
high income	0.30	0.77	0.40	0.26	0.73	0.19	0.41	0.43	0.48	0.32		0.05	**0.77**	0.63	0.38
low income	0.62	0.13	0.52	0.27	0.21	0.47	0.22	0.39	-0.06	-0.10	0.05		0.25	0.36	0.46
young	0.28	0.76	0.44	0.21	0.72	0.44	0.32	0.27	0.34	0.42	0.77	0.25		0.41	0.23
middle-aged	0.41	0.67	0.32	0.40	0.69	0.23	0.28	**0.54**	0.43	0.47	0.63	0.36	0.41		0.42
old	0.58	0.40	0.38	0.55	0.40	-0.19	0.33	0.53	0.60	0.45	0.38	0.46	0.23	0.42	

* in bold: highest positive and negative correlations for the column variable

Table 4: Analytical Procedure

Methodological Step	Relevant Literature	Research Questions
1. Stationarity Unit-root test Cointegration test	Enders (2004); Johansen, Mosconi, and Nielsen (2000)	Are variables stationary or evolving? Are evolving variables in long-term equilibrium?
2. Granger Causality	Granger (1969); Freeman (1983); MacKuen, Erikson, and Stimson (1992); Sides & Vavreck (2013)	Which variable's changes precede an outcome variable's changes over time?
3. Vector Autoregressive (VAR) model	Sims (1980); Freeman et al. (1989)	How do all endogenous variables interact over time?
4. Out-of-sample forecast accuracy of VAR model	Theil (1966)	How large is the forecasting error compared with a naive model?
5. Generalized Impulse Response Function (GIRF)	Dekimpe and Hanssens (1999)	What is the net outcome effect of a change in each variable?
6. Forecast error variance decomposition (FEVD)	Lütkepohl (1990); Nijs et al. (2007)	What is the relative importance of each variable in driving outcomes?

Table 5: Granger Causality Test Results by Relevant Demographic Subgroups

	traditional	women	men	middle income	high income	low income	Black	Hispanic	White
Clinton Donations	**0.028**	0.693	0.570	0.295	0.494	0.347	0.831	0.500	0.394
Insta Women Clinton	0.222	0.509	**0.015**	0.683	**0.010**	0.150	0.348	0.327	0.135
TV Economy Clinton	0.401	0.587	0.168	0.015	0.287	0.078	**0.001**	0.085	**0.001**
TV Terror Trump	0.472	0.255	0.248	**0.012**	0.176	**0.043**	**0.002**	0.101	**0.011**
SM Sentiment Clinton	0.134	0.649	0.656	0.519	0.337	0.286	**0.043**	**0.030**	0.154
Authority Virtue Cl FB	**0.030**	**0.000**	**0.046**	**0.000**	0.458	**0.003**	**0.000**	**0.001**	**0.000**
Fairness Vice Clinton	0.120	**0.005**	**0.033**	**0.030**	0.313	**0.000**	**0.020**	0.290	0.174
Fake News Benghazi	0.596	**0.007**	**0.008**	**0.000**	0.106	**0.000**	**0.000**	**0.000**	**0.000**
Fake News Emails	**0.021**	**0.001**	**0.000**	**0.000**	**0.022**	**0.000**	**0.000**	**0.000**	**0.000**
Fake News Muslims	**0.004**	**0.036**	0.548	0.164	0.580	**0.012**	0.277	0.210	0.523
News Clinton Emails	0.474	0.105	0.243	0.327	0.260	0.532	0.294	**0.035**	0.289
News Clinton Sanders	**0.000**	0.148	0.315	0.069	0.444	**0.038**	0.859	0.076	0.376
News Trump Sex	**0.001**	0.502	0.062	0.156	0.079	0.340	**0.041**	0.535	0.347
Twitter Trump Joy	0.401	0.074	0.158	0.083	0.450	**0.007**	**0.028**	**0.001**	0.058
Twitter Trump Positive	0.748	**0.001**	0.187	**0.031**	0.072	**0.010**	**0.008**	**0.004**	0.202
Clinton Deplorables	0.328	0.231	**0.025**	0.659	0.206	0.127	0.316	0.149	0.608
Comey Emails letter	0.656	0.203	0.223	0.453	0.059	0.506	0.909	**0.015**	0.458
Trump Grab Them	**0.015**	0.439	0.506	0.226	**0.035**	0.194	0.456	0.589	0.509

Table 6: Descriptive Statistics and Correlations

	Traditional poll gap	Probabilistic poll gap	TwitterClWomen	InstaClWomen	TVClEconomy	TVClGunControl	TVTrTerror	ClVADER	ClAuthorityVirtue	ClFairnessVice	FakeClEmails	FakeClMuslim	NewsClEmails	NewsClSanders	NewsTrSex	TwitterTrJoy	TwitterTrPosSentiment
Mean	4.48	-1.76	2.71	0.21	1,105.43	112.26	886.49	0.00	3,456.66	0.26	41.26	13.80	49.17	55.09	107.40	0.28	0.10
Median	4.00	-1.71	2.00	0.00	66.57	0.00	420.50	0.00	2,989.00	0.00	27.00	11.00	43.00	48.00	104.00	0.28	0.10
Max	8.90	4.78	13.00	2.00	6,029.00	660.00	5,500.00	0.20	12,733.00	3.00	329.00	90.00	241.00	237.00	325.00	0.38	0.11
Min	0.60	-7.29	0.00	0.00	0.00	0.00	0.00	-0.12	310.00	0.00	0.00	0.00	7.00	10.00	12.00	0.21	0.09
SD	2.14	2.51	2.42	0.46	1,617.31	186.26	1,209.03	0.05	2,134.68	0.59	53.86	15.22	35.52	38.35	53.99	0.03	0.01
Traditional poll gap		0.48	-0.05	0.01	0.05	0.09	-0.31	-0.03	-0.38	-0.17	-0.14	0.46	-0.27	-0.15	0.44	-0.22	-0.47
Probabilistic poll gap	0.48		-0.20	-0.10	0.41	0.28	-0.26	-0.28	-0.50	0.08	-0.27	0.12	-0.09	-0.44	0.12	-0.25	-0.22
TwitterClWomen	-0.05	-0.20		0.08	-0.18	-0.18	-0.03	0.17	0.13	-0.07	-0.03	0.00	-0.08	0.44	0.16	-0.05	0.29
InstaClWomen	0.01	-0.10	0.08		0.02	0.01	0.20	0.08	-0.06	0.02	-0.03	-0.01	-0.09	0.14	0.08	0.07	0.06
TVClEconomy	0.05	0.41	-0.18	0.02		0.37	-0.07	-0.15	-0.11	0.00	-0.06	-0.10	0.15	-0.08	0.02	-0.20	-0.24
TVClGunControl	0.09	0.28	-0,18	0.01	0.37		0.03	0.10	0.00	0.03	-0.14	-0.23	-0.06	-0.12	0.06	-0.13	-0.24
TVTrTerror	-0.31	-0.26	-0.03	0.20	-0.07	0.03		0.17	0.12	-0.04	0.14	-0.04	0.08	0.07	0.00	0.22	0.17
ClVADER	-0.03	-0.28	0.17	0.08	-0.15	0.10	0.17		0.17	-0.11	-0.17	-0.18	-0.05	0.29	-0.07	-0.12	0.14
ClAuthorityVirtue	-0.38	-0.50	0.13	-0.06	-0.11	0.00	0.12	0.17		0.04	0.70	-0.12	0.33	0.38	-0.12	0.26	0.21
ClFairnessVice	-0.17	0.08	-0.07	0.02	0.00	0.03	-0.04	-0.11	0.04		-0.07	-0.17	-0.15	-0.19	-0.20	0.06	0.15
FakeClEmails	-0.14	-0.27	-0.03	-0.03	-0.06	-0.14	0.14	-0.17	0.70	-0.07		0.02	0.45	0.22	0.00	0.44	0.12
FakeClMuslim	0.46	0.12	0.00	-0.01	-0.10	-0.23	-0.04	-0.18	-0.12	-0.17	0.02		-0.12	0.04	0.47	-0.02	-0.23
NewsClEmails	-0.27	-0.09	-0.08	-0.09	0.15	-0.06	0.08	-0.05	0.33	-0.15	0.45	-0.12		0.17	-0.07	0.36	0.21
NewsClSanders	-0.15	-0.44	0.44	0.14	-0.08	-0.12	0.07	0.29	0.38	-0.19	0.22	0.04	0.17		0.10	0.05	0.30
NewsTrSex	0.44	0.12	0.16	0.08	0.02	0.06	0.00	-0.07	-0.12	-0.20	0.00	0.47	-0.07	0.10		-0.16	-0.32
TwitterTrJoy	-0.22	-0.25	-0.05	0.07	-0.20	-0.13	0.22	-0.12	0.26	0.06	0.44	-0.02	0.36	0.05	-0.16		0.31
TwitterTrPosSentiment	-0.47	-0.22	0.29	0.06	-0.24	-0.24	0.17	0.14	0.21	0.15	0.12	-0.23	0.21	0.30	-0.32	0.31	

Table 7a: Cumulated Significant Impulse Response for traditional and probabilistic poll

Poll gap effect of	Variable Description	Traditional	Probablilistic
TwitterClWomen	Clinton promoting women issues on Twitter	0.00	-2.43
InstaClWomen	Clinton promoting women issues on Instagram	0.00	0.21
TVClEconomy	Clinton TV ads on the economy	0.00	1.27
TVClGunControl	Clinton TV ads on gun control	0.00	0.26
TVTrTerror	Trump TV ads on terror threats	-2.33	0.00
ClVADER	VADER compound score related to Clinton	0.17	-0.70
ClAuthorityVirtue	Moral language (Authority Virtue) related to Clinton	0.00	-5.37
ClFairnessVice	Moral language (Fairness Vice) related to Clinton	-0.97	0.00
FakeClEmails	Fake news related to Clinton and emails	0.79	-12.74
FakeClMuslim	Fake news related to Clinton and Muslims	2.25	0.45
NewsClEmails	News coverage related to Clinton and emails	-0.24	-1.45
NewsClSanders	News coverage related to Clinton and Bernie Sanders	1.37	-1.71
NewsTrSex	News coverage related to Trump and sexual misconduct	0.00	0.00
TwitterTrJoy	Moral language (Joy) related to Trump on Twitter	-0.06	0.00
TwitterTrPosSentiment	Positive sentiment related to Trump on Twitter	-1.66	-1.07
DeplorablesCl	Clinton's “Basket of Deplorables” statement	-0.59	-3.63
ComeyemailCl	FBI Director Comey's Letter to Congress on Clinton's email	-0.85	-2.67
TrumpGrabPussy	Trump's ‘Grab Them' tape	1.51	0.00

Table 7b: Cumulated Significant Impulse Response for probabilistic poll demographics

	women	men	middle income	high income	low income	Black	Hispanic	Other races	White	middle-aged	young	old	bachelor	college	no college
TwitterClWomen	0.65	-3.04	-1.46	-0.71	-3.84	-0.74	0	-5.99	-2.16	-1.52	-2.21	-1.01	-2.07	-2.41	0
InstaClWomen	-0.22	0.84	-1.37	0.30	1.86	4.62	-2.08	0	0	0	1.05	0	-1.05	0	0.55
TVClEconomy	0.79	1.05	-0.18	0.90	5.11	4.71	-0.85	3.06	0.41	2.75	0	0.88	0	0	3.62
TVClGunControl	0.41	1.09	-1.83	1.39	4.89	0.43	0	0.75	0.63	0.30	0.38	0.96	0.49	0	0.86
TVTrTerror	0	0	-2.14	0	0.21	1.23	0	0	-0.11	0	0	0	-3.31	0.18	0.65
ClVADER	3.11	-3.26	-0.39	-1.11	0	-2.78	0	0	0	-0.42	-1.81	4.04	-0.18	0.22	-1.75
ClAuthorityVirtue	-6.11	-0.51	-1.74	-4.52	0	0	-5.38	-1.06	-0.13	-0.79	-2.78	-8.98	0	0	-9.02
ClFairnessVice	0.44	0	0	0.99	0	0	3.27	-0.55	0.12	0.11	0	0.31	-1.21	0	1.14
FakeClEmails	-13.06	-0.42	-0.24	-20.23	0	0	-45.49	-0.71	0	-0.39	-14.38	-20.98	-2.71	0	-19.93
FakeClMuslim	0.46	0	-0.21	0.47	1.35	7.99	-0.43	-0.69	0	1.23	0	0.41	0	1.97	0
NewsClEmails	-1.46	-0.19	-1.15	-1.62	0	-0.36	-4.68	0	-1.15	-0.98	-0.69	-1.89	-0.49	-1.04	-1.48
NewsClSanders	-1.53	-0.57	-1.76	-1.92	-0.26	0	0	-4.90	-1.69	0	-4.7	-1.14	-2.28	-2.08	-0.30
NewsTrSex	0.13	0	-1.80	0	0	0	-5.29	1.23	0	0	0	0.29	-0.14	-0.16	0
TwitterTrJoy	0	-1.75	-1.70	0.23	-2.52	0	0.50	0	-1.24	0.17	0	-1.61	-1.80	0.17	0.28
TwitterTrPositive	-0.65	-1.04	-0.24	0	-2.68	0	0	-3.21	-0.99	0.17	-1.88	-1.92	-0.67	-0.67	-1.23

Table 8: Probabilistic poll Variance decomposition by demographic*

% importance of row variable in explaining:	**women**	**men**	**middle income**	**high income**	**low income**	**Black**	**Hispanic**	**Other races**	**White**	**middle-aged**	**young**	**old**	**bachelor**	**college**	**no college**
TwitterClWomen	0.60	2.67	3.66	0.21	3.58	0.91	0.08	2.21	3.09	3.71	1.06	0.38	3.84	**6.32**	0.41
InstaClWomen	0.67	1.21	2.43	0.22	2.56	**14.17**	1.23	2.40	0.90	0.12	0.95	0.47	1.90	0.97	0.29
TVClEconomy	2.30	2.77	1.49	3.50	**9.71**	**7.87**	1.76	2.69	2.04	**15.14**	1.22	1.99	1.47	0.92	3.45
TVClGunControl	5.04	3.04	6.67	4.60	6.61	1.77	4.24	3.71	5.54	1.99	4.59	4.62	5.33	1.70	4.12
TVTrTerror	3.77	4.42	**13.28**	1.66	1.58	1.53	2.56	1.66	4.92	5.09	3.76	4.18	**10.91**	1.84	4.39
ClVADER	4.13	**6.39**	2.12	1.74	1.44	**11.03**	1.96	2.33	2.41	2.55	3.36	3.81	2.01	1.43	3.30
ClAuthorityVirtue	**17.02**	6.71	10.01	12.62	9.09	0.41	**14.44**	10.94	11.44	6.62	11.92	**16.39**	9.42	4.07	**14.95**
ClFairnessVice	5.83	3.61	2.94	6.73	2.75	0.43	6.61	3.98	4.97	2.44	5.91	5.86	7.77	2.72	6.99
FakeClEmails	36.08	22.78	14.41	**43.70**	17.81	0.38	**45.52**	27.10	26.03	13.44	31.20	36.72	25.81	10.38	34.61
FakeClMuslim	0.90	0.23	0.63	0.39	1.66	**6.22**	0.19	0.39	0.68	**5.82**	0.27	0.39	0.21	3.41	0.68
NewsClEmails	**4.44**	1.93	3.22	3.42	2.10	0.58	3.91	2.74	3.48	4.03	2.78	4.74	3.79	3.39	3.06
NewsClSanders	**8.69**	3.13	3.24	6.20	3.07	1.72	8.17	5.48	5.61	1.81	**8.26**	**8.31**	6.39	4.57	5.94
NewsTrSex	0.30	0.27	0.55	0.14	0.48	0.42	0.87	0.81	0.21	0.30	0.26	0.43	0.39	0.90	0.26
TwitterTrJoy	0.80	**4.84**	3.69	0.94	4.09	0.21	1.05	1.37	**4.69**	1.07	2.52	1.84	3.33	0.84	1.08
TwitterTrPositive	0.86	0.97	1.01	0.52	1.57	0.14	0.51	0.97	1.01	**1.87**	1.26	1.07	0.48	1.36	1.34
Past poll gap	8.57	**35.03**	**30.65**	13.39	**31.90**	**52.22**	6.92	**31.23**	22.99	**34.00**	20.69	8.79	16.93	**55.17**	15.13

* in bold the estimates significantly higher than those of the overall probabilistic poll

Figure 1: Dynamic Political Will Formation Framework

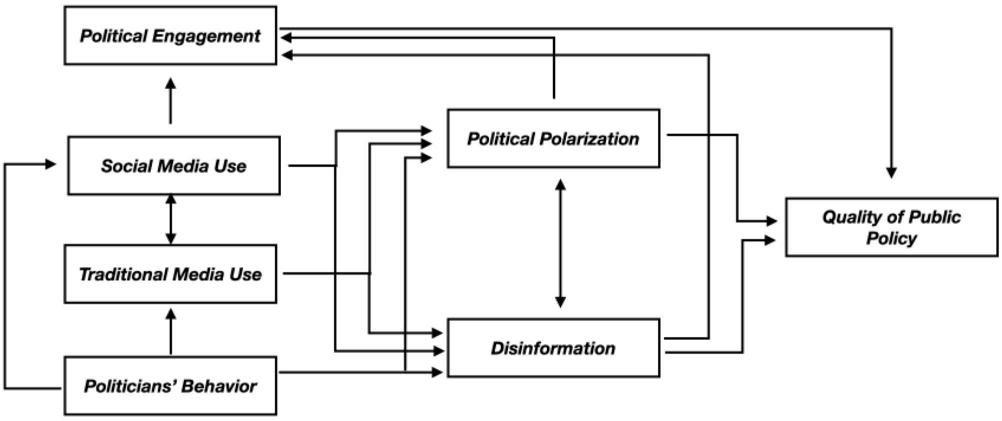


Figure 2: Conceptual Model

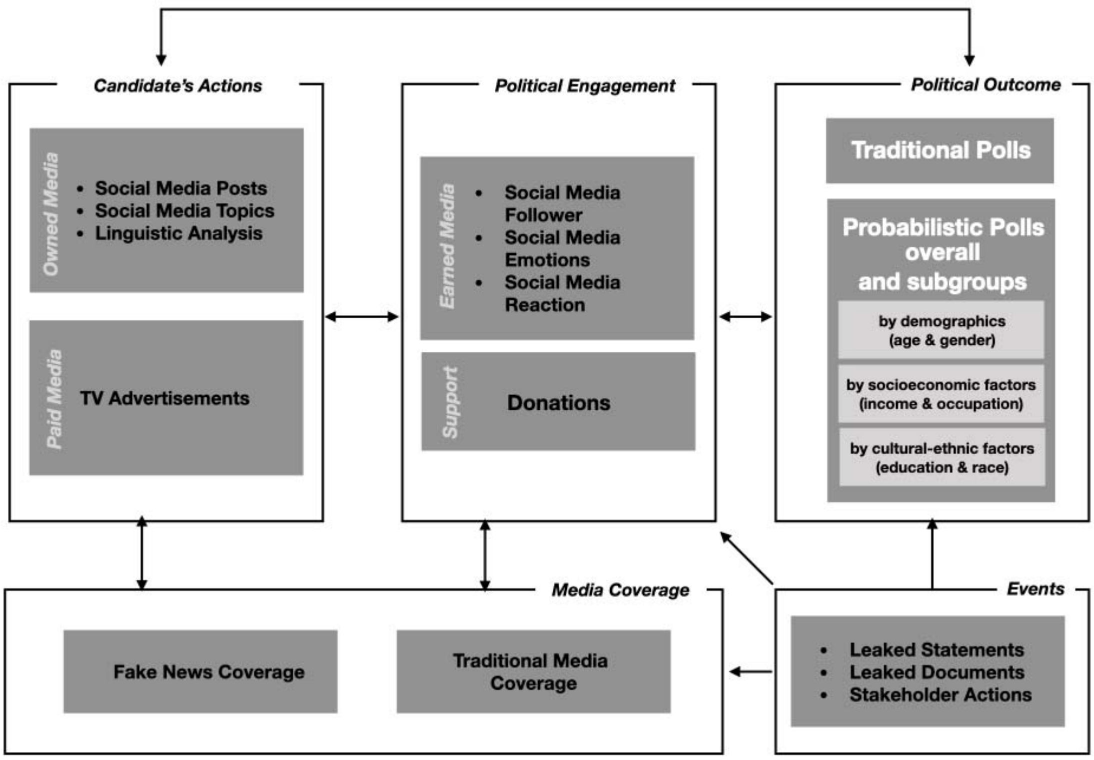


Figure 3: Probabilistic Polls

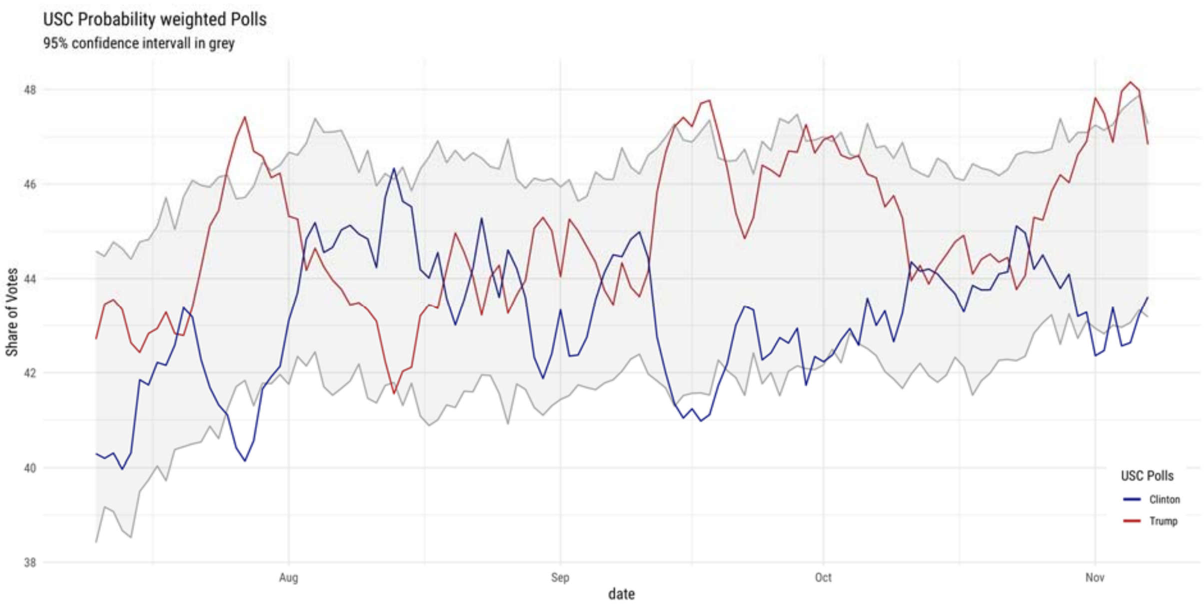


Figure 4a: The 2016 Clinton-Trump probabilistic poll gap by ethnicity demographic

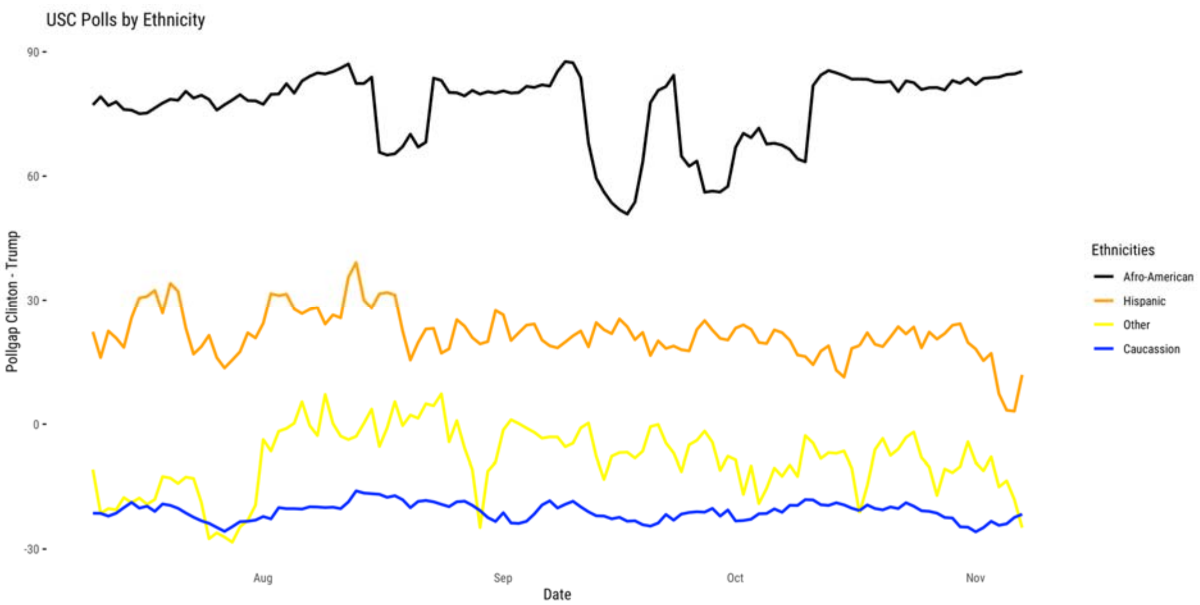


Figure 4b: The 2016 Clinton-Trump probabilistic poll gap by income demographic

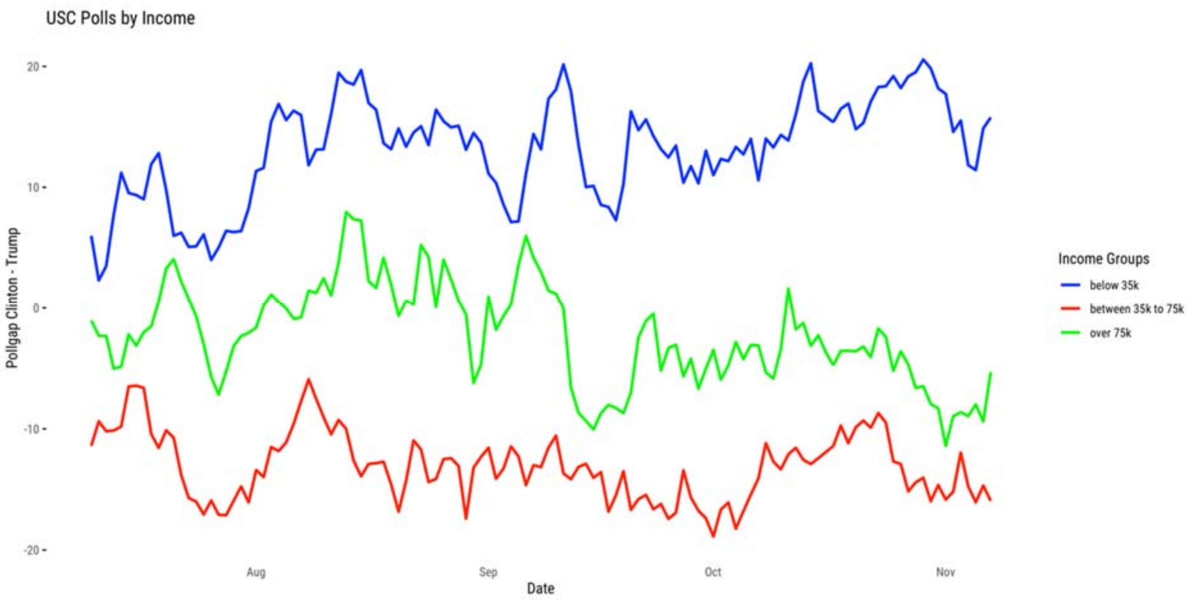


Figure 5: Traditional Polls

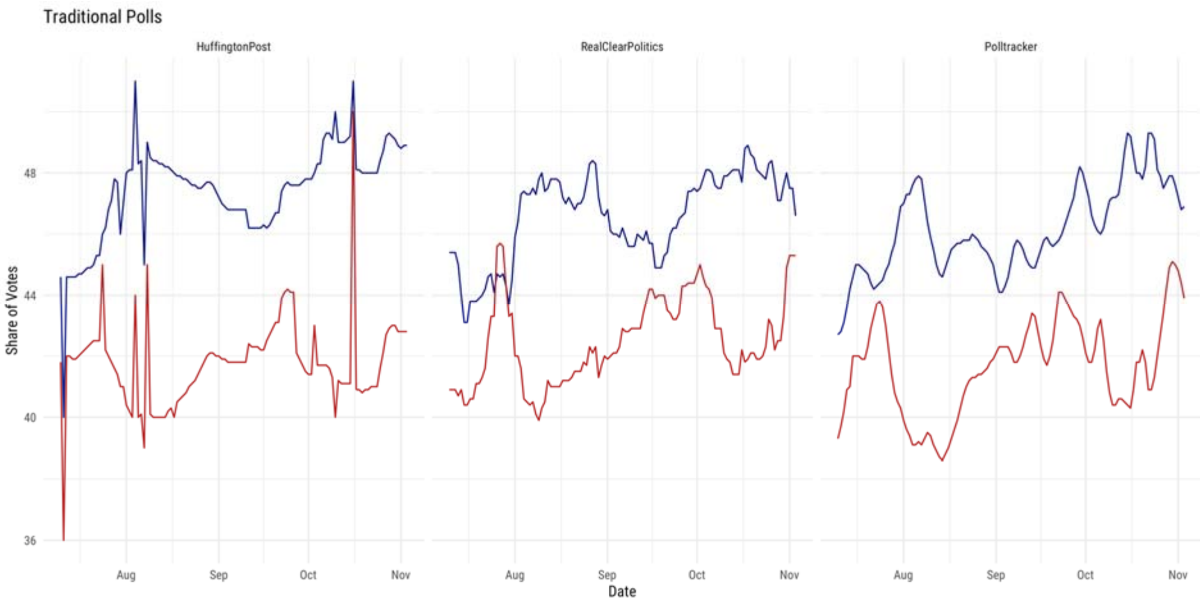


Figure 6a: TV Ad Topic Distribution for Hillary Clinton

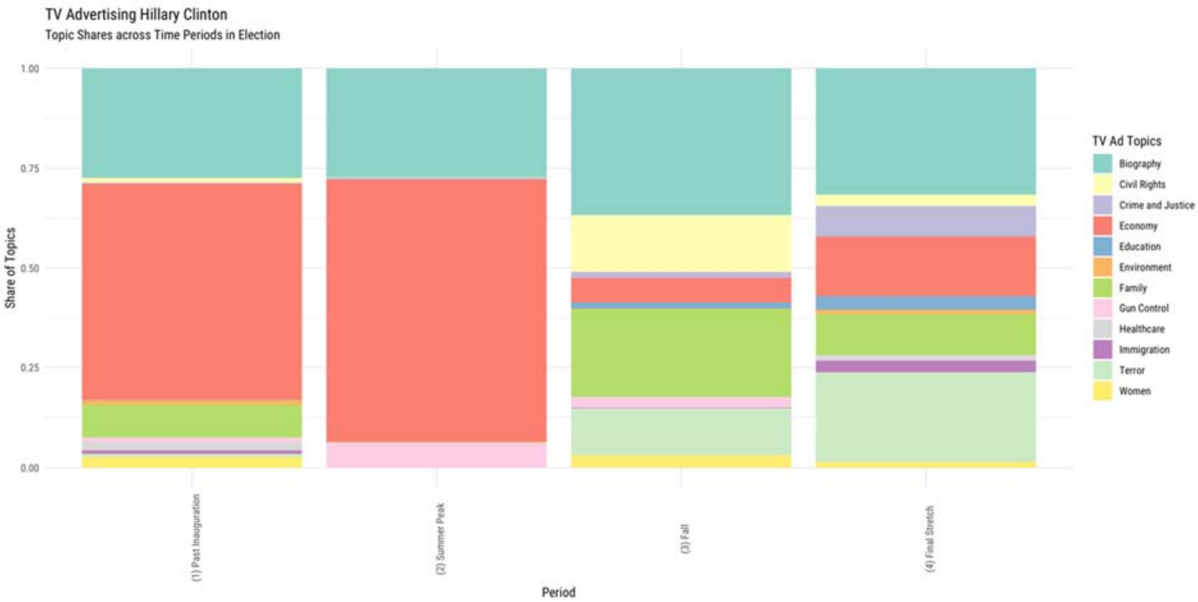


Figure 6b: TV Ad Topic Distribution for Donald Trump

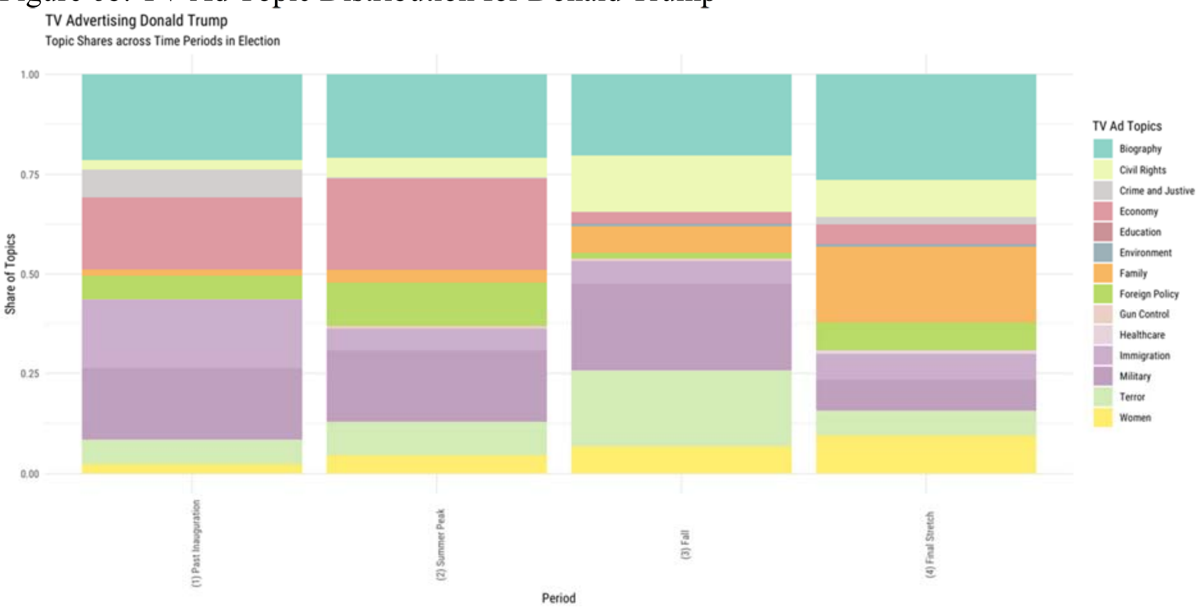


Figure 7: Authority Virtue Moral Language in user comments on Clinton's Facebook page

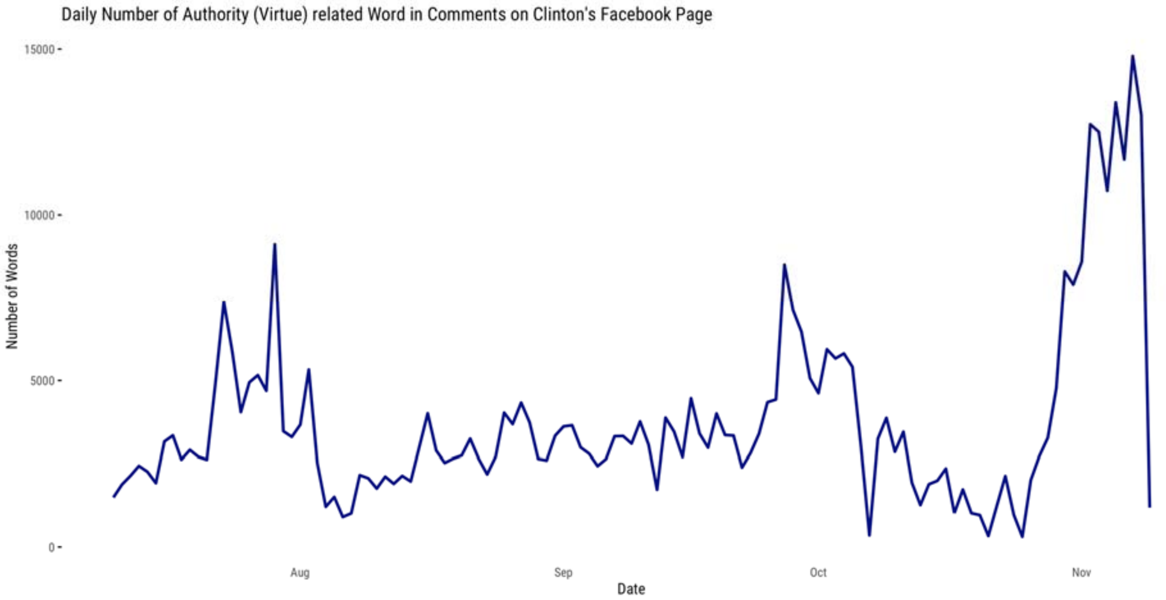


Figure 8a: Topics of False News Links shared by users on Trump's page

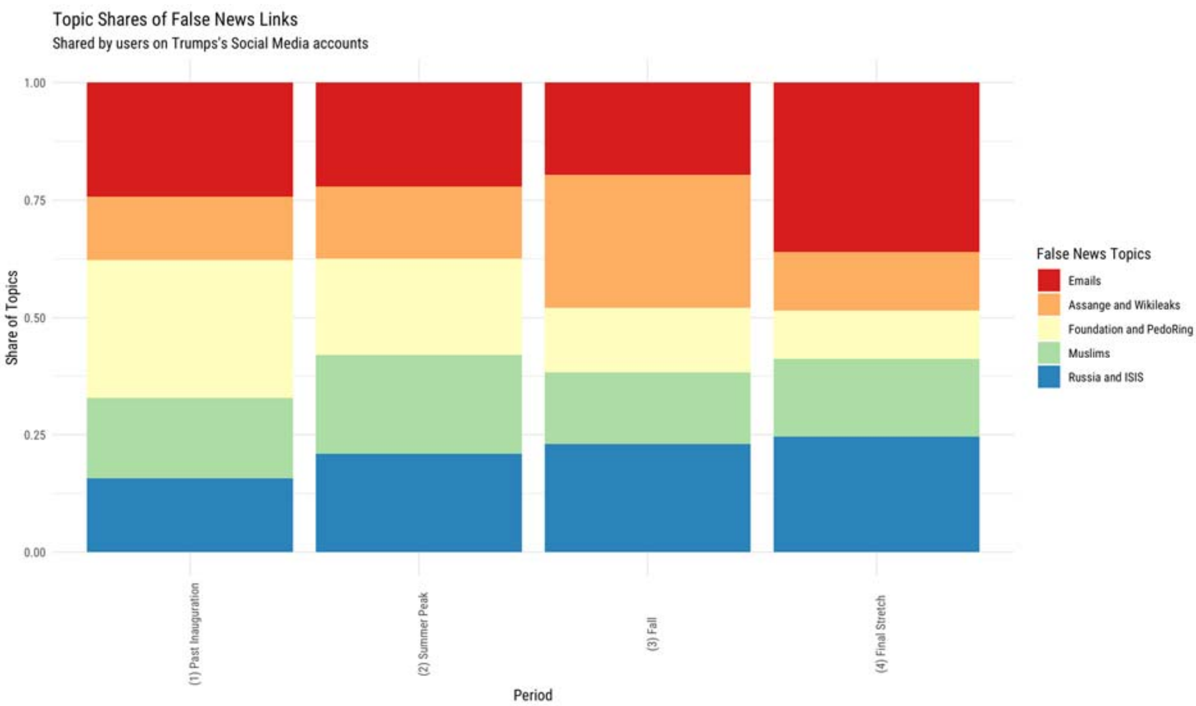


Figure 8b: Topics of False News Links shared by users on Clinton's social media accounts

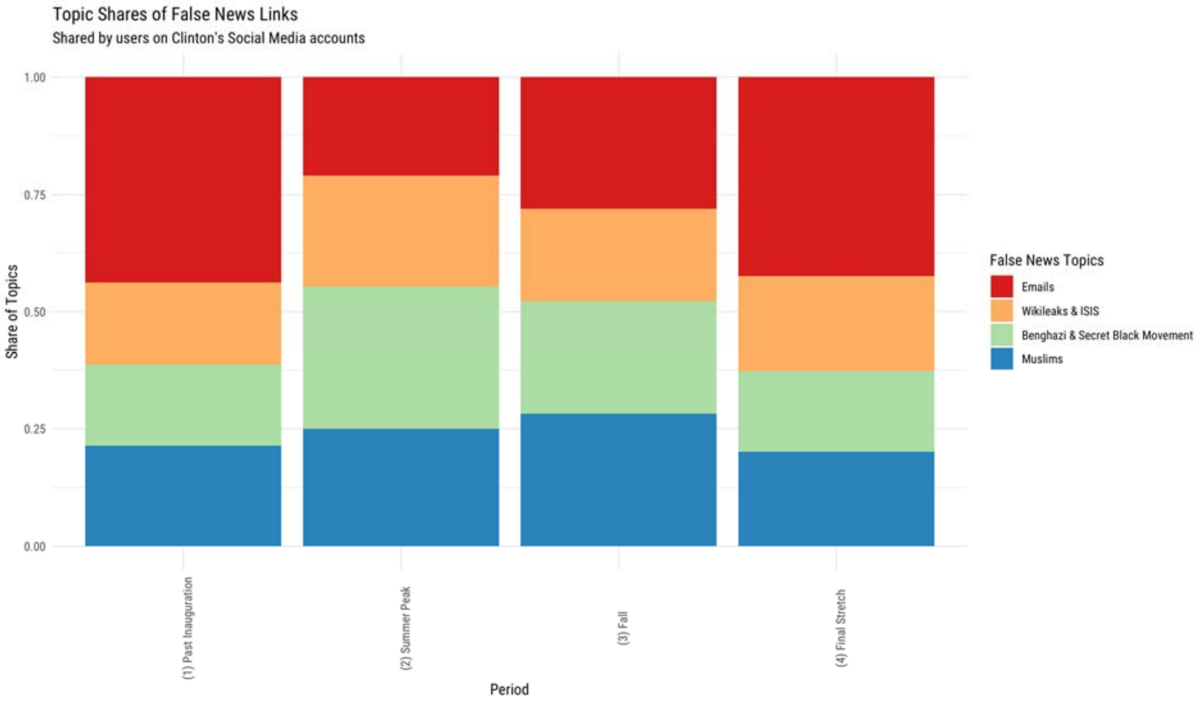


Figure 9: Fake News related to 'Clinton and Muslims' on Trump's Facebook Page and to 'Clinton and Emails' on Clinton's Facebook Page

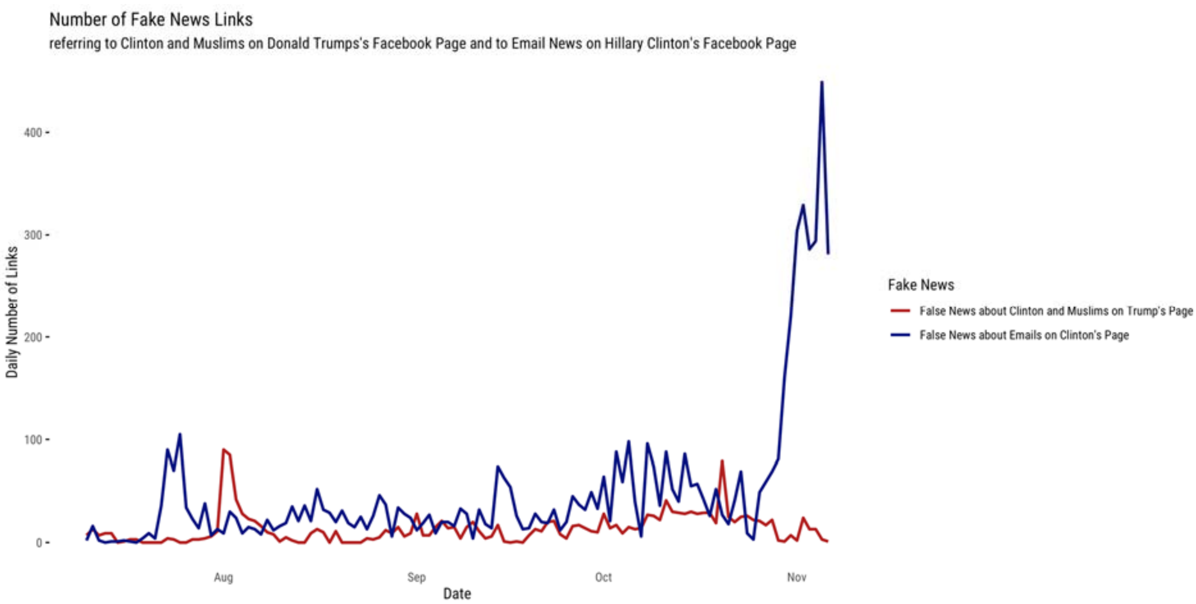


Figure 10a: Media Coverage of Donald Trump

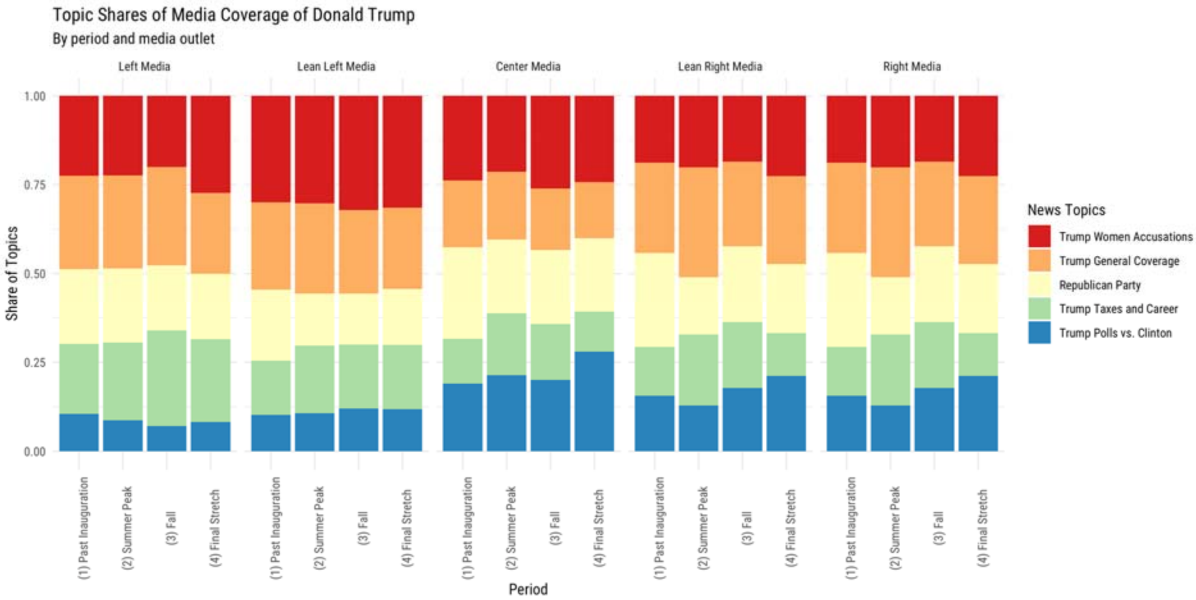


Figure 10b: Media Coverage of Hillary Clinton

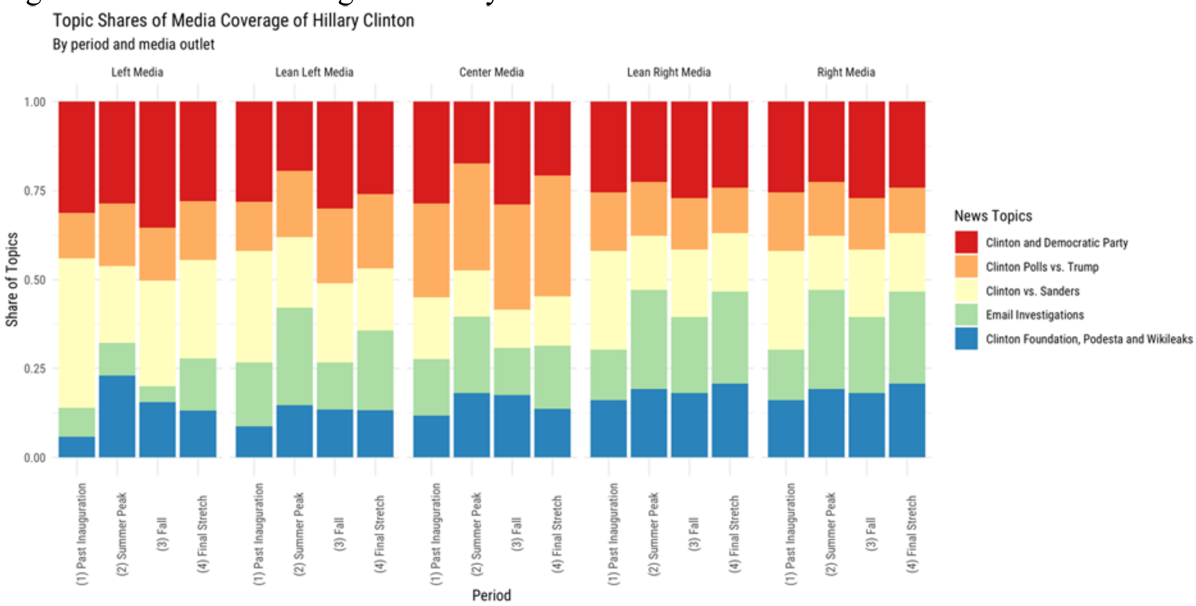
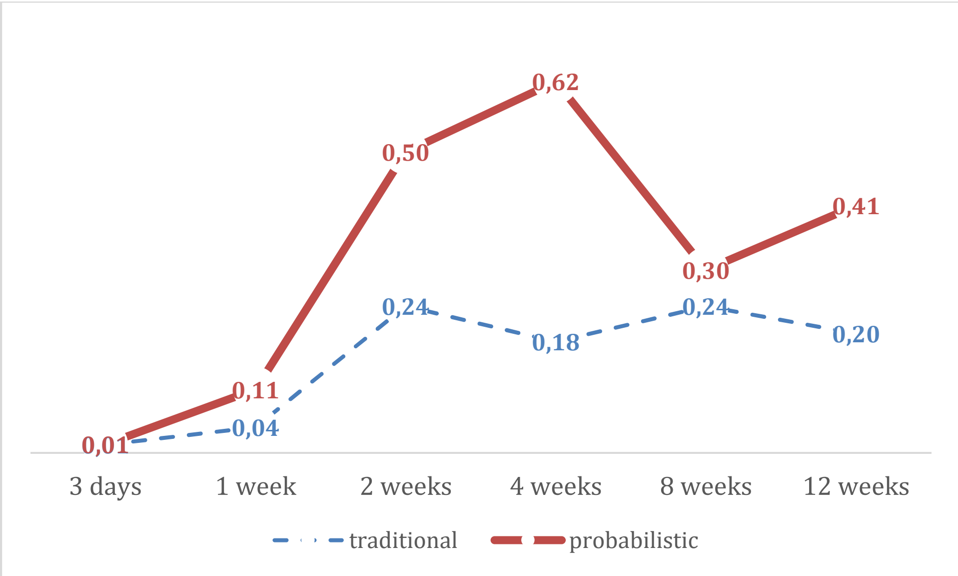


Figure 11: Theil's Inequality Coefficient (TIC) for traditional and probabilistic poll gap



Figures 12a and 12b: IRF of Clinton Women Posts on Twitter and Instagram

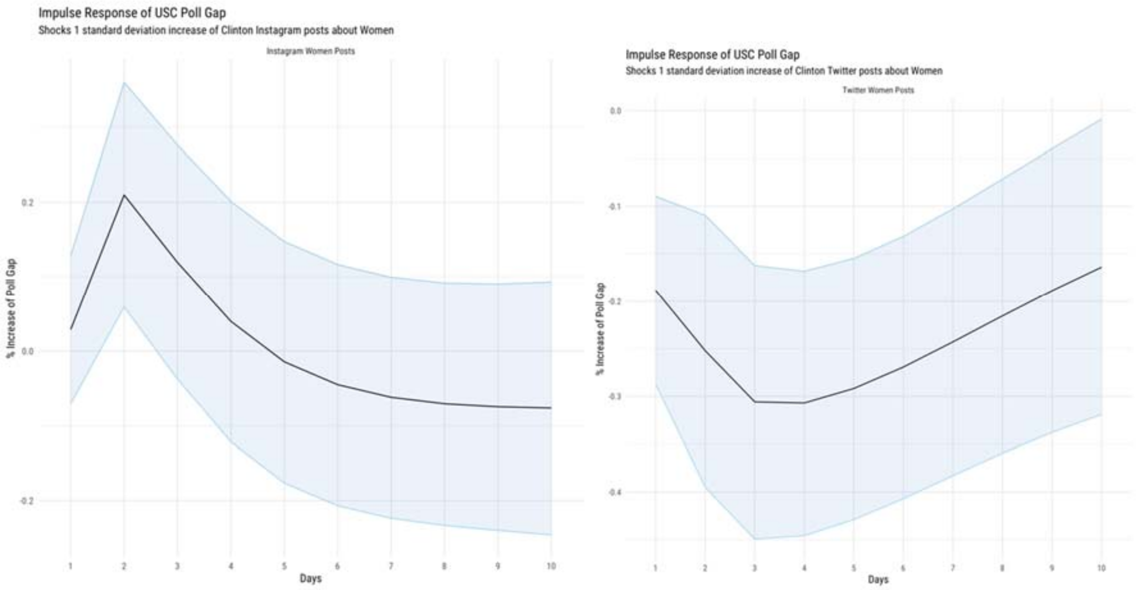


Figure 13: Clinton-Trump poll gap effect for each endogenous variable

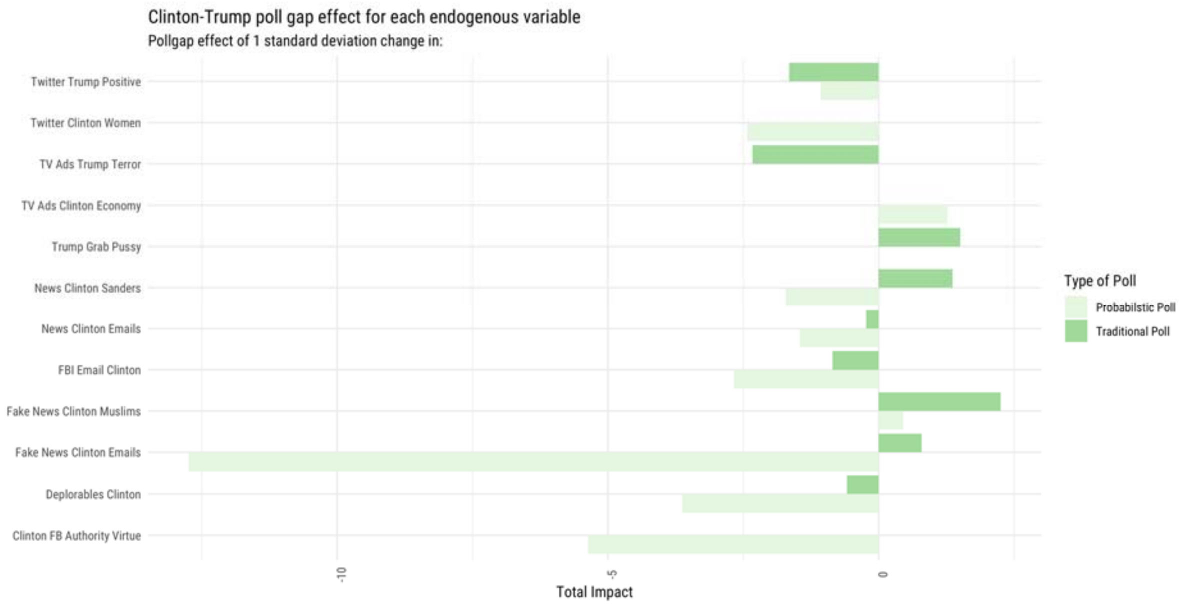


Figure 14: Forecast Error Variance Decomposition of Probabilistic Poll Gaps

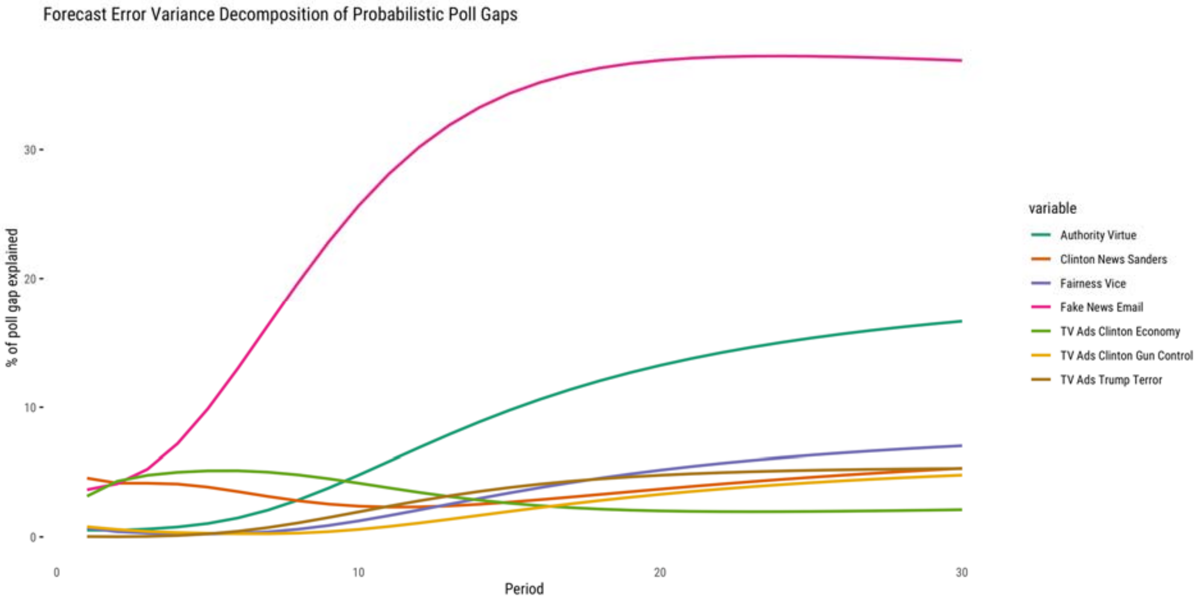


Figure 15: Traditional vs Probablistic Poll variance explained by each driver (change greens for polls)

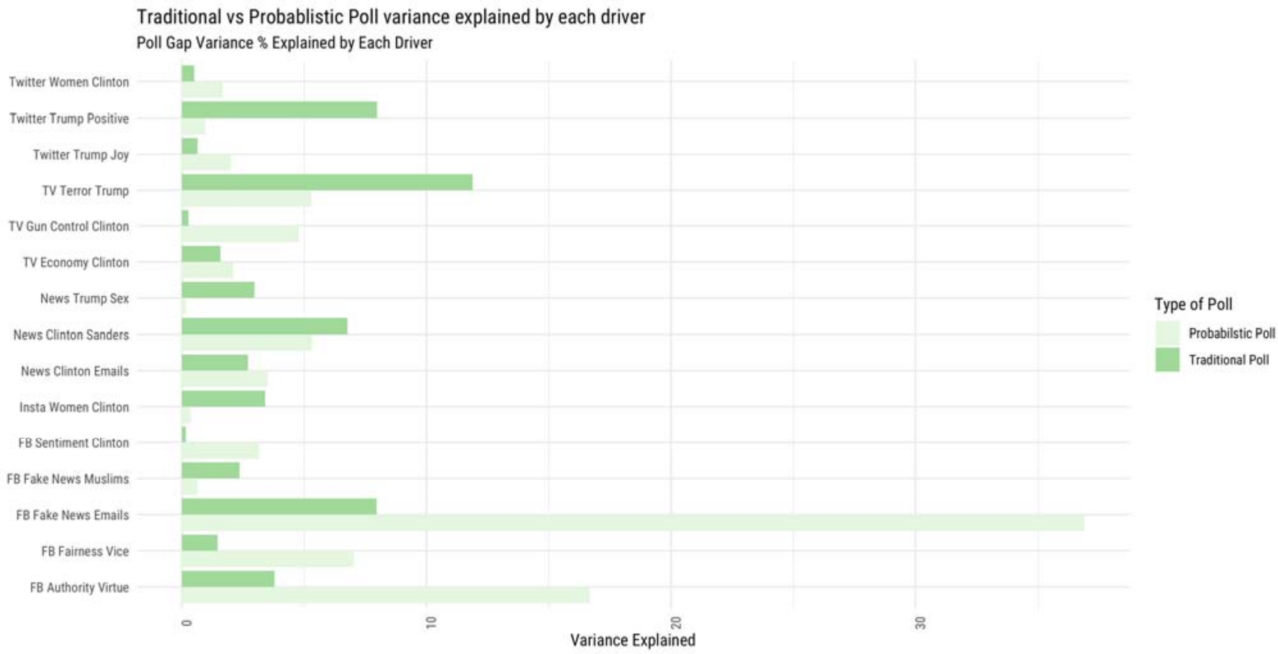
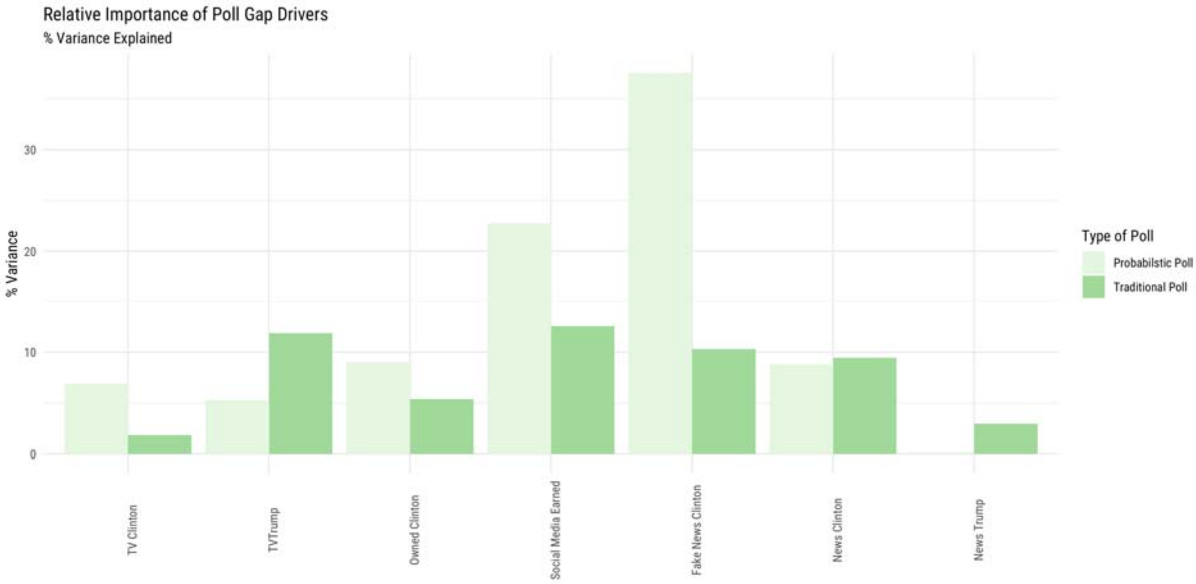


Figure 16: Relative importance of driver groups for the Clinton-Trump poll gap



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Web Appendix

Web Appendix WA1: Fake News Identification and LDA Analysis

To identify topic patterns within the fake news links shared on both candidate's official Facebook pages, we relied on the common structure of fake news website links that commonly includes the headline of the featured article. E.g. the link https://newspunch.com/wikileaks-reveal-clinton-ties-to-rothschilds-and-occult-cabal/amp/ refers to an article that spreads misinformation about Clinton's alleged role in a pedophile satanic ring. The article's headline is 100% covered in the main link.

To simplify data collection and avoid a biased data set through e.g. having to exclude links that refer to deleted content, we use the link structure to extract information about the article's main content.

To automatically detect latent topics amongst all links we extracted, we rely on the well-established text mining approach of Latent Dirichlichet Allocation (LDA). LDAs are widely applied in automatic topic detection and text mining and have been also frequently applied in marketing research (see e.g. Büschken and Allenby 2016).

We follow common practice and first clean our text by deleting white spaces, numbers and stop words. Given that our corpus consists mainly of single sentences (i.e. headlines) we do not follow Büschken and Allenby who use sentence level LDAs assuming that a single document may feature several topics hidden in individual sentences. Instead we apply the standard LDA algorithm as implemtend in R's topicmodels package (Version 0.2-9).

As with traditional hierarchical cluster analyses, one has to determine the number of latent topics in a text a priori when conducting an LDA. To determine the optimal number of topics, different approaches are discussed by e.g. Griffiths and Steyvers (2004) as well as Arun et al. (2010). We followed common practice and relied on the coherence scores, which indicated an optimal number of 5 topics for Trump and 4 topics for Clinton.

Once each link has been assigned to a topic (by the topcimodels package highest probability function), we use the term-frequency inverse document frequency information (tf-idf) to identify the most typical words per topic to interpret the content of each topic.

To add validity, we furthermore asked to un-involved coders to assign links into the identified topics. LDA-coder reliability was above 95% and can thus be considered as satisfactory.

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Web Appendix WA2: Text Mining Analysis of Candidates' Social Media Posts

Appendix A: Latent Topics

To systematically identify topics within the candidates' social media posts we similarly relied on the help of an LDA analysis. Given that posts are commonly rather short (especially in case of Twitter and Instagram) and often address only one topic, we followed the same approach as descriped in Web Appendix WA1 and applied the traditional LDA as implemented in R's topicmodels package.

The coherence scores marginally varied across platforms for the two candidates. In case of Hillary Clinton the coherence scores suggested a 7 topic model for Facebook, a 9 topic model for Instagram and a 8 topic model for Twitter. In case of Trump the coherence scores suggested for Facebook a 5 topic model, for Instagram a 6 topic model and for Twitter a 6 topic model. To ensure comparable solutions across platforms and candidates we then aimed for an average solution. In case of Clinton we decided to run an 8 topic model for each platform. In case of Trump we ran a 6-topic model for each platform.

As in case of the Fake News LDA we used the topic specific tf-idf scores to identify the most specific words per category for content interpretation and relied again on the help of 2 different and un-invovled coders who needed to assign 100 random posts to the topics. Coder-LDA reliability was again high with 89%. The LDA analysis results are displayed in Table WA2.1 and WA2.2

Table WA2.1: Aggregated number of topic specific posts across social media channels for Hillary Clinton

Social Network	Attack Trump	Other Topics	Clinton Personal	Democratic Party	Family	Rally Support	USA Unity	Women
Facebook	229	130	165	180	147	156	88	120
Instagram	31	10	10	18	15	12	20	27
Twitter	279	276	275	360	332	193	276	346

Table WA2.2: Aggregated number of topic specific posts across social media channels for Donald Trump

Social Network	Attack Clinton	Attack Democrats	MAGA	Other Topics	Trump Movement	Trump Rallies
Facebook	286	249	211	0	19	471
Instagram	38	84	38	88	75	67
Twitter	224	249	175	184	149	308

Figures WA2.3 as well as WA.2.3 furthermore show how the candidates post topics varied over the four months of our samples.

Figure WA2.3: Social Media Posting Behavior of Hillary Clinton

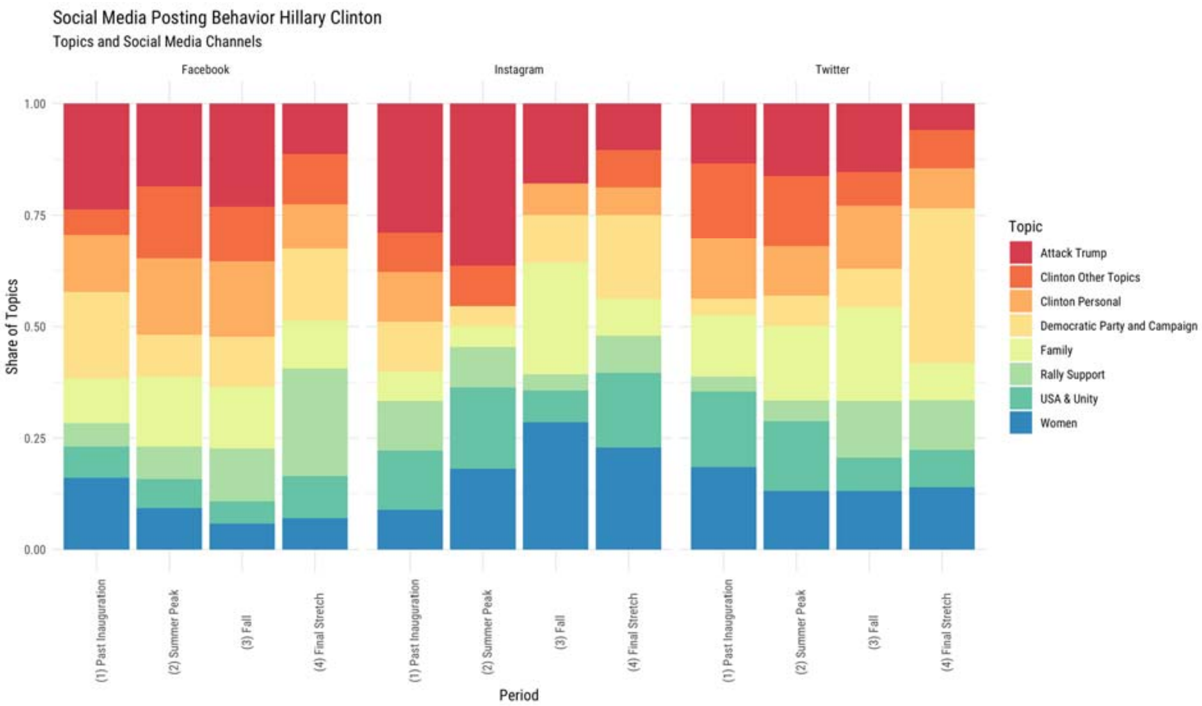
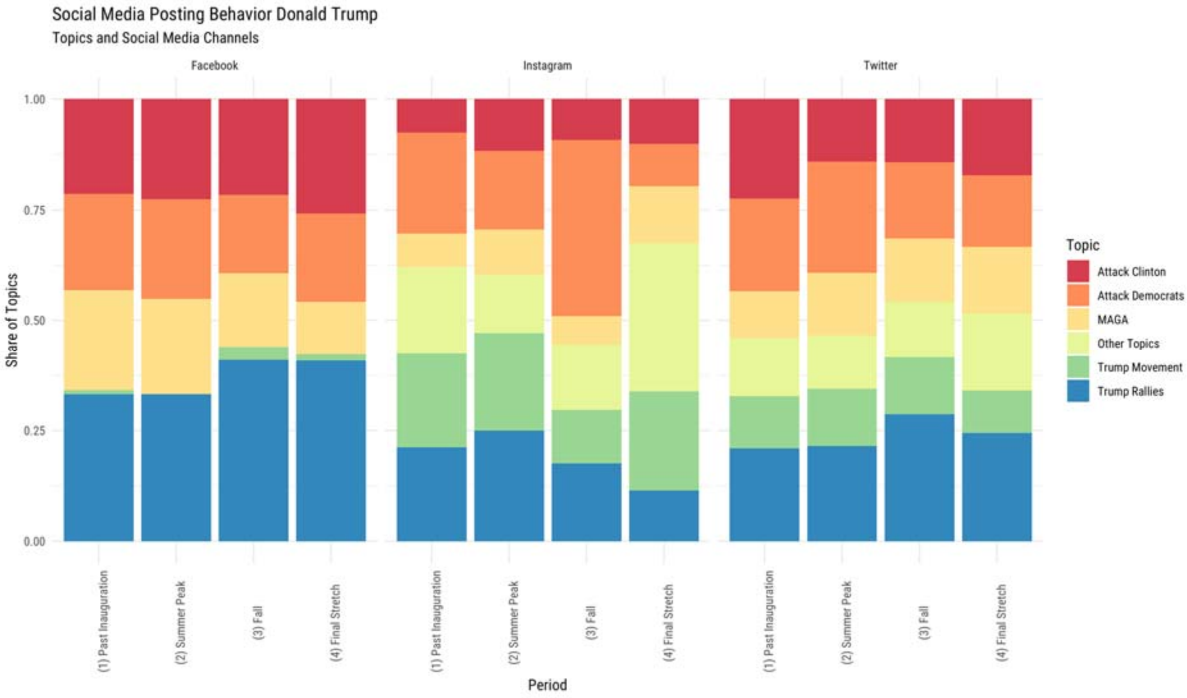


Figure WA2.4: Social Media Posting Behavior of Donald Trump



As reported in the main document we furthermore conducted several text mining analyses. To measure sentiment we relied on VADER, that was developed for measuring text based sentiment in social media posts and that is able to account for basic negations as well as for the use of emojis and other social media specifics.

To measure emotions within the posts we furthermore used the common NRC dictionary implemented in R's tidytext package (Version 0.2.3).

To account for the moral emotions in the candidates' posts we furthermore applied the Moral Foundation Theory (MFT) dictionary available on https://moralfoundations.org.

Table WA2.5 provides the summary statistics for all sentiment, emotions and moral emotion measures for both candidates and all three platforms. Figures WA2.6 and WA2.7 finally present how the use of emotions varied for each candidate during the 4 months prior to the election.

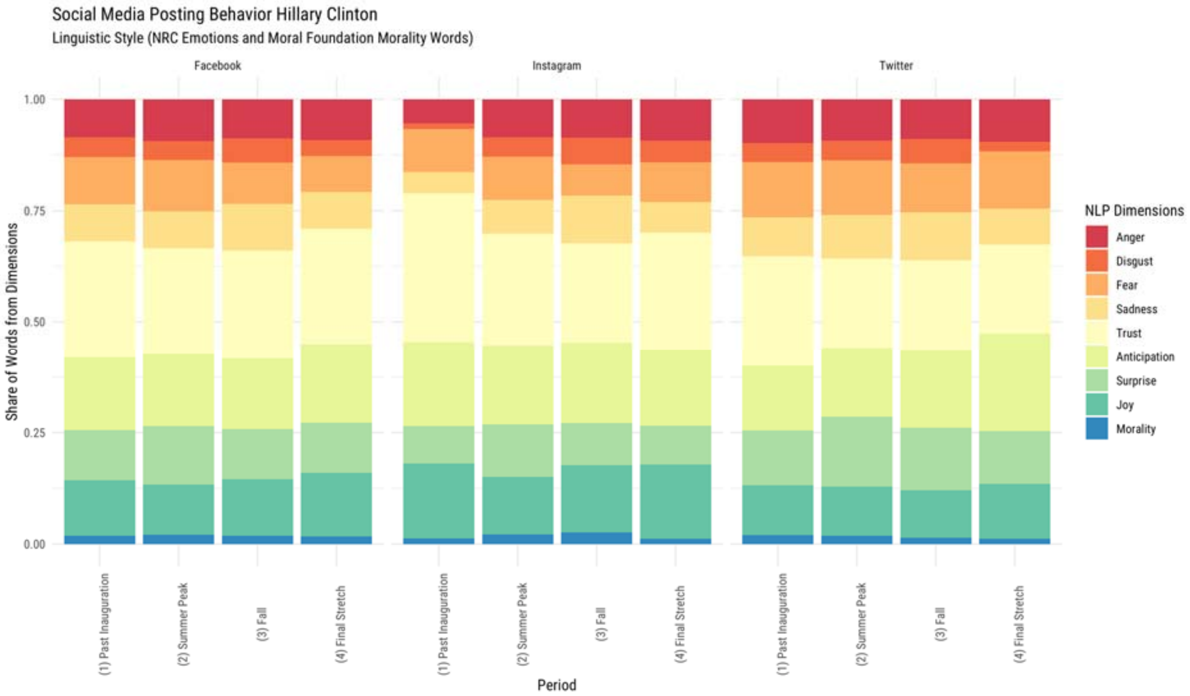
Table WA2.5: NLP Descriptives of Social Media Posting Behavior Clinton and Trump

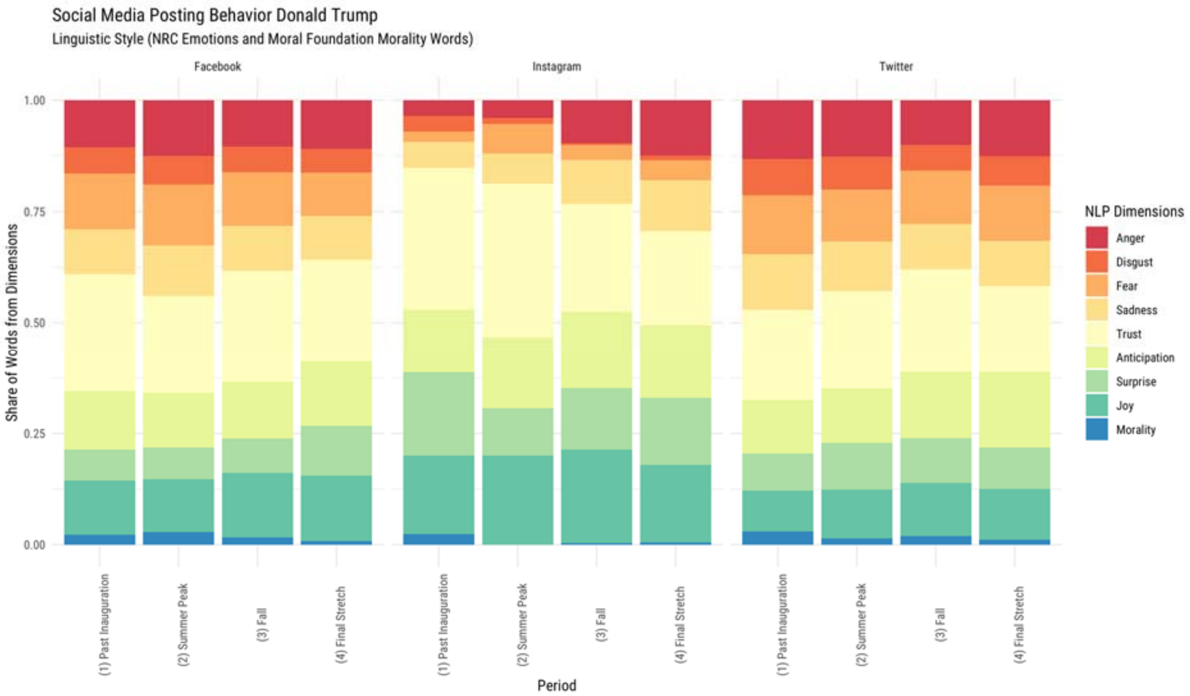
		Clinton			Trump		
	Platform	Facebook	Instagram	Twitter	Facebook	Instagram	Twitter
VADER Compound	Mean	0.16	0.32	0.13	0.33	0.33	0.16
	Median	0.18	0.39	0.12	0.39	0.31	0.14
	Min	-0.26	-0.90	-0.13	-0.52	-0.43	-0.53
	Max	0.52	0.98	0.52	0.87	0.95	0.70
	First Quintile	0.09	0.15	0.05	0.20	0.11	0.03
	Third Quintile	0.23	0.54	0.19	0.49	0.45	0.31
	Std. Dev.	0.17	0.45	0.13	0.29	0.31	0.27
Anger	Mean	4.73	0.87	5.89	8.40	0.93	4.02
	Median	4.00	0.00	5.00	4.00	0.00	3.00
	Min	0.00	0.00	0.00	0.00	0.00	0.00
	Max	18.00	10.00	19.00	126.00	8.00	16.00
	First Quintile	2.30	0.00	3.00	3.00	0.00	2.00
	Third Quintile	6.00	1.00	6.00	6.00	1.00	4.74
	Std. Dev.	3.44	1.75	4.42	16.39	1.70	3.58
Anticipation	Mean	8.75	1.91	11.08	9.78	1.47	4.69
	Median	8.00	1.00	9.00	5.00	1.00	4.00
	Min	1.00	0.00	0.00	0.00	0.00	0.00
	Max	35.00	13.00	38.00	98.00	12.00	23.00
	First Quintile	6.00	1.00	6.00	4.00	0.00	2.00
	Third Quintile	10.00	2.00	13.00	8.00	1.37	5.00
	Std. Dev.	5.45	2.45	8.02	14.00	2.23	3.61
Disgust	Mean	2.32	0.45	2.48	4.42	0.10	2.25
	Median	2.00	0.00	2.00	2.00	0.00	2.00
	Min	0.00	0.00	0.00	0.00	0.00	0.00
	Max	13.00	7.00	15.00	76.00	2.00	10.00
	First Quintile	1.00	0.00	1.00	1.00	0.00	1.00
	Third Quintile	3.00	0.00	2.00	4.00	0.00	2.00
	Std. Dev.	2.31	1.17	2.82	9.13	0.35	2.26
Fear	Mean	5.01	0.93	7.53	9.05	0.38	4.06
	Median	4.00	0.00	6.00	4.00	0.00	3.00
	Min	0.00	0.00	0.00	0.00	0.00	0.00
	Max	16.00	11.00	33.00	128.00	5.00	15.00
	First Quintile	3.00	0.00	4.00	2.00	0.00	2.00
	Third Quintile	6.00	1.00	9.00	6.00	0.00	5.00
	Std. Dev.	3.49	1.77	5.88	17.57	0.82	3.50
Joy	Mean	6.79	1.67	7.08	10.01	1.66	3.52
	Median	6.00	1.00	6.00	6.00	1.00	3.00
	Min	0.00	0.00	0.00	0.00	0.00	0.00
	Max	30.00	10.00	26.00	106.00	10.00	15.00
	First Quintile	4.00	1.00	4.00	4.00	0.00	2.00
	Third Quintile	8.00	2.00	8.74	8.04	2.00	4.00
	Std. Dev.	5.06	1.88	5.37	13.58	2.14	2.68

Table WA2.5: NLP Descriptives of Social Media Posting Behavior Clinton and Trump (cont).

		Clinton			Trump		
	Platform	Facebook	Instagram	Twitter	Facebook	Instagram	Twitter
Sadness	Mean	4.66	0.79	5.80	7.83	0.90	3.59
	Median	4.00	0.00	5.00	4.00	0.00	3.00
	Min	0.00	0.00	0.00	0.00	0.00	0.00
	Max	20.00	8.00	19.00	108.00	8.00	17.00
	First Quintile	2.00	0.00	3.00	2.00	0.00	1.00
	Third Quintile	6.00	1.00	6.00	6.00	1.00	4.00
	Std. Dev.	3.58	1.57	4.45	14.35	1.58	3.37
Surprise	Mean	6.11	1.01	8.28	6.05	1.32	3.07
	Median	6.00	1.00	7.00	4.00	1.00	2.00
	Min	0.00	0.00	0.00	0.00	0.00	0.00
	Max	22.00	7.00	34.00	60.00	10.00	13.00
	First Quintile	4.00	0.00	4.60	3.00	0.00	1.00
	Third Quintile	7.00	1.00	9.00	5.04	1.00	4.00
	Std. Dev.	3.56	1.34	6.12	7.77	1.89	2.71
Trust	Mean	13.34	2.90	13.28	17.94	2.14	6.80
	Median	11.00	2.00	10.00	10.00	1.00	6.00
	Min	0.00	0.00	1.00	0.00	0.00	0.00
	Max	48.00	17.00	48.00	178.00	10.00	32.00
	First Quintile	8.00	1.00	7.00	6.00	0.00	4.00
	Third Quintile	14.07	3.00	14.74	14.00	3.00	8.00
	Std. Dev.	8.93	3.36	9.70	24.87	2.42	5.11
Morality	Mean	0.98	0.18	0.98	1.44	0.05	0.60
	Median	0.00	0.00	1.00	0.00	0.00	0.00
	Min	0.00	0.00	0.00	0.00	0.00	0.00
	Max	7.00	3.00	5.00	17.00	1.00	5.00
	First Quintile	0.00	0.00	0.00	0.00	0.00	0.00
	Third Quintile	1.00	0.00	1.00	1.00	0.00	1.00
	Std. Dev.	1.40	0.49	1.27	3.02	0.23	1.00

Figures WA2.6 & WA2.7: NRC and Morality in Posts from Clinton and Trump





Web Appendix WA3: LDA Analysis of Candidates' News Coverage

To track media coverage topics, we again rely on the help of the link structure of social media posts (see WebAppendix WA1). For all media outlets in our media classification we identified the corresponding official Twitter accounts and tracked for each account any posts with a link to media outlet's main page that features either Trump or Clinton. Twitter messages commonly rely on short URLs which do not feauture the necessary long content for our approach described in Web Appendix WA1. We therefore needed to resolve all short urls to obtain the long versions which then contained the necessary content for our LDA analysis. Similar to our approach in Web Appendix WA1 we then applied a basic topic model and let us guide by the the coherence scores for the topic number selection. For both candidathes the coherence scores indicated a 5-topic solution. Again, we relied on the tf-idf scores for interpretation purposes and asked independent coders to assign 100 randomly selected links to topics. LDA-coder reliability was again satisfactory with 91% reliability.

Web Appendix WA 4 Granger Causality Test Results

Null Hypothesis	traditional	probabilistic	women	men	young	middle-aged	old	middle income	high income	low income	Black	Hispanic	other race	White	bachelor	college	no college
DONATIONS_CLINTON does not Granger-cause POLLGAP	**0.028**	0.801	0.693	0.570	0.070	0.407	0.124	0.295	0.494	0.347	0.831	0.500	0.082	0.394	0.733	0.469	0.322
POLLGAP does not Granger-cause DONATIONS_CLINTON	0.266	**0.009**	0.084	**0.033**	**0.022**	0.099	0.080	**0.009**	**0.010**	0.789	0.394	**0.024**	0.083	**0.017**	0.160	0.224	**0.025**
USPAGELIKES_TRUMP does not Granger-cause POLLGAP	0.121	0.142	0.062	0.374	0.329	0.668	0.095	0.128	0.055	0.062	0.464	**0.001**	**0.009**	0.163	0.072	0.182	0.277
POLLGAP does not Granger-cause USPAGELIKES_TRUMP	0.172	0.715	0.149	0.426	**0.048**	**0.002**	0.474	0.711	0.348	**0.022**	0.448	0.432	**0.011**	0.528	0.306	0.168	0.321
HCFBFNBENGHAZIBLACK does not Granger-cause POLLGAP	0.596	0.099	**0.007**	**0.008**	0.428	0.283	**0.001**	**0.000**	0.106	**0.000**	**0.000**	**0.000**	**0.015**	**0.000**	**0.003**	**0.002**	**0.005**
POLLGAP does not Granger-cause HCFBFNBENGHAZIBLACK	0.336	0.202	0.140	0.010	0.270	**0.020**	**0.013**	**0.000**	**0.030**	**0.001**	**0.000**	0.064	**0.003**	**0.000**	**0.045**	**0.009**	**0.044**
HCFBFNEMAILS does not Granger-cause POLLGAP	**0.021**	**0.018**	**0.001**	**0.000**	**0.035**	**0.003**	**0.000**	**0.000**	**0.022**	**0.000**	**0.000**	**0.000**	**0.015**	**0.000**	**0.000**	**0.002**	**0.002**
POLLGAP does not Granger-cause HCFBFNEMAILS	0.063	0.282	0.089	**0.013**	0.513	0.102	**0.002**	**0.000**	**0.037**	**0.007**	**0.000**	0.095	**0.027**	**0.000**	0.203	**0.012**	0.098
DTFBFNMUSLIMSHARIA does not Granger-cause POLLGAP	**0.004**	0.121	**0.036**	0.548	0.248	**0.041**	0.267	0.164	0.580	**0.012**	0.277	0.210	0.643	0.523	0.401	0.187	0.616
POLLGAP does not Granger-cause DTFBFNMUSLIMSHARIA	**0.007**	0.128	**0.070**	0.791	0.432	0.239	0.097	0.281	0.581	0.437	0.879	0.078	**0.033**	0.591	0.352	0.599	0.210
HCFBCOM_MEANVADERCOMPOUN does not Granger-cause POLLGAP	0.134	0.553	0.649	0.656	**0.014**	0.358	**0.036**	0.519	0.337	0.286	**0.043**	**0.030**	0.293	0.154	0.169	0.698	0.827
POLLGAP does not Granger-cause HCFBCOM_MEANVADERCOMPOUN	0.342	**0.036**	**0.007**	0.166	**0.046**	0.676	0.084	0.225	0.288	0.167	**0.044**	0.210	0.277	0.647	**0.001**	0.203	0.144
HCFBCOM_SUMAUTHORITYVIRT does not Granger-cause POLLGAP	**0.030**	**0.034**	**0.000**	**0.046**	0.130	0.232	**0.008**	**0.000**	0.458	**0.003**	**0.000**	**0.001**	0.120	**0.000**	**0.000**	**0.021**	**0.048**
POLLGAP does not Granger-cause HCFBCOM_SUMAUTHORITYVIRT	**0.020**	0.078	0.242	**0.000**	0.404	**0.004**	**0.000**	**0.000**	0.005	**0.000**	**0.000**	0.246	**0.008**	**0.000**	0.284	**0.000**	**0.013**
HCFBPOSTS_SUMFAIRNESSVIC does not Granger-cause POLLGAP	0.120	0.234	**0.005**	**0.033**	0.112	0.467	0.235	**0.030**	0.313	**0.000**	**0.020**	0.290	0.376	0.174	0.065	0.728	0.413
POLLGAP does not Granger-cause HCFBPOSTS_SUMFAIRNESSVIC	0.074	0.369	0.836	0.312	0.205	0.678	0.478	0.233	0.314	0.224	0.494	0.056	0.540	0.657	0.305	0.081	0.551

Null Hypothesis	traditional	probabilistic	women	men	young	middle-aged	old	middle income	high income	low income	Black	Hispanic	other race	White	bachelor	college	no college
INSTACLINTONLDA8_WOMEN does not Granger-cause POLLGAP	0.222	0.162	0.509	**0.015**	0.089	0.492	0.400	0.683	**0.010**	0.150	0.348	0.327	0.357	0.135	0.217	0.052	0.059
POLLGAP does not Granger-cause INSTACLINTONLDA8_WOMEN	0.235	0.130	0.332	0.206	0.241	0.112	0.286	0.324	**0.025**	0.131	0.301	0.139	0.213	0.318	0.175	0.177	0.211
TVADECONOMYTIMECLINTON does not Granger-cause POLLGAP	0.401	0.308	0.587	0.168	0.103	0.153	**0.034**	0.015	0.287	0.078	**0.001**	0.085	0.076	**0.001**	**0.018**	0.075	0.132
POLLGAP does not Granger-cause TVADECONOMYTIMECLINTON	0.287	0.183	0.230	0.341	0.148	0.076	0.182	0.755	0.054	**0.025**	0.076	0.130	0.159	0.053	0.084	0.152	0.318
TVADGUNCONTROLCLINTON does not Granger-cause POLLGAP	0.604	0.789	0.123	0.349	0.275	0.669	0.357	0.088	0.528	0.428	0.855	0.255	0.198	0.771	0.240	0.759	0.397
POLLGAP does not Granger-cause TVADGUNCONTROLCLINTON	0.503	0.103	0.124	0.298	0.142	0.136	0.336	0.242	0.243	0.387	0.322	0.162	**0.005**	0.331	0.250	0.233	0.129
TVADTERRORTIMETRUMP does not Granger-cause POLLGAP	0.472	**0.047**	0.255	0.248	0.076	**0.037**	0.701	**0.012**	0.176	**0.043**	**0.002**	0.101	0.235	**0.011**	0.090	0.283	0.246
POLLGAP does not Granger-cause TVADTERRORTIMETRUMP	0.172	0.566	0.602	0.139	0.341	0.057	0.078	**0.037**	0.099	**0.042**	**0.070**	0.351	0.398	**0.007**	0.013	0.108	0.388
EVENTS:																	
ASSANGE does not Granger-cause POLLGAP	0.083	0.213	0.109	0.110	0.236	0.270	0.090	0.745	0.236	0.378	0.669	0.728	0.793	0.942	0.522	0.125	0.175
WIKICAMPCHAIR does not Granger-cause POLLGAP	**0.000**	0.532	0.813	0.637	0.389	0.185	0.244	0.805	0.593	0.080	0.819	0.228	0.259	0.923	0.448	0.102	0.518
WIKIMIRANDA does not Granger-cause POLLGAP	0.466	0.199	**0.038**	0.449	0.421	0.131	0.068	0.319	0.556	0.392	0.959	0.127	0.051	0.577	0.710	0.102	0.150
FIRSTDEBATE does not Granger-cause POLLGAP	0.268	0.172	0.154	0.380	0.285	0.072	0.266	0.263	0.339	0.619	0.846	0.684	0.395	0.679	0.365	0.472	0.709
SECONDDEBATE does not Granger-cause POLLGAP	0.170	0.087	0.693	0.170	0.275	0.097	0.083	0.755	**0.013**	0.593	0.171	0.522	0.093	0.547	0.502	0.672	0.147
THIRDDEBATE does not Granger-cause POLLGAP	**0.000**	0.384	0.712	0.649	0.257	0.617	0.263	0.618	0.734	0.614	0.851	0.598	0.554	0.807	0.837	0.029	0.732
CLINTONACCEPTS does not Granger-cause POLLGAP	0.133	0.417	0.220	0.694	0.547	0.186	0.469	0.540	0.745	0.691	0.970	0.075	0.064	0.884	0.506	0.489	0.652

Null Hypothesis:	traditional	probabilistic	women	men	young	middle-aged	old	middle income	high income	low income	Black	Hispanic	other race	White	bachelor	college	no college
CLINTONDEPLORABLES does not Granger-cause POLLGAP	0.328	0.131	0.231	**0.025**	0.162	**0.037**	0.426	0.659	0.206	0.127	0.316	0.149	0.231	0.608	0.469	0.391	0.204
CLINTONFBIEMAIL does not Granger-cause POLLGAP	0.863	0.453	0.458	0.654	0.683	0.522	0.486	0.369	0.201	0.356	0.886	0.636	0.830	0.808	0.141	0.783	0.380
NYTENDORSE does not Granger-cause POLLGAP	0.494	0.521	0.311	0.346	0.445	0.607	0.435	0.365	0.506	0.606	0.710	0.476	0.282	0.743	0.470	0.696	0.587
NYTNORUSSIA does not Granger-cause POLLGAP	0.656	0.072	0.203	0.223	0.073	0.054	0.225	0.453	0.059	0.506	0.909	**0.015**	0.412	0.458	0.393	0.071	0.358
TRUMPASSINATES does not Granger-cause POLLGAP	0.752	**0.037**	0.115	0.258	0.032	0.206	0.264	0.702	0.051	0.144	0.760	**0.008**	0.761	0.528	0.263	0.279	0.190
TRUMPGOLDIRAQ does not Granger-cause POLLGAP	0.241	0.156	0.072	0.237	0.477	0.086	0.444	0.482	0.373	0.329	0.716	**0.041**	0.643	0.702	0.672	0.203	0.328
TRUMPGRABPUSSY does not Granger-cause POLLGAP	**0.015**	0.181	0.439	0.506	0.644	0.097	0.139	0.226	**0.035**	0.194	0.456	0.589	0.368	0.509	0.235	0.474	0.326
TRUMPTAXEVASION does not Granger-cause POLLGAP	0.129	0.339	0.178	0.177	0.319	0.138	0.255	0.183	0.471	0.544	0.808	0.471	0.066	0.670	0.403	0.417	0.377