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Abstract

We study how individuals comment on political news posted on Reddit's main political forum during the 2016 US Presidential Election. We present two main findings. First, opposite partisan users comment on the same news sources, but on different news. Second, partisan users behave very differently from independents if the news is bad for a candidate. Compared to independents, partisan comments on bad news are less frequent on the own candidate, and more frequent on the opponent. The content of the comments also suggests that partisan users are less likely to accept bad news on their candidate, and more likely on the opponent. This behavior is consistent with motivated reasoning, and with the predictions of a model of rational inattention where the cost of attention depends on whether the news is pleasant or unpleasant.

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Introduction

Supporters of opposite political parties often hold very different beliefs, over the features of immigrants (Alesina, Miano, and Stantcheva, 2022), the extent of inequality and social mobility (Alesina, Stantcheva, and Teso, 2018), the causes of climate change (Kahan, 2015), the risks associated with Covid (Allcott et al., 2020a) and other controversial issues. A common explanation is that beliefs do not only perform a cognitive function, but they also shape one's self image and provide anticipatory utility (or disutility). Perhaps unconsciously, individuals trade-off these cognitive and psychological effects, and as a result their beliefs are systematically distorted in predictable ways (Bénabou and Tirole, 2006, 2011). The idea that individuals hold motivated beliefs is supported by a large empirical literature (Bénabou and Tirole, 2016; Flynn, Nyhan, and Reifler, 2017; Thaler, 2021). Most of the supporting evidence is of two kinds, however. Either it concerns the content of beliefs from survey data; this can document the correlation of beliefs with specific individual features, but it is silent about the mechanisms leading to belief distortions. Or else it comes from experiments in the lab; in this case it can shed light on specific mechanisms, but it is subject to the usual caveats of external validity and low stakes.

The goal of this paper is to provide evidence on some of the mechanisms that may lead to the formation of distorted political beliefs, using non experimental data on how individuals behaved on a widely used web platform, Reddit, during the period June-November 2016, just before the 2016 US presidential election of Trump vs Clinton. We do so in two ways. First, we document different patterns of engagement across different political news, based on users' ideology. Second, we interpret such patterns in light of alternative explanations.

Reddit was the 7$^{\text{th}}$ most visited website in the US in 2016, behind Facebook and YouTube but ahead of Twitter. We mostly focus on the platform's main political community, `r/politics`, which hosted 8 million comments made by 285,000 unique users to more than 120,000 news articles shared in our period of interest. Users of `r/politics` are obviously a selected sample of the aggregate population, but they constitute an interesting one that is relevant for our questions. They are interested in politics and heavily engaged in political news, and their online activity suggests that they could be opinion leaders offline. They also hold a variety of political views and their engagement with news on the platform is highly consistent with the online behavior of the general US population. As shown below, comments to different sources in `r/politics` closely track the online visits to those sources' websites, as constructed from a representative sample of the online US population. Two other features of the platform stand out. First, `r/politics` rules mandate that posts must concern US politics and exclusively contain a news article, rather than the users' thoughts (which belong to the comment section). Thus, posts on `r/politics` approximate a flow of political news. This allows us to focus on political discussions, without relying on hard-to-validate topic models to identify a political debate. Second, in our period Reddit did not select, within each community, which post to present to different users based on their revealed tastes. Thus, different individual engagement across posts is exclusively due to users' decisions—not those of an engagement-maximizing algorithm. No other major social media platform has such advantages.

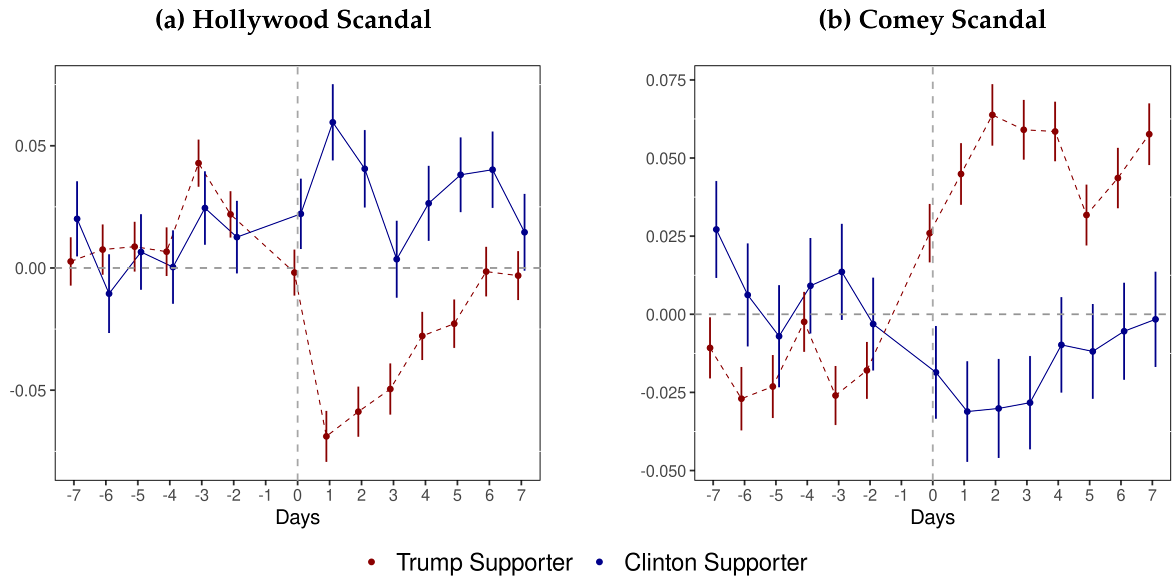
We start by showing that opposite partisan users comment on different news. This may seem in contrast to Gentzkow and Shapiro (2011), who documented how individuals visited similar online news sources, but it is not. Like Gentzkow and Shapiro (2011), we also find that opposite partisan users in `r/politics` comment on news from very similar news sources. Nevertheless, within each source, they comment on different pieces of news. Only half of the posts in our sample feature some comments by both Trump and Clinton supporters, while for the other half the groups never interact with each other. This finding, that individuals segregate by news but not by news source, is relevant, because it casts doubts on a popular explanation for differential exposure to news: lack of trust on the reliability of the source. If individuals with opposite political affiliations trust different news sources, then it should be reflected in what sources they engage with (Gentzkow and Shapiro, 2010). Yet this is not what we observe.

To interpret this particular kind of partisan segregation, we study a theoretical model where individuals choose how to allocate costly attention to political news concerning two candidates. Although we assume that the ultimate goal of individuals is to rank candidates, the model also allows for other motives related to emotions. The theory highlights three reasons that may explain partisan segregation in political news. First, individuals with opposite political preferences may be interested in different content, because they care about different policy issues. Second, they have different prior beliefs, and in particular they are uncertain about different things. Third, they draw intrinsic utility or disutility from engaging with specific kinds of news, for reasons other than ranking candidates.

The rest of the paper isolates and quantifies the last mechanism, highlighting how users' behavior is influenced by the congruence of the news with their ideology. Specifically, we identify `r/politics` posts that contain "bad news" about Trump or Clinton: either political scandals casting doubts on the competence or integrity of the candidate, or new information showing that the candidate was behind in the latest polls. We then employ a Diff-in-Diff estimation strategy that compares the behavior of independent vs partisan users across different types of news. In particular, we estimate the difference in the number and content of comments by partisan users on bad news of each candidate vs. their comments on general news, and compare it with that same difference for independent users.

Our first result is that partisan users are less likely to comment on bad news concerning their candidate than to bad news on the opponent, compared to non-partisan users. Figure 1 illustrates the gist of this finding. It depicts two event studies one week before/after the dates in which two prominent scandals concerning Donald Trump and Hilary Clinton were first announced. Panel (a) refers to the Access Hollywood videotape with the lewd statements of Donald Trump about women. Panel (b) refers to the declaration by James Comey that the FBI would re-open the investigation of Clinton's email controversy. The solid (blue) line depicts the fraction of daily comments on all Reddit political fora by Clinton supporters, relative to their daily comments on the entire Reddit platform, expressed as a difference with the same fraction for independents. The dotted (red) line does the same for Trump supporters. These two lines thus measure how partisan users allocate their activity on Reddit between political and non-political fora, compared to non-partisan users.

Figure 1: Share of Comments in Political Fora



Notes: The figure presents the average ratio of daily comments on Reddit political fora, over their total daily comments on the entire Reddit platform, for Trump supporters (dotted red line) and Clinton supporters (solid blue line), expressed as a difference with the same average fraction for independent users. The vertical lines denote 95% confidence intervals (standard errors clustered by user). Panel (a) refers to the Access Hollywood videotape scandal that hit Trump. Panel (b) refers to the declaration by James Comey that the FBI would re-open the investigation of Clinton's email controversy. The sample is restricted to categorized authors' posts one week before and after the scandal announcement. All regressions control for individual fixed effects. The point estimate at time t-1 is omitted due to collinearity.

Clearly, partisan users are relatively less active in political fora, compared to independents, in the days immediately following the scandal on their candidate, and more active in the days after the scandal of his / her opponent. For instance, the day after the Access Hollywood scandal became public, Trump supporters decreased their share of comments on political fora by 16.5%, compared to the 7 days before the scandal, while Clinton supporters increased it by 14.8%. As in the "ostrich effect" documented in finance by Karlsson, Loewenstein, and Seppi (2009), when political news are likely to focus on scandals on their own candidate, partisan users detach themselves from politics and are instead relatively more active on fora that discuss sports, entertainment, financial news and the like. Conversely, when the political debate is likely to focus on scandals about the opponent, they are attracted to political fora.

In the paper we explore this pattern more systematically for a wider set of bad news posted on `r/politics` on either Trump or Clinton during the entire period June-November 2016. On average partisan users are 30% less likely to comment a bad news if it concerns their candidate, and 30% more likely if it concerns his/her opponent, compared to independents, relative to the difference between partisan and independents in their propensity to comment general news. Which mechanisms can rationalize this behavior? It cannot be explained by the fact that opposite partisan users care about different topics, since bad news refer to the same concept: either a candidate's integrity or his/her likelihood of winning the election. The second possible explanation, namely different prior uncertainty on the feature/event underlying the news piece, is also hardly consistent with the data. In particular, we distinguish between bad news due to scandals and bad news due to a negative poll outcome. While opposite partisan users may be more or less confident in their assessment of the integrity and competence of one or the other candidate, the outcome of polls refers to the same underlying event: the probability of winning the election. Bad news on the polls for a candidate is good news for his/her opponent. And yet, we find that, relative to independents, partisan users comment less frequently on negative polls for their candidate, compared to negative polls for his/her opponent. This result is hard to explain without appealing to the idea that users are less willing to engage with news whose content they dislike.

Finally, we study the content of comments, to shed light on the feelings and thoughts of users when they engage with different kinds of news. We continue to focus on how comments by partisan users on consonant and non-consonant bad news differ from comments by independents on the same news, relative to the difference between partisans and independents when they comment on general news. Our analysis is guided by the simple assumption that comments express the user's true feelings and opinions. We study four outcomes: (i) an indicator used by Gennaro and Ash (2021), which measures the share of emotional relative to cognitive content; (ii) a commonly used indicator of sentiment, namely whether the comment expresses positive vs negative feelings or opinions (Liu et al., 2019; Heitmann et al., 2020); (iii) whether a comment on a scandal about a candidate evokes a scandal concerning his/her opponent; (iv) how many "likes", net of "dislikes", a comment receives from other users.

We find that partisan comments on consonant scandals are more emotional and more likely to express positive content, while those on non-consonant scandals are less emotional and more negative, compared to the comments of independents, relative to the partisan vs independent difference on general news. In other words, when they comment on a scandal on the opponent, partisan users display a more positive and emotional reaction, as if they liked the news. When commenting on a scandal on their candidate, instead, they are more negative and rational, as if they tried to rationalize and explain an undesirable event. Compared to independents, partisan users are also more likely to speak about scandals concerning the other candidate, if the scandal they comment on is unpleasant given their ideology, than if it is pleasant. In other words, if a post casts doubts on the valence of their candidate, partisan users are more likely to highlight controversies on his/her opponent, compared to independents. Finally, partisan users receive more likes when they comment consonant (i.e. pleasant) scandals, and less likes on non-consonant scandals, than when they comment general news, compared to independents commenting on the same news. As described below, the bulk of activity on `r/politics` comes from users without a clear partisan affiliation.[1] Hence, an interpretation of this finding is that the views of partisan users are more aligned with those of the non-partisan majority when they comment a scandal on the opposed candidate, because they draw similar inferences. When commenting on scandals of their own candidate, instead, partisan users try to find excuses or justifications that the non-partisan majority disagrees with. Alternatively, this

[1] the majority of users in `r/politics` cannot be easily classified in terms of their partisan preferences.

result can be interpreted as a confirmation that partisan users are more attentive to debates on consonant scandals, and less attentive on non-consonant scandals, resulting in a different composition of the audience depending on the scandal.

Overall, the entirety of these findings are difficult to explain without invoking some form of motivated cognition. Confidence in different news sources cannot explain why partisan individuals segregate by news, rather than by source. Differences in policy preferences cannot explain why they engage differently with news concerning the scandals of different candidates. Differences in prior uncertainties cannot explain asymmetric engagement with negative vs positive polls outcomes. Finally, the content of the comments and the number of "likes" reinforces the interpretation that these patterns reflect feelings of pleasure or discomfort when faced with different kinds of news.

This paper is related to several strands of the literature. The motivation of this work is tied to understanding the ideological polarization of beliefs (besides the papers quoted above, see also Glaeser and Ward, 2006, and Alesina, Miano, and Stantcheva, 2020 for a recent review). A common explanation of this polarization rests on differential exposure to information across ideological lines. On the theoretical side, Mullainathan and Shleifer (2005) and Gentzkow and Shapiro (2006), among others, provide models of ideologically-biased consumption of traditional media, while a more recent literature (Acemoglu and Ozdaglar, 2011; Golub and Jackson, 2012; Acemoglu, Ozdaglar, and Siderius, 2021) focuses on information dynamics in social networks (see Golub and Sadler, 2016 for a review). Empirically, Gentzkow and Shapiro (2011), An, Quercia, and Crowcroft (2014), Bakshy, Messing, and Adamic (2015), and Angelucci and Prat (2021), among others, relate ideology and news consumption. Within this strand, to the best of our knowledge, our paper is the first to document and quantify ideological segregation within news sources, rather than across (as in Gentzkow and Shapiro, 2011), and in the context of social media.[2] Our theoretical model relates to the literature on rational inattention and its application to politics (see Matějka and Tabellini, 2020 and Mackowiak, Matějka, and Wiederholt, 2021 for a general review). Our paper is also related to the large literature on motivated beliefs, surveyed by Bénabou and Tirole (2016). Most of the existing evidence of motivated cognition is based on experiments, with the exception of Di Tella, Galiani, and Schargrodsky (2007) and Karlsson, Loewenstein, and Seppi (2009) . Our result indicate that the “ostrich effect” found in finance by Karlsson, Loewenstein, and Seppi (2009) is also present in online political debates.[3]

Finally, our findings shed light on how the political debate unfolds on social media and broadly

[2]In this regard, the closest papers to ours are An, Quercia, and Crowcroft (2014) and Bakshy, Messing, and Adamic (2015). The former investigates the extent to which partisan users share different posts on Facebook, finding evidence for asymmetric patterns across ideological lines. The latter focuses on how ideological homophily in Facebook friends’ and Facebook’s algorithm exacerbate partisan differences in exposure to news.

[3]This part of our findings is related to Garz, Sörensen, and Stone (2020). They analyze Facebook posts by German news sources covering the lifting of immunity for German politicians between 2012 on 2017 and find that posts that are congenial with the outlet’s ideology receive more likes, shares, and comments. In their case, congeniality of a post is defined as the ideological distance between the outlet and the party whose member has received the lifting of immunity. Differently from their paper, we focus on evidence at the individual-post level and define whether a given post is consonant for each single user in our sample. This allows us to capture observed and unobserved individual heterogeneity (most importantly in partisanship) and to discriminate across different individual-level motives of engagement with news.

relate to the literature on the effects of social media on political ideology and information acquisition (Bail et al., 2018; Sunstein, 2018; Allcott et al., 2020b). Within this literature, we are amongst the first to study data on the Reddit platform and to highlight its advantages for applied economic and political analysis (following D'Amico, 2018).

The outline of the paper is as follows. The next section describes the context of the web platform and our data. Section 2 explores the extent to which individuals segregate along partisan lines. Section 3 studies a model of how costly attention is allocated to different kinds of news and derives a number of predictions. Section 4 studies the propensity to comment different kinds of news, while the content of the comments is studied in section 5. A final section concludes.

1 Data

1.1 Reddit

Our main data set consists of the record of every comment and post on the web platform Reddit during the last five months of the 2016 US Presidential Campaign (June 1 – November 7, 2016). Reddit is a social network where users post content, either produced by them or obtained from a variety of sources (mostly news media), and comment on those posts (or on the comments of others). The platform is divided into a hierarchy of subreddits, themselves created and moderated by users. Each Subreddit is defined by the topics discussed, ranging from sports to hobbies to politics. We will also refer to a subreddit as a forum.

For any post or comment, we know the author and exact time and date of the posting, the subreddit where it is posted, its complete text content; if it is a post, we know the original source from which it is drawn, if any (f.e., for posts sharing a news article, we know the original website); if it is a comment, we know the post (or comment) to which it refers and whether it is a first level or a higher level comment (i.e. whether it is a comment on a post or on another comment).

Unlike other social networks, Reddit has no individual-level algorithm to increase users' engagement. Users are supplied content according to the subreddits to which they are subscribed, but beyond that Reddit does not operate any individual-level customization. Users can either browse a specific subreddit, or the general Reddit home page (in which case they see only the content posted on the subreddits to which they subscribed). Within a subreddit, every user sees exactly the same posts, sorted by novelty, popularity, or a combination of both, depending on the criterion chosen by the user. Thus, there are no unobserved confounding factors that determine which content is presented to each user, something that is unique to Reddit.[4]

Political discussions take place in a wide variety of subreddits, which we group into three categories: partisan, ideological, and independent. We define as *partisan* all those subreddits explicitly centered around the support of a given candidate. The most prominent example is `r/The_Donald`, a subreddit for supporters of Donald Trump, created in June 2015, which rallied more than 790,000 subscribers and was then banned in June 2020 for violating Reddit rules on harassment and tar-

[4]In Appendix B.1, we offer a more detailed discussion of how a user can engage with Reddit.

geting. *Ideological* fora, on the other hand, are defined by supporting a political ideology, such as conservatism, liberalism or feminism. For instance, `r/republican` defines itself as a "place for Republicans to discuss issues with other Republicans".[5] Finally, we define as *independent* those fora that are explicitly open to all views and opinions and have no stated ideology or affiliation. Table B.1 in the Appendix reports all the political fora, along with their classification and a precise description of the classification method (in Section B.2). Users can be active on several fora at once.

Most of our analysis focuses on `r/politics`, the largest and most active of the independent political fora. In 2016, `r/politics` had 3 million subscribers,[6] making it the 55th largest one on Reddit (out of 900,000 subreddits in June 2016). In our period of interest, it hosted 8.3 million comments made by 287 thousand authors.[7] Individuals from all political sides can post and comment content strictly concerning current US politics. The forum is explicitly open to all ideologies, and it forbids political advertisements, hateful speech, and satire. It is heavily moderated by a team of users that ensure a civil debate.[8] Importantly for our purposes, the etiquette of the forum expects users to write posts only sharing the title of the news source and the links, while their thoughts on the article should be in the form of comments to the post. In this way, each posting does not reflect the authors' views on the topic, which are relegated to the comments section. Thus, given the general rules of Reddit and the specific rules of `r/politics`, the forum approximates a continuous feed of political news on which users can post comments. While browsing it, a user is presented with a stream of titles and links to news articles, which also reveal the source of the article. Figure 2 shows an example of a posting related to the "Access Hollywood Tape" scandal.

In 2016, 7% of all US adults used Reddit (11% in 2019), with 78% of them reporting they get their news there. As shown in Appendix Table B.2 users of Reddit, across the entire platform, tend to be younger, more liberal, more educated and more likely to live in large cities, compared to users of other popular web platforms (Pew Research Center, 2016, 2019).

Even though the sample is selected, the patterns of engagement with sources on r/politics are similar to the online visits to those sources' web pages, as collected by Comscore for a representative sample of the US online population between May 2017 and May 2021 (earlier dates are not available). That is, the news sources attracting more comments in `r/politics` tend to be those that

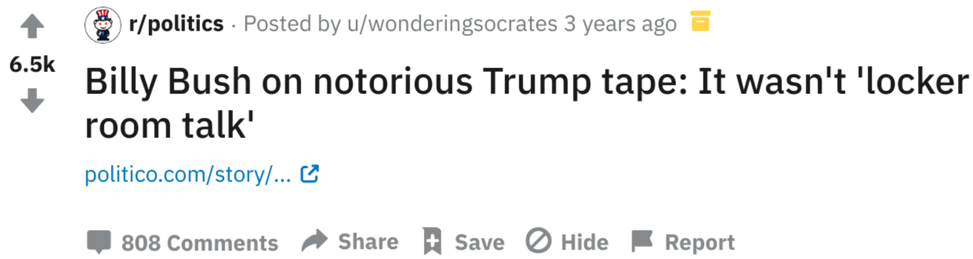
[5] Fora supporting candidates (eg. `r/The_Donald` and `r/hillaryclinton`) differ from ideological fora (eg. `r/republican`, or `r/Democrats`), because parties may have more than one candidate and users are active also in non-election periods.

[6] 7 million as of January 2021 (subredditstats.com/r/politics).

[7] The total number of comments available to us is 9.3 millions, but we exclude 1 million of comments made by either automated bots that post the rules of the forum under every post, together with comments that were deleted by the moderators for violating the rules, for which we have no information on the author.

[8] Users are not supposed to comment a story with the only objective of angering others or to inflame the debate. Insightful comments, even if stating unpopular opinions, are rewarded by the community, whereas derogatory comments are banned or "downvoted". The guidelines, which are always printed on the side of the webpage, state, among other things *"Be civil"* and *"Vote based on quality, not opinion"*. Upon hovering on these two buttons, a user is reminded, respectively, *"[to] treat others with basic decency. No personal attacks, hate-speech, flaming, baiting, trolling, witch-hunting, or unsubstantiated accusations. Threats of violence will result in a ban"*, and that *"Political discussion requires varied opinions. Well written and interesting content can be worthwhile, even if you disagree with it. Downvote only if you think a comment/post does not contribute to the thread it is posted in or if it is off-topic in* `r/politics` *."*. Comments that do not comply with the rules get banned. The rules of the forum, as of June 2, 2016 are available at:
https://web.archive.org/web/20160602161333/https://www.reddit.com/r/politics/wiki/rulesandregs

Figure 2: Example of Posting



also attract more online page views in the Comscore sample. Appendix Table B.3 reports the share of comments that each source has in `r/politics` (out of the top 50 sources in `r/politics`), and compares it to the share of pageviews of the same source online (out of the the top 50 sources in Comscore). The major differences between the two samples are due to the fact that many sources are not exclusively political, such as USAToday. Whereas our sample only reports comments to political news, Comscore reports all pageviews, political and non-political. Appendix Table B.3 also reports the share of comments (resp. pageviews) of all the exclusively political sources that are common to `r/politics` and Comscore, and the two shares now become more similar.[9]

1.1.1 Measuring Political Preferences

Reddit users are anonymous, but we observe their behavior on the social network. We exploit this information to measure their political preferences, using two alternative methods. Our first and preferred indicator uses Algorithm 1 to classify a user i as a Trump supporter ($\mathcal{A}_i = TS$), a Clinton supporter ($\mathcal{A}_i = CS$), or as independent ($\mathcal{A}_i = I$). Independents are predominantly active on independent fora, while partisan supporters are predominantly active in the partisan fora of either Trump or Clinton. We do not classify users that have low activity or an inconsistent partisan activity.[10]

[9] The correlation coefficient between the share of comments and the share of page views is 0.79 for the political sources, and 0.32 for all sources.

[10] As a robustness check, when discussing ideological segregation we extend our results by classifying users as Republican or Democrats, based on their activity on ideological forums, as detailed in Section C.1 of the Appendix. Results are qualitatively identical and numerically very similar.

Algorithm 1 User Classification

for user i **do**
  if i commented more than 5 times in `r/politics` or other fora labeled as independent **and** more than 95% of the comments of user i on all political fora are in independent fora **then**
    $\mathcal{A}_i$ = independent
  else if i commented more than 5 times in all partisan fora **and** more than 95% of the comments of user i on all partisan fora are in partisan fora supporting candidate P **then**
    $\mathcal{A}_i$ = supporter of P
  else
    $\mathcal{A}_i$ = non-classified

As reported in Panel A of Table 1, this classification yields 71,344 users, of which 20,725 are Trump Supporters, 5,740 are Clinton Supporters and 44,879 are independent. We are unable to classify about 215,000 users due to an inconsistent pattern of partisan activity or because they have made very few comments during our five months period. Both Trump and Clinton supporters active on `r/politics` allocate a considerable share of their activity on this forum. When considering their activity within `r/politics` and partisan fora, Clinton supporters make 46.7% of their overall comments on `r/politics`, Trump supporters 22.9%.

Table 1: Authors affiliation and share of total comments per fora by affiliation of comment author

Panel A: Discrete Classification		*Relative Activity by Fora*		
	N	`r/politics`	Pro-Clinton Fora	Pro-Trump Fora
Trump Supporters	20,725	0.229	0.001	0.769
Clinton Supporters	5,740	0.467	0.532	0.001
Independents	44,879	0.996	0.002	0.002
Non-classified	215,243	0.802	0.071	0.127
Panel B: Continuous Classification				
	N	Mean	St. Dev.	
Pro Trump Partisanship	125,555	0.324	0.436	
Pro Clinton Partisanship	125,555	0.15	0.321	

Notes: discrete classification was performed for all users that either commented or posted on `r/politcs`. Continuous classification was performed for all users with at least one comment/post on `r/politics` and at least 6 comments on non partisan fora or on partisan fora. Here, furthermore, we restrict the sample to authors with at least one comment on either `r/politics` or a partisan fora. The relative activity is measured by the share of total comments for each type of fora, over all comments in `r/politics`, Pro Trump, and Pro Clinton fora.

Despite the large number of non-classified users, most of the activity comes from classified users. Table 2 shows that these users are responsible for 61.6% of the total comments on r/politics in our period. Of these, 71.5% come from independents, 11.1% from Clinton supporters, and the remaining 17.4% from Trump supporters.

Table 2: Activity on r/politics, by affiliation

	# of comments on r/politics	% over total
Trump Supporters	887,181	10.69
Clinton Supporters	570,380	6.87
Independents	3,656,270	44.04
Non-classified	3,187,664	38.40

Nevertheless, given the large fraction of non-classified users resulting from this categorical classification, we also rely on a continuous measure of political preferences. Here we consider all users who have posted a total of more than 5 comments on non partisan fora or more than 5 comments on all partisan fora. We then measure his/her political preferences for candidate P by the continuous variable

$$V_i^P = \frac{\text{\# of comments of } i \text{ on partisan subreddits supporting } P}{\text{\# of comm. of } i \text{ on all partisan fora}}$$

for P = Trump and Clinton, and during the period June 1–November 7, 2016. If user i never commented on any partisan fora, we impute $V_i^P = 0$.

Panel B of Table 1 provides descriptive statistics for these continuous classifications, while their distributions are reported in Figure B.1 in the Appendix. This measure of political preferences can be computed for a larger sample of 125,555 individuals, since we only require users to be sufficiently active in all political fora together. In particular, the variable V_i^P is defined also for users active on both partisan fora, while such users tend to be excluded as non-classifiable in the three-way classification. On the other hand, the continuous variable V_i^P could be measured with more error, since we attribute political preferences also to individuals whose behavior is more ambiguous. This larger sample accounts for practically all comments (99%).

1.2 Features of the Debate

Before turning to our empirical analyses, we provide a general description of the features of the online debate. Table 3 reports the average number of comments per post by categorical affiliation. Each post on r/politics receives on average 68.4 comments, of which 7.3 are from Trump supporters, 4.7 from Clinton Supporters, 30.1 from independents, and 26.3 from users that we are unable to classify. Clinton supporters tend to be more active (recall that they are fewer), with each Clinton supporter making an average of .00082 comments per post.

Table 3: Features of the debate: average number of comments per post by affiliation, `r/politics`

	Group Average	Individual Average
Trump Supporters	7.31	0.00035
Clinton Supporters	4.7	0.00082
Independents	30.11	0.00067
Non-classified	26.26	0.00012
Total number of comments	8,301,495	
Total number of posts	121,411	
Average number of comments per post	68.38	

Appendix Figure B.2 shows the distribution of the temporal distance between a comment and the time of the post, for different kinds of users. Most comments are within 24 hours of the post, with approximately 50% of the total comments from each group of users occurring within 5 hours. Trump supporters tend to comment later, and the distribution of independents is more positively skewed than the others.

2 Ideological Segregation in News Consumption

Do Reddit users comment on different pieces of news depending on their ideology? In this section we address this question, adapting the methodology of Gentzkow and Shapiro (2011) to our setting. We consider two kinds of segregation: by news story, and by source. That is, we measure the extent by which opposite partisan users comment on different news articles and on different news sources, respectively.

Construction of the Index We consider partisan users active on `r/politics` and study their activity in both `r/politics` and partisan fora. Let TS_j^F and CS_j^F denote the number of comments by Trump and Clinton supporters, on outlet j in forum F between June 1 and November 7, 2016. F can indicate either `r/politics` or the entire set of partisan fora. If j refers to a news source, let $TS_j = \sum_F TS_j^F$ and $CS_j = \sum_F CS_j^F$ denote the total number of comments to news source j in both `r/politics` and the partisan fora by Trump and Clinton supporters respectively. If j refers to a single news posts, then $TS_j = TS_j^F$ and $CS_j = CS_j^F$ because posts only live in one forum. Adapting Gentzkow and Shapiro (2011) to our context, we measure segregation in forum F by:

$$S^F = \sum_{j \in F} \left(\frac{TS_j}{TS_j + CS_j} \right) t_j^F - \sum_{j \in F} \left(\frac{TS_j}{TS_j + CS_j} \right) c_j^F \tag{1}$$

where $t_j^F = TS_j^F / \sum\limits_{j \in F} TS_j^F$ and $c_j^F = CS_j^F / \sum\limits_{j \in F} CS_j^F$ measure the fraction of comments of Trump and Clinton supporters to outlet j in forum F, respectively (i.e. their relative exposure to outlet j in forum F).[11] Following Gentzkow and Shapiro (2011), we refer to the term in parenthesis as the *share conservative* of outlet j: the number of comments to outlet j from Trump supporters, relative to the total number of comments to that outlet by Trump and Clinton supporters. Loosely speaking, this measure, which we keep identical across fora, is a data-driven proxy for the "conservative bias" of an outlet.[12] The first and second summation thus measure the *conservative exposure* of Trump and Clinton supporters in forum F, respectively. Namely, these terms capture the average exposure of Trump and Clinton supporters to other conservatives in forum F, defined as the weighted average of the share conservative of each outlet, weighted by the relative attention devoted to that outlet in forum F by either Trump or Clinton supporters. If all outlets receive the same fraction of comments by both partisan supporters, then $t_j^F = c_j^F$ and $S^F = 0$. If opposite partisan supporters always comment on different outlets, then $S^F = 1$. More generally, the index ranges from zero to one, and the higher is S^F the more opposite partisan users comment on different outlets.

If index j refers to different media sources, such as CNN, or Fox News, S^F measures the extent to which partisan users segregate by source, and we study this segregation separately on `r/politics` and on partisan fora. If index j refers to the single piece of news, S^F measures segregation by post (i.e whether opposite partisan users comment on different news, irrespective of their source). By definition of partisan user, segregation by posts on partisan fora is almost 1, so here we only compare segregation by post and by source in `r/politics`.

Results Table 4 summarizes our results. In each Panel, the last column reports the isolation index S^F (along with bootstrap standard errors in parenthesis), while the first two columns report the conservative exposures of Trump and Clinton supporters, respectively.

Table 4: Average Conservative Exposure and Isolation Index

	Conservative Exposure of			
	Trump Supp.	Clinton Supp.	Isolation Index (SE)	
Panel A: `r/politics`				
Across Sources	0.612	0.595	0.016	(0.001)
Across News	0.702	0.462	0.240	(0.006)
Panel B: Partisan Fora				
Across Sources	0.829	0.514	0.315	(0.006)

[11] As in Gentzkow and Shapiro (2011), this analysis requires two groups of individuals. Since we are focusing on segregation of partisan users, we drop independents and not classified. As shown in Section C.2 of the Appendix, results are virtually unchanged if we impute the ideology of independents as in Gentzkow and Shapiro (2011).

[12] Fixing the measure across fora allows us to fix the proxy for the "bias of the source" when comparing activity on `r/politics` and partisan fora. That is, when comparing, across fora, how much Clinton and Trump supporters differentially pay attention to Fox News, f.e., we keep fixed our measure of how conservative is Fox News (which is based on the activity on all fora) and only allow a change in the amount of relative attention that these supporters pay to Fox News in forum F, relative to the attention paid to all sources in F, i.e. t_j^F and c_j^F. This is relaxed in Section C.2 in the Appendix, which shows that our results are qualitatively unchanged when computing the share conservative separately in each forum, as reported in Table C.2b.

Panel A considers only the activity of partisan users in $F =$ r/politics. The first row refers to segregation across news sources, and shows that it is almost null, thus extending to a different context the finding of Gentzkow and Shapiro (2011). The conservative exposure of Trump supporters (61.2%) is almost identical to that of Clinton supporters (59.5%).[13] The index S^F is hence 1.6%, even lower than Gentzkow and Shapiro's estimate of 7.5% for online news websites. In other words, when browsing r/politics, Trump and Clinton users do not comment news from ideologically distinct sources.

Nevertheless, even if users comment the same sources, they do not comment the same pieces of news. The second row shows that segregation by posts is 24.0%. Compared to segregation across sources, conservative exposure of Trump supporters is 70.2%, almost 10 percentage points higher than the respective figure for sources, while the conservative exposure of Clinton supporters is 46.2%, 13.3 percentage points lower. Thus, it is not the bias of source that drives ideological segregation in news consumption, it is the content of the news.

Panel B considers the activity of the same users in the partisan fora. Here segregation across sources is 31.5%, much higher than in r/politics. As a term of comparison, Gentzkow and Shapiro (2011) estimated that segregation in face-to-face interactions among political discussants was 39.4% in their sample. These two estimates are loosely comparable, in the sense that partisan fora can be thought as the online equivalent of face-to-face political interactions amongst self-selected individuals. As discussed below, a plausible explanation for the stark difference in segregation across sources between r/politics and partisan fora relates to Sunstein's (2017) idea of "unplanned, unanticipated encounters" across individuals with different ideologies, which can happen in r/politics but not on partisan fora.

Section C of the Appendix reports more details on the construction of the measure and various robustness checks. There is no temporal variation in segregation and results are robust to many margins. They are virtually unchanged if: *i.* we consider the extensive margin of segregation (given by the probability of commenting), rather than the intensive one (the number of comments), *ii.* we impute the ideology of independents and not classified instead of dropping them, *iii.* we include also Democrats and Republicans, instead of only Trump and Clinton supporters, *iv.* we construct the conservative share of a source separately in r/politics and in partisan fora.

2.1 Segregation Across Sources: r/politics vs. Partisan Fora

The finding that segregation across sources is absent in r/politics but high in partisan fora for the same set of users suggests that they behave very differently in the two contexts.

Before discussing why, we validate this finding with an alternative measure of media bias, which allows us to include the activity of independents. Developed by the website mediabiasfactcheck.com, the so called Political Bias Index assigns to several media sources a score on a 7-point scale, from "Extreme Left" to "Extreme Right".[14] Figure 3 depicts the fraction of comments of different users

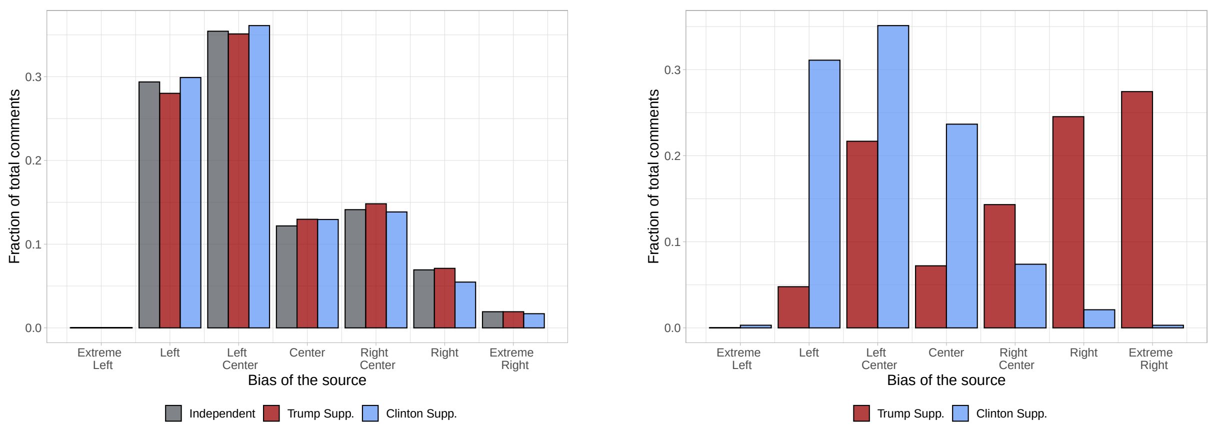
[13]When interpreting results, it is useful to keep in mind that in our setting 78.3% of partisan users on r/politics are Trump supporters and 60.8% of partisan comments to postings in r/politics are by Trump supporters.

[14]The score is based on four evaluations, namely whether: (i) the source uses biased wording or headlines; (ii) it reports

to sources with a given bias. The left hand panel reports activity on `r/politics`, showing virtually no segregation across sources. For instance, roughly 37.5% of all comments made by independents are on sources with a Left Center bias, and this number is identical also for Clinton and Trump supporters. Panel B, on the other hand, reports their activity on partisan fora, and segregation is much higher. Activity on the extensive margin, reported in Figure C.1 the Appendix, displays similar patterns. Note that, by construction, in both Figure 3a and Figure 3b we consider only partisan supporters who are active both on `r/politics` and on their respective partisan fora, as done for the isolation index. By fixing the same set of users, these two Figures thus show that ideological segregation by source is highly context-dependent. In an independent forum, opposite partisan users comment on news from similar sources, while in a partisan context they do not.[15]

Figure 3: Fraction of Comments by Bias of the Source

(a) Activity of `r/politics` users on `r/politics` **(b) Activity of `r/politics` users on PF**



Notes: The set of partisan fora (PF) includes only pro-Trump and pro-Clinton partisan fora, as defined in Table B.1. For each political affiliation p and for each category b of media bias the height of the bar is: $S_I = \text{Commments}_{pb}/\text{Comments}_p$, where Comments_{pb} is the number of comments by users with affiliation p to posts sharing news from sources with a bias of b and Comments_p is the overall number of comments by users with affiliation p on `r/politics`. Of all posts in `r/politics` (PF) whose source has a political bias classification, 0.2% (0.1%) are extreme left biased, 25.5% (18.4%) are left biased, 37.2% (30.2%) are left-center biased, 10.6% (8.7%) are in center, 12.6% (11.6%) are right-center biased, 9.3% (15.3%) are right biased and 4.6% (15.6%) are extreme right biased.

Why is segregation different based on the context? A plausible reason is that the news that are posted on partisan fora are systematically different from those posted in `r/politics`. In other words, users have a different menu of news to choose from, when they comment in `r/politics` vs in partisan fora. Indeed, Figure 4a shows that posting activity reflects the ideology of the author of the post (a finding in line with An, Quercia, and Crowcroft, 2014). It plots the distribution of news posted in `r/politics` by different authors, by ideology of the source. Unlike for comments, there is a sizable amount of segregation in posting activity. For instance, posts from right sources are

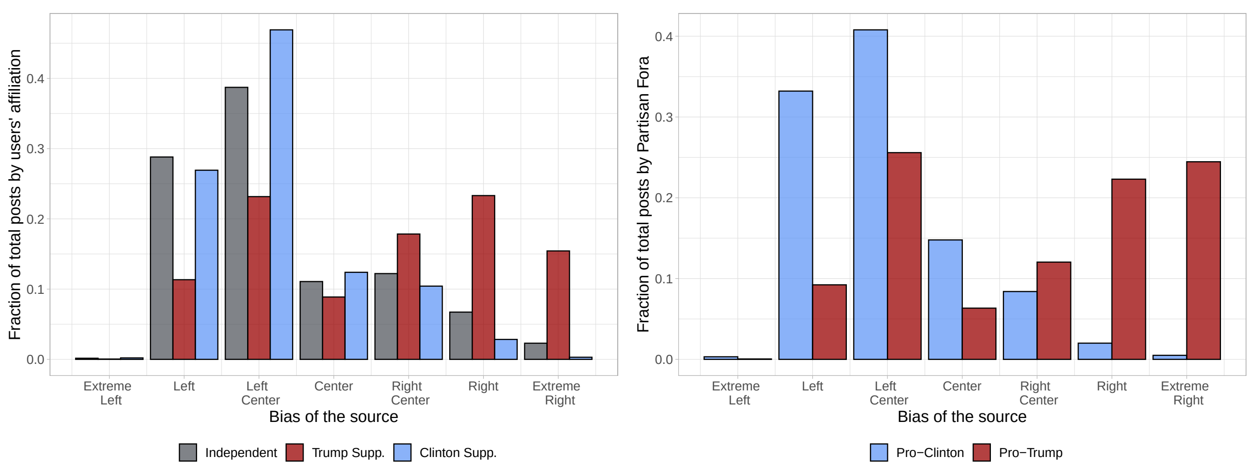
stories factually and documents the evidence presented; (iii).it reports news from both the democratic and the republican side; (iv),it endorses a particular political ideology. See `mediabiasfactcheck.com/methodology/`

[15] For completeness, in the Online Appendix we also report segregation of `r/politics` users when jointly considering their activity both on partisan fora and on `r/politics`, and of users active only on partisan fora.

almost four (seven) times more likely to be posted by Trump supporters, compared to independents (Clinton supporters). Similarly, posts from Left Center sources are twice as likely to be posted by Clinton supporters, compared to Trump supporters. Thus, users on `r/politics` segregate in what they decide to post but not in what they decide to comment on.

Figure 4: Segregation in Postings

(a) Posts by `r/politics` Users on `r/politics` **(b) Distribution of Bias of Posts in Partisan Fora**



In other words, `r/politics` is populated by users with different ideologies, who share news from aligned sources. This exposes users of `r/politics` to a variety of sources, in line with Sunstein's (2017) argument. Partisan fora, instead, have much less variety, because they are populated by ideologically homogeneous individuals. This is shown in Figure 4b, which depicts the distribution of posts by ideology of the source, in Pro-Clinton and in Pro-Trump fora. For instance, the fraction of posts from right sources in Pro-Trump fora is roughly ten times that in Pro-Clinton fora. That is, partisan fora are a homogeneous environment, where each user is exposed to an ideologically skewed distribution of sources, and this results in a skewed distribution of comments.

2.2 Interpreting the Segregation Index

How can we interpret a magnitude of 24% for the segregation index in `r/politics`? Consider Figure 5, which illustrates the distribution of the share conservative across postings. The probability density function is shown as the solid line in Panel A. The distribution is clearly trimodal. One peak is made of postings visited both by Trump and Clinton supporters, and the share conservative around this peak is distributed somewhat normally. The other two peaks consist of postings commented only by one type of user. The CDF is depicted by the solid (black) line in Panel B. One quarter of the posts are commented only by Clinton supporters (those for which the share conservative is zero), approximately one quarter are commented only by Trump supporters, and the remaining half is commented by both types of supporters.[16]

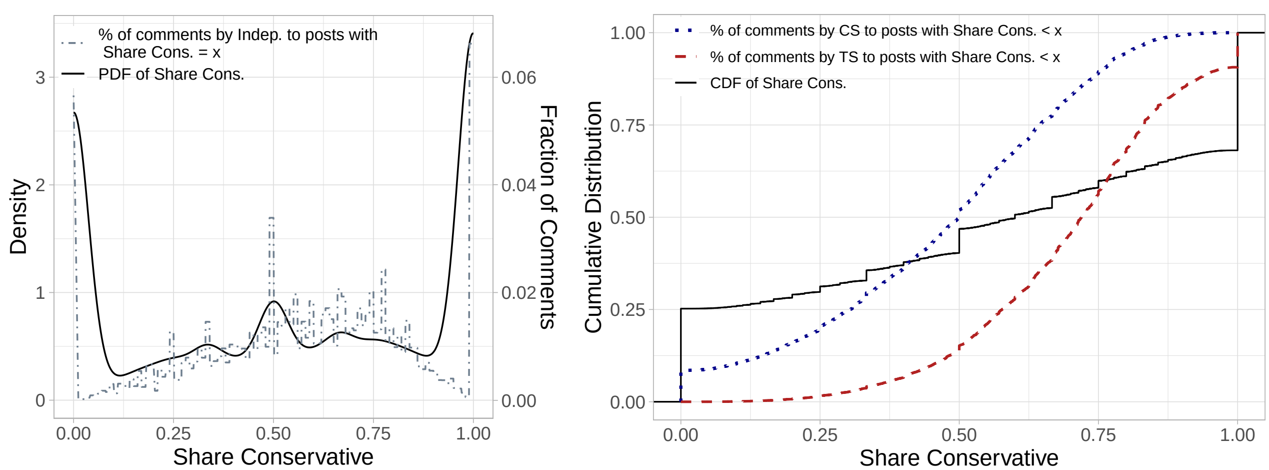
[16]The jumps observed at certain points of the CDF are due to the presence of numerous postings with a very small number of comments.

As a sanity check on our exercise, the dot-dashed (gray) line in Panel A shows the fraction of comments made by independents to posts with a given value of share conservative, over all comments made by independents. Independents allocate a proportionally identical amount of attention to fully conservative posts and fully liberal ones, thus corroborating our interpretation that these users can truly be treated as non-partisan. Furthermore, their allocation of activity closely tracks the overall distribution of posts, suggesting that their attention is, in general, independent of the share conservative of the post.

How are partisan comments distributed across postings? The dotted (blue) and dashed (red) lines in Panel B report the cumulative fraction of activity of Clinton and Trump supporters, respectively, across posts ordered by their share conservative.[17] For both Clinton and Trump supporters, approximately 10% of their comments are made on fully-segregated postings. Furthermore, 50% of comments by Trump supporters are made on postings where at least $\sim$ 75% of partisan comments are by Trump supporters. 50% of comments by Clinton supporters are on postings where at least 50% of comments are by Clinton supporters.[18]

Figure 5: Distribution of Share Conservative Across Postings in `r/politics`

(a) PDF **(b) CDF, Along with Activity of Partisan Users**



Notes: The solid (black, online) line in Panel A reports the probability density function of the fraction of comments by Trump supporters over visits by all supporters (the share conservative), across all posts in `r/politics`. The dot-dashed (grey) line in Panel A reports the fraction of comments by Independents to posts with a given value of share conservative over all their comments. The solid (black) line in Panel B reports the cumulative density function of the share conservative. The dotted (blue) line reports the cumulative fraction—across postings ordered by share conservative—of comments by Clinton supporters over all their comments. The dashed (red) line reports the same quantity for Trump supporters.

[17] More precisely, each point (x, y) of the dotted (dashed) line reports the share of comments made by Clinton (Trump) supporters (y) to postings with a share conservative lower than x. That is, each curve reports the integral of the exposure weights in the isolation index, c^F and t^F , across postings ordered by their share conservative.

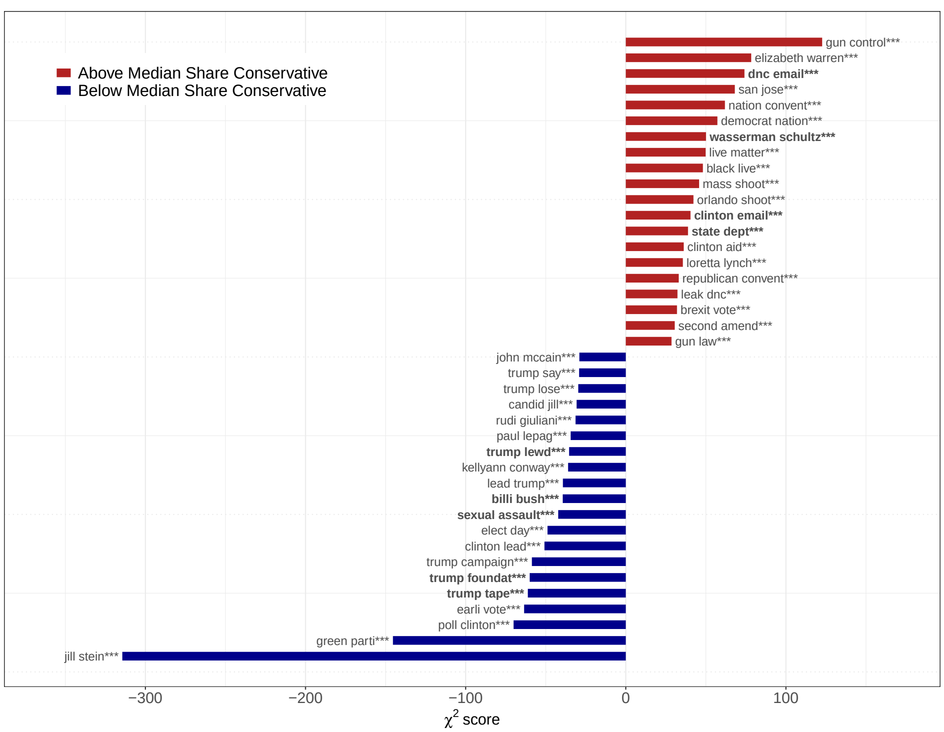
[18] To interpret the estimates it is useful to recall that 60.8% of partisan comments are made by Trump supporters.

2.3 Segregation in News Stories

The finding that, on `r/politics`, opposite partisan users engage with different pieces of news, and yet they do not discriminate across sources with different ideologies, is puzzling. One would expect partisan users to have more trust (and hence engage more) in politically aligned sources. Moreover, sources with opposite ideological biases are likely to cover different news, or to present the same news somewhat differently. If it is not the ideological orientation of the source that drives partisan segregation by news, what is it?

To shed some light on this question, we investigate how the text in the posts titles relates to the fraction of comments by opposite partisan users. We divide our posts in those with a share conservative above and below the overall median. We then perform a χ^2 test (as in Gentzkow and Shapiro, 2006) that, for each word, reports the associated Pearson's χ^2 statistic testing against the null that a word is distributed equally across the two sets of posts. Figure 6 reports the results using 2-grams (two-words expressions, such as "Trump University"). It shows in red the 20 words that are most typical (in the sense of having the highest χ^2 score) of posts with above-median share conservative and in blue the 20 words for below-median posts. Tables C.2 and C.3 in the Appendix extend this Figure by reporting the 50 most common tokens (both 1- and 2-grams) for posts above and below the median.

Figure 6: χ^2 Test Statistics of Relative Words Frequencies across `r/politics` Posts with an Above Median versus a Below Median Share Conservative



As expected, words with the highest χ^2 are associated with partisan topics; for instance, "gun control" is the most typical word occurring in titles of posts with above median share conservative.

In addition to partisan topics, words concerning scandals (in boldface) also have large χ^2. Posts with an above median share conservative often concern scandals on Clinton and the Democratic party. Similarly, posts commented relatively more often by Clinton supporters (i.e. with below median share conservative) deal with scandals on Trump. That is, partisan users seem to disproportionately comment on scandals about the opponent of their favored candidate.[19]

These findings, namely that segregation occurs across news, rather than across sources, and that scandals on opposing candidates are among the most common words in highly-partisan posts, motivate the remainder of this paper. Before returning to the data, the next section formulates a theoretical model, to illustrate different mechanisms that can rationalize this evidence and to guide the subsequent empirical analysis.

3 Theory

Posting a comment on political news can have several motivations: to form an opinion in view of the imminent election, to persuade others, to share emotions, to defend or enhance one's self image. In this section we interpret comments as a proxy for attention, and we study how voters allocate costly attention to news concerning two competing candidates. The voters' ultimate goal is to rank candidates, but emotions and social motives can also play a role, since the model allows voters to neglect unpleasant news or to seek news that they enjoy. Of course, attention is a pre-requisite for writing a comment. Moreover, attention is not just time spent reading the news, but also thinking about them, elaborating the content and forming an opinion.

Nevertheless, there are two differences between comments and attention, that the model does not capture. First, attention is chosen ex-ante, while comments are written ex-post, once the news content has been discovered. Hence, comments may be driven by an element of surprise that is missing from the model. Second, comments may have a purely social motivation of persuading others, or reacting to the comments of others, while the model studies a single decision maker. We discuss these differences between comments and attention in the empirical analysis.

3.1 The Model

Let subscript $c = T, C$ denote the two candidates (for Trump and Clinton respectively). Each candidate has unobserved true features that are captured by a normally distributed random variable, q_c. Think of q_c as summarizing the candidate policy positions and his/her personal attributes. Since the allocation of attention only depends on voters' prior beliefs, no assumption is needed about its true mean and variance. Voters' priors about q_c are drawn from independent normal distributions with prior means μ_c^i and prior variances $(\sigma_c^i)^2$.

[19]In particular, the words "dnc email", "wasserman schultz", "leak dnc" all refer to the 2016 DNC email leak, over which the DNC chair Debbie Wasserman Schultz resigned. "clinton email" refers to Clinton's handling of her email server. "state dept" is likely to refer to articles concerned with Clinton's handling of the Benghazi attack. The words "trump lewd", "billi bush" (stemmed version of Billy Bush), "sexual assault", "trump tape" all likely refer to Trump's "Access Hollywood" scandal. "trump foundation" refers to the multiple investigations on the Trump Foundation during the 2016 Presidential campaign.

Voters may have different preferences, and voter i has preferences $Q_c^i = \chi_c^i q_c$ over the true features of candidate c, where $\chi_c^i > 0$ denotes the weight assigned by voter i to the true features of candidate c. In what follows we refer to Q_c^i as the candidate quality for voter i. In the appendix we allow each candidate to have multiple unobserved features that are weighted differently by different voters, and signals are specific to each feature (eg., the title of the news reveals the feature to which the signal refers). The main results continue to hold, but we get some additional predictions discussed below.

Voters observe a noisy signal s_c^i about the true features of each candidate, $s_c^i = q_c + \varepsilon_c^i$, where ε_c^i is normally distributed with mean 0 and variance $(\eta_c^i)^2$. As in the literature on costly attention (Mackowiak, Matějka, and Wiederholt, 2021), the choice of attention is modelled as the choice of the variance of the signals, $(\eta_c^i)^2$. Specifically, voters choose the attention levels ξ_c^i defined as:

$$\xi_c^i = \frac{(\sigma_c^i)^2}{(\sigma_c^i)^2 + (\eta_c^i)^2} \tag{2}$$

Political beliefs Voters' expectations of candidates' quality conditional on the observed signals (i.e their posterior means) are denoted by $\widehat{\ }$ and are formed according to Bayes rule, namely:

$$\hat{Q}_c^i = \chi_c^i \hat{q}_c^i = \chi_c^i[(1-\xi_c^i)\mu_c^i + \xi_c^i s_c^i] \tag{3}$$

If voters pay more attention, their posterior means reflects observed signals more closely. Thus, posterior means are also normally distributed, with mean and variance in turn given by:

$$\begin{aligned} E(\hat{Q}_c^i) &= \chi_c^i[(1-\xi_c^i)\mu_c^i + \xi_c^i E(s_c^i)] = \chi_c^i \mu_c^i \\ Var(\hat{Q}_c^i) &= (\chi_c^i)^2 (\xi_c^i)^2 Var(s_c^i) = \xi_c^i (\chi_c^i)^2 (\sigma_c^i)^2 \equiv \zeta_c^i \end{aligned} \tag{4}$$

where $E(s_c^i)$ and $Var(s_c^i)$ are computed based on the prior distribution of q_c and the distribution of the noise term ε_c^i. In other words, these expressions define the *ex-ante* mean and variance of conditional expectations of candidate quality, before attention is chosen and signals are observed. Attention only affects the ex-ante variance of conditional expectations, not their ex-ante means, which are pinned down by prior beliefs. Intuitively, more attention implies that the voter puts more weight on the true underlying variables, so the variance of his posterior means reflects more closely what the voter believes is the true variance of quality. If the voter paid no attention, he would not expose himself to any randomness, thereby keeping his posterior mean identical to his prior (0 variance).[20]

Below, we exploit the properties of the distribution of the random variable $\Delta^i = \hat{Q}_T^i - \hat{Q}_C^i$, which measures the expected difference in candidates quality for voter i, conditional on observing the signals. Ex-ante (i.e. before observing the signal), Δ^i is also normally distributed, with mean $\chi_T^i \mu_T^i - \chi_C^i \mu_C^i$ and variance $(\theta^i)^2 = \zeta_T^i + \zeta_C^i$. Higher attention increases the (ex-ante) variance of Δ^i,

[20] Note that the variance of posterior means, $Var(\hat{Q}_c^i)$, should not be confused with the variance of posterior beliefs on q_c^i (i.e the posterior variance), which instead is: $\rho_c^i = \xi_c^i (\eta_c^i)^2$.

because voters' expectations reflect more closely the signals received.

Throughout we assume that:

$$(\chi_T^i \mu_T^i - \chi_C^i \mu_C^i)^2 \ < \theta^i \tag{A1}$$

As shown in the appendix, this implies that the sufficient second order conditions for an optimum are satisfied.

Objective functions The purpose of paying attention is to rank candidates. Thus, voters' preferences are:

$$\Omega(\xi_T^i, \xi_C^i) = EMax[\hat{Q}_T^i, \hat{Q}_C^i]$$

where E is the expectations operator over the posterior means $\hat{Q}_T^i$, $\hat{Q}_C^i$ described above. Voters know that they will choose the candidate with the higher expected quality in the imminent election. They then allocate attention to maximize expected utility from their best choice, given the perceived distribution of expected qualities.

Attention is costly, with a convex cost function $M(\xi_T^i, \xi_C^i)$ separable in all its elements. We follow the literature on rational inattention and assume that the cost of attention is proportional to the relative reduction of uncertainty upon observing the signal, measured by entropy, namely:

$$M(\xi_T^i, \xi_C^i) = -[\lambda_T^i \log(1 - \xi_T^i) + \lambda_C^i \log(1 - \xi_C^i)] \tag{5}$$

where λ_c^i reflects the attention cost for voter i from observing signal s_c^i (Mackowiak, Matějka, and Wiederholt, 2021). The term $-\log(1 - \xi_c^i)$ measures the reduction of uncertainty about candidate c upon observing the signal.[21] The parameter λ_c^i reflects the material or time cost of paying attention to a particular news, but also the psychological cost of paying attention to an uncomfortable news, in line with research on motivated beliefs (see Bénabou and Tirole, 2016). In particular, we can interpret a higher value of λ_c^i as saying that the voter prefers a late resolution of uncertainty (it dislikes resolution of uncertainty), and a lower value of λ_c^i as a preference for early resolution of uncertainty.

Putting all this together, attention weights are chosen to solve $Max_{\xi_T^i, \xi_C^i}[\Omega(\xi_T^i, \xi_C^i) - M(\xi_T^i, \xi_C^i)]$. The specific functional form of the cost of attention only matters for the closed form solution described below, and the qualitative results would be similar for any strictly convex function of attention.

[21] The term $1 - \xi_c^i$ is the ratio between the posterior variance (i.e the variance of posterior beliefs defined in the previous footnote) and the prior variance $(\sigma_c^i)^2$ (i. the variance of prior beliefs). More attention to the signal (higher ξ_c^i) thus corresponds to a reduction of uncertainty upon observing the signal.

Optimal Allocation of Attention As shown in the appendix, the first order conditions for an interior optimum imply:[22]

$$\xi_c^i = 1 - \frac{\lambda_c^i}{(\chi_c^i)^2(\sigma_c^i)^2}\alpha^i \tag{6}$$

where $\alpha^i = 2\theta^i/\phi(\frac{\chi_T^i\mu_T^i - \chi_C^i\mu_C^i}{\theta^i})$ and $\phi(.)$ is the density of the standard normal. Note that, despite the closed form solution, attention weights are only defined implicitly by(6), because, by (4), θ^i is an increasing function of attention weights on both candidates, (ξ_T^i, ξ_C^i). This also implies that attention weights are mututal substitutes. If the voter pays more attention to one candidate, then θ^i rises, and by (6) he pays less attention to the opponent.[23] Nevertheless, these indirect effects are second order relative to the direct effects captured by the parameters on the RHS of (6). Specifically, the appendix proves:

Proposition 1 *Suppose that (A1) holds. Then:*
(i) Voter i pays more attention to candidate c and less attention to his/ her opponent if the cost of attention is lower and prior uncertainty is higher on candidate c:

$$\frac{\partial \xi_c^i}{\partial \lambda_c^i} < 0 < \frac{\partial \xi_c^i}{\partial (\sigma_c^i)^2}, \qquad \frac{\partial \xi_{c'}^i}{\partial \lambda_c^i} > 0 > \frac{\partial \xi_{c'}^i}{\partial (\sigma_c^i)^2} \text{ for } c' \neq c$$

(ii) Holding constant the weights χ_c^i, voter i pays more attention to both candidates if $|\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|$ is lower:

$$\frac{\partial \xi_c^i}{\partial |\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|} < 0$$

(iii) An increase in the weight χ_c^i induces voter i to pay more attention to candidate c if $\chi_c^i\mu_c^i < \chi_{c'}^i\mu_{c'}^i$, and less attention to his opponent if $\chi_c^i\mu_c^i > \chi_{c'}^i\mu_{c'}^i$ for $c' \neq c$; in the other cases, the effect of changes in χ_c^i is ambiguous:

$$\begin{aligned} \frac{\partial \xi_c^i}{\partial \chi_c^i} &> 0 \text{ if } \chi_c^i\mu_c^i < \chi_{c'}^i\mu_{c'}^i \text{ for } c \neq c' \\ \frac{\partial \xi_{c'}^i}{\partial \chi_c^i} &< 0 \text{ for } c \neq c' \quad \text{if } \chi_c^i\mu_c^i > \chi_{c'}^i\mu_{c'}^i \text{ for } c \neq c' \end{aligned}$$

Point (i) says that voters pay more attention to a candidate if the time or psichological cost of attention to that candidate is lower, and if they are less confident about its true features (cf. Matějka

[22]In deriving (6), we used the fact that, since $\hat{Q}_T^i, \hat{Q}_C^i$ are jointly normal :

$$EMax[\hat{Q}_T^i, \hat{Q}_C^i] = \chi_T^i\mu_T^i\Phi(\frac{\chi_T^i\mu_T^i - \chi_C^i\mu_C^i}{\theta^i}) + \chi_C^i\mu_C^i\Phi(\frac{\chi_C^i\mu_C^i - \chi_T^i\mu_T^i}{\theta^i}) + \theta^i\phi(\frac{\chi_T^i\mu_T^i - \chi_C^i\mu_C^i}{\theta^i})$$

where $\Phi(.)$ and $\phi(.)$ are respectively the cumulative distribution and the density functions of the standard normal distribution (see Nadarajah and Kotz (2008)).

[23]Recall that θ^i is the variance of $\Delta^i = \hat{Q}_T^i - \hat{Q}_C^i$, namely of the expected relative quality of candidates conditional on observing all signals. Higher attention to say candidate T increases the volatility of this conditional expectation, which now reflects more closely the true quality of one of the candidates. Because voters ultimately care only about the best candidate for them, this in turn reduces the marginal benefit of paying attention to signals on the other candidate.

and Tabellini (2020) and Mackowiak, Matějka, and Wiederholt (2021)); the opposite effect on the opponent follows from attention weights being substitutes. Point (ii) says that voters who ex-ante are more in favor of one or the other candidate pay less attention to all news, compared to voters who are more neutral, as captured by the absolute difference $|\chi_T^i \mu_T^i - \chi_C^i \mu_C^i|$. The reason is that the marginal benefit of attention is higher for these more neutral voters. This result is similar to the idea in Bartos at al (2016), that attention is higher on signals that are more discriminating, i.e signals concerning outcomes that ex-ante are closer to the decision threshold (here equal weighted qualities).

With regard to point (iii), the effect of changes in the weight parameter χ_c^i is more complex, because attention is affected in three ways. First, there is a direct effect: as χ_c^i rises, the relevance of being informed about candidate c rises for voter i. This induces him to pay more attention to this candidate, as in Matějka and Tabellini (2020). Second, by (4), a higher χ_c^i increases the variance θ^i of expected relative quality conditional on all signals. As discussed above, this in turn induces voter i to pay less attention to all signals. Third, χ_c^i also affects the expected difference between the two candidates, $|\chi_T^i \mu_T^i - \chi_C^i \mu_C^i|$, in a direction that depends on the relative sizes of $\chi_c^i \mu_c^i$ and $\chi_{c'}^i \mu_{c'}^i$. The final effect on attention depends on whether these effects reinforce or offset each other, and in some cases this is ambiguous.

3.2 Empirical predictions

In the empirical analysis, we discriminate between alternative drivers of attention by comparing the behavior of partisan supporters and independent voters towards different kinds of news. To generate relevant predictions, we need an enriched version of the model with different types of voters and of news, which we now discuss.

Partisan vs Independent Voters To reduce the number of cases, suppose that there are only two types of voters: independents $(i = I)$ and partisans $(i = P)$ and impose some symmetry assumptions. Independent voters have the same parameters for all candidates, namely:

$$\chi_c^I = \chi^I, \qquad \sigma_c^I = \sigma^I, \qquad \lambda_c^I = \lambda^I \tag{7}$$

Equation (6) then implies that independents pay the same attention to both candidates: $\xi_T^I = \xi_C^I$. We exploit this implication in the empirical analysis by comparing how partisan voters differ from independents when commenting the same piece of news, in a difference-in difference analysis. This allows news to differ in their general relevance, since we study how partisan react to the same news, compared to independents.

Partisan voters support one of the two candidates, but are otherwise identical. Throughout let subscript c refer to the own candidate, while subscript c' refers to his/her opponent. Thus, ξ_c^P, $\xi_{c'}^P$ denote the attention of partisan voters for their own candidate (c) and for his/her opponent (c'), respectively. We assume:

$$\chi_c^P \geq \chi^I \geq \chi_{c'}^P \tag{8}$$

$$\sigma_c^P \leq \sigma^I \leq \sigma_{c'}^P \tag{9}$$

Assumption (8) says that partisan voters assign (weakly) greater weight to the (unobserved) feature q_p of their own candidate, and less weight on the opponent, compared to independents. If the prior means of q_p and $q_{p'}$ are positive, this explains why these voters favor one or the other candidates. This can be interpreted as partisan voters having opposite policy preferences. Assumption (9) says that partisan voters are (weakly) better informed about their own candidate than about the opponent, compared to independents. By (6), these two assumptions have opposite implications on attention. Assumption (8) makes partisan voters more attentive to their own candidate than to the opponent, because his/her features are more relevant, while asymmetric ex-ante uncertainty, (9), has the opposite effect.[24]

Bad News vs. General News The psychological cost of processing and absorbing new information may differ across types of news. To allow for this, in the appendix we distinguish between two kinds of news on the same candidate. Specifically, we add a second unobserved and negative feature of each candidate, b_c, which is disliked equally by all voters, and that can be interpreted as incompetence or lack of moral integrity. Thus, the overall (unknown) utility drawn by voter i from candidate c is: $Q_c^i = \chi_c^i q_c - b_c$. The variable q_c refers to general features of the candidate, including his policies, that are valued differently by different voters, while b_c refers to unpleasant personal traits that are weighted equally by all voters irrespective of their political prefences. This corresponds to our empirical setting, where news that we classify as "bad" refer to scandals that cast doubts on the personal competence or integrity of the candidate, and there is no a priori reason why voters with different political preferences should weight these personal traits differently. Voters observe separate signals on q_c and b_c for each candidate (eg. the news' title reveals whether it is is about q_c or b_c). We thus interpret signals on b_c as possible bad news on a candidate. The appendix shows that optimal attention to signals on b_c is also given by an expression like (6), with σ and λ now referring to feature b_c, except that $\chi_c^i = 1$ in the denominator of the RHS, and the definition of α^i in (6) is slightly different.

This extension allows us to capture another difference between partisan and independent voters, linked to emotions and motivated cognition (eg. Bénabou and Tirole, 2016). Specifically, let λ_c^{bi} be the cost of attention to a signal on b_c for voter i, while λ_c^i is the cost of attention to a signal on q_c, as above. We assume that independent voters have the same cost of attention to bad news on either candidate and to all kind of news: $\lambda_c^{bI} = \lambda^I$. Partisan voters, instead, dislike paying attention to news on bad features of their candidate, while they draw some utility from paying attention to

[24]Note however that prior uncertainty could have different effects on ex-ante attention and ex-post comments: if the prior variance is lower, ex-post surprises could be larger. If comments reflect surprise rather than attention, this could make partisans more likely to comment on their own candidate than on the opponent, in which case (8) and (9) have similar implications.

news on bad features of his/ her opponent, compared to general political news (i.e news about q_c):

$$\lambda_c^{bP} > \lambda_c^P = \lambda_{c'}^P > \lambda_{c'}^{bP} \tag{10}$$

As discussed above, (10) can be interpreted as saying that partisans prefer late resolution of uncertainty on bad news concerning their own candidate, and early resolution of uncertainty concerning his/her opponent.

Predictions What do these assumptions imply for how partisan voters allocate attention to different kinds of news? In our data we can only match news to candidates for news that we classify as bad. For general political news (i.e. signals about q_c in the model), we cannot tell whether it refers to one candidate or the other (or neither) - we just know that it is not bad news for any candidate. As explained in the next section, we thus classify news as either bad news for a specific candidate, or as general political news. Retaining the assumption that voters instead always know to which candidate the signal refers to, and whether it is a signal about b_c or q_c, we get the following predictions (see the appendix for a proof):

Prediction *Suppose that (7)-(10) hold. Then, compared to independents, partisan voters: (i) pay less attention to bad news on their own candidate than to bad news on his/her opponent; (ii) either they pay less attention to bad news on their candidate than to general political news, or they pay more attention to bad news about the opponent than to general political news, or both.*

Hence, the model explains the segregation discussed in the previous section as resulting from three mechanisms. First, partisan voters care about different content (they have different weights χ_c^P) - eg. guns control vs the environment. This can explain segregation in general political news. Second, they have different prior uncertainties σ_c^P about opposite candidates. This can explain segregation both in general political news and over bad news. Third, they have different costs of attention λ_c^{bP}, which induces them to neglect uncomfortable news and to engage with news that comform with their political preferences. Note that, by Proposition 1, different prior means on the relative strength of the candidates determine the overall level of attention of each voter type, but on its own it cannot explain why different voters pay attention to different items - i.e. it cannot explain partisan segregation.

Finally, without additional assumptions or information, we cannot separately identify these three mechanisms. Contrasting attention to bad news allows us to rule out that partisan segregation is due to differences in the relevance of content. Partisan segregation on bad news concerning a candidate, however, could result from differences in either the cost of attention or in prior uncertainties. Partisan voters could disregard bad news on their candidate because they are very confident of their priors, and viceversa for bad news on the opponent. To overcome this problem, in the empirical analysis we also consider how voters engage with news concerning voting polls - i.e. how likely is a candidate to win the upcoming election. Here prior uncertainty is obviously symmetric, since the probability that one candidate wins is equal to the probability that the other candidate loses.[25]

[25]Note that the model does not speak about what drives attention to political polls. To do so, one would have to

4 What Kind of News Attracts Partisan Comments?

We now test the predictions derived in the previous section, and ask whether partisan users of `r/politics` comment more frequently on bad news on the opponent than on their own candidate, compared to independent users and to other political news. We start by illustrating an even study around two prominent scandals inolving each candidate. Then, we investigate more systematically users behavior in reaction to a large set of bad news that emerged during the electoral campaign and that we manually classified.[26]

We first present the event study. Next, we discuss the broader sample of bad news and our classification. Then, we explain the econometric strategy and present the results.

4.1 Event Study

The hypothesis that political scandals deflect or attract users' activity, depending on their congruence with political preferences, can be tested by studying users' activity over time. As in the "ostrich effect" first studied in finance by Karlsson, Loewenstein, and Seppi (2009), in days when political news are likely to focus on scandals on their own candidate, we expect partisan users to detach themselves from politics, and devote instead more attention to sports, entertainment, financial news and the like. Conversely, when the political debate is likely to focus on scandals about the opponent, we expect them to be attracted to political fora. Studying these patterns by means of event studies for all political scandals is not feasible, because they occur too frequently in our sample. Neverthless, some scandals attracted more media attention than others. We thus analyze an event study around the two most prominent scandals of the Presidential campaign: the Access Hollywood videotape of Trump and the re-opening of the FBI investigation of Clinton's emails.

We estimate the following regression in a two-week window around each scandal:

$$Y_{it} = \alpha_i + \beta_t + \sum_{\tau=-7}^{-2} \left(\gamma_\tau^T * TS_i + \gamma_\tau^C * CS_i\right) * D_\tau + \sum_{\tau=0}^{7} \left(\gamma_\tau^T * TS_i + \gamma_\tau^C * CS_i\right) * D_\tau + \varepsilon_{it}$$

where Y_{it} denotes the fraction of comments by user i in day t on all political fora relative to all his comments in the entire Reddit platform, α_i and β_t are individual and day fixed effects, and TS_i and CS_i are dummy variables defined above for Trump and Clinton supporter respectively, and D_τ are day dummy variables. The sample includes all users classified either as independent or partisan, and $\tau = 0$ refers to the day in which the scandal first became known (October 7, 2016 for the Access Hollywood tape; October 28, 2016 for the re-opening of the email investigation). Figure 1 plots the estimated coefficients γ_τ^T and γ_τ^C for each scandal, with their 95% confidence intervals (standard errors are clustered by individual). Each coefficient thus measures how partisan users allocate their activity on Reddit between political and non-political fora, compared to independents, in the days

consider endogenous turnout or anticipatory utility.

[26]Ho rimosso e messo dopo, cosi da rednere la transizione meno abrupt. For this purpose, we classified a selected sample of news based on their content, so as to distinguish general political news from bad news about a candidate. Bad news refer to content about a candidate that is liked or disliked depending on the user's political preferences.

surrounding each scandal. Political fora include `r/politics`, partisan fora, and all other subreddits devoted to discussions of US politics.[27]

As expected, Trump supporters are more active on political fora compared to independents right after the Comey scandal, and less active after the Acess Hollywood scandal, while the reverse is true for Clinton supporters. There is no obvious evidence of pre-trends. For the Access Hollywood scandal the effect vanishes after one week, while for the Comey scandal it seems to last longer, but recall that this second scandal occurred shortly before the presidential election.

The effect of these scandals is sizable in magnitude. The day after the Access Hollywood scandal became public, Trump supporters decreased their share of comments on political fora by 7 percentage points, a 16.5% decrease compared to a mean of 41.8% in the 7 days before the scandal. Clinton supporters increased it by 6 percentage points, a 14.8% increase compared to the pre-period. For the Comey scandal, the pattern is similar: Clinton supporters decreased their share of comments by 7% on the day after, while Trump supporters increased it by 14% at the peak of the effect (which occurred at $t + 2$).

4.2 Classification of Political News

We now turn to a systematic investigation of a larger set of bad news about each candidate that emerged during the six months preceding the presidential election. To do so, we classified a selected sample of news based on their content, so as to distinguish general political news from bad news about a candidate. Bad news refer to content about a candidate that is liked or disliked depending on the user's political preferences.

To minimize measurement error, the classification was done manually. Given the large number of items, we restrict attention to two types of postings in `r/politics`. The first set contains all 1,350 posts which shared articles from the media agency Reuters during our sample period. The second set contains 97 "Megathreads". These are collections of postings on the same topic aggregated by the moderators of `r/politics`, with the goal of facilitating discussion of salient events. The comments appearing in the Megathreads are only those posted after the Meagthread was created. Throughout we refer to a Megathread as a post, since the comments in it refer to the whole Megathread, although strictly speaking it consists of a collection of news postings.[28]

These two subsamples are representative of two types of debates that can take place on the platform. The posts from Reuters are short articles that report new specific facts with minimal or absent editorial comment (e.g. an article reporting a new declaration by Billy Bush concerning the "Access Hollywood" scandal). Comments on these posts capture the reaction to new information, and thus are more effective proxies of attention as studied in the previous section. Megathreads are on the opposite side of the spectrum: they are chances for debate of general events that became known in the days preceding the thread (e.g. a large thread discussing the entire "Access Hollywood" scandal); comments here are more likely to reflect a social motive, and the desire to participate in a lively

[27] The exhaustive list is reported in Appendix Table B.1.

[28] The total number of Megathreads in our period is 110, but we drop thirteen that do not concern political news and are called "Friday Fun Off-topic Megathread". Including them in the sample does not change our results.

discussion. Coherently with these differences, the total number of comments on Megathreads is an order of magnitude larger than on Reuters posts (note that a single Megathread consists of a collection of posts). As shown in Appendix Table D.1, the average number of comments on a Megathread (by all authors) is 7,280.7 versus 44.2 on a post from Reuters. The 97 Megathreads alone account for 8.5% of the entire activity in `r/politics` during our sample period, with the remaining activity spread across 121,314 posts.

Each Reuter post and each Megathread was manually classified as either a general news or as a bad news about either Trump or Clinton. Reuters posts were read by a research assistant, and in case of doubt we reviewed and discussed the classification. Classification of the Megathreads was simpler, since there is few of them and their topic is clear from the title.

Bad news are defined as any post or objective fact concerning a candidate that might damage his/her image or hurt his/her chances of election, and that might provoke an emotional reaction amongst partisan users. Typical examples of bad news are scandals that emerged because a candidate was under investigation by the FBI or special prosecutors. For instance, scandals on Trump are allegations of sexual misconduct, or episodes referring to Russian interferenceres colluding with the Trump campaign. Examples of scandals on Clinton are email leaks or Clinton handling of the Benghazi attack. We do not classify as bad news episodes such as racist or islamophobic comments by Trump, since these could be received favorably by some of his supporters. Similarly, we do not classify as bad news derogatory comments on the two candidates by foreign leaders (e.g. the President of Mexico) or by US personalities (e.g. Robert De Niro), nor statements concerning conspiracy theories, since such statements could be interpreted differently by different voters. If a post focuses on a specific negative episode for a candidate (e.g. Clinton's emails), but attenuates a candidate's responsibility (e.g. Clinton relied on her staff to deal with classified information), we still classify it as bad for the candidate, in line with the idea that users may avoid topics that concern shortcomings of their preferred candidate, and viceversa for the opponent.[29]

Scandals and misbehavior are not the only source of bad news for a political candidate. Another bad news is the publication of unfavorable polls on the candidate. Since these negative polls are objective facts concerning a candidate, and they have the same relevance for voters with opposite political orientation, we included them in our classification of bad news. Specifically, we also classified as bad news on a candidate any new poll reported by Reuters that highlighted a drop in his/her popularity, or a persistent large negative gap with the other candidate. In the appendix we show that the results are robust to alternative definitions of bad polls.[30]

[29] Some articles within those covering Russia's involvement in the DNC email hacking hint at Trump's involvement in the hack. As such, it is ambiguous for whom these are emotionally charged news. In our main specification, articles mentioning the possibility of Trump's involvement in the hack are tagged as bad news for both candidates. Results are robust to either tagging these only as bad news for Clinton, dropping them, or tagging them as general news.

[30] The poll was defined as bad for a candidate if one of the following is true: (i) The text of the Reuters post unambiguously describes the poll outcome as bad news for that candidate (e.g., the article states: "Clinton's lead over Trump slips after Florida shooting"). (ii) There is a drop of at least 1.5 percentage points in his/her probability of victory, relative to the previous Reuters poll. (iii) The candidate was trailing behind in the previous poll by at least 3 percentage points, and the latest poll does not improve his/her chance of winning by at least 1.5 percentage point (e.g., we consider as bad poll for Trump a July 15 article titled: "Clinton leads Trump by 12 points ahead of Republican convention", which states "[...] little change from Tuesday, when Clinton had led Trump by 13 percentage points."). This last criterion mainly

Table 5: Cross Tabulation of Posts Content and Posts Authors

Panel A: Reuters	Scandals Trump	Scandals Clinton	Bad Poll Trump	Bad Poll Clinton	Other
Non-classified	50	72	50	7	666
Independent	20	25	23	11	303
Trump Supporter	0	5	0	6	51
Clinton Supporter	2	2	5	0	60
Moderator	0	0	0	0	1

Panel B: Megathreads	Scandals Trump	Scandals Clinton	Polls	Other
Moderator	5	8	18	66

On the basis of this classification, we thus construct two dummy variables defined for all Reuters posts and Megathreads in our sample (BNT and BNC), that equal one if the post or Megathread refers to bad news for Trump and Clinton respectively. By default, all other Reuters posts and Megathreads are coded as 0, and they refer to general political news. These general news are not attributed to one candidate or the other, but we control for how many times they mention each candidate in the text of the post. To distinguish between bad news originating from scandals and from polls, we also created two additional sets of dummy variables, one for bad polls and one for scandals, both concerning Trump and Clinton separately. In what follows, we use the term bad news when referring to either a scandal or a bad poll, and the more specific terms when we discriminate between these two different kinds of bad news.

Table 5 reports the total number of scandals and bad polls, by candidate and by subsample. The rows disaggregate by type of author of the posting. Most bad news are posted by either independent or non-classified users, but partisan supporters are more likely to post bad news on the opponent than on their preferred candidate.[31]

Appendix Tables D.3 and D.4 provide some examples of scandals and bad polls, for Reuters, and the entirety of scandals posted as Megathreads. The Online Appendix, available here, reports the exhaustive list of all bad news on Reuters and the links to the original article. Appendix Table D.1 reports the average number of comments in each subsample, disaggregated by affiliation of the author of the comment and by whether the post reports a bad news. As already noted, Megathreads attract many more comments than Reuter posts. Within Reuters, bad news attract more comments than other political news. Appendix Table D.2 reports the number of authors of comments, by type,

refers to the early part of the electoral campaign, when Trump was lagging behind Clinton by a wide margin and his popularity was not yet improving. In the appendix we show that the results are robust if we instead consider a narrower classification of bad polls, based exclusively on criterion (i) above. We cannot classify Megathreads as referring to a bad poll, because they aggregate several polls together, and the poll outcomes vary across pollsters and dates within each meagthread.

[31] Panel B shows that some Megathreads were posted by authors that are tagged as Clinton supporters. Since the only users allowed to post Megathreads are moderators, this shows that some moderators are tagged as Clinton supporters. This speaks to the point, raised by some users, that `r/politics` is somewhat allegedly left leaning. Note that moderators are always excluded in all our analyses.

active on the whole `r/politics` and in the two sub-samples. Users active on Reuters are 17,422 (9,700 classified), those active on the Megathreads are 78,074 (30,886 classified). Figures D.1 and D.2 in the Appendix show the distributions of number of comments in Reuters and Megathreads, disaggregated in different ways.

4.3 Econometric Framework

Our goal is to test whether partisan users react differently to bad news concerning their own candidate vs the opponent, and to explore the mechanisms that may lead to this. The outcome of interest, Y_{ip}, refers to the comments of user i to post p. We study both the intensive margin (the number of comments to the post made by the user) and the extensive margin (whether the user commented the post). We count both comments made directly to the posting ("first level" comments) and comments made to comments ("higher level"). The sample consists of a balanced panel of all posts in `r/politics` sharing Reuters articles and of all Megathreads (always analyzed separately), and of active partisan and independent users as defined in Section 1.1.1. Appendix Table D.5 reports the relevant summary statistics (all variables are multiplied by 100).

The treatment variables of interest are whether post p reported a bad news on the candidate supported by a partisan user or on his/her opponent. In line with the theory—and also to gain statistical power—we restrict partisan differences in activity to be symmetric across ideologies. Thus, we define two treatment variables:

$$\begin{aligned} \textit{Consonant News}_{ip} &= BNC_p * TS_i + BNT_p * CS_i \\ \textit{Non-consonant News}_{ip} &= BNT_p * TS_i + BNC_p * CS_i \end{aligned} \tag{11}$$

where BNT and BNC are the dummy variables defined above for bad news concerning Trump and Clinton respectively (or on scandals and bad polls when disaggregating between these events), and TS_i and CS_i are dummy variables that equal 1 if user i is a partisan supporter of Trump and Clinton respectively. Thus, the dummy variable $\textit{Non-consonant News}_{ip}$ is 1 if post p is a bad news on a candidate supported by partisan user i, and $\textit{Consonant News}_{ip}$ is 1 if post p is a bad news on his/her opponent.

We estimate the following regression:

$$Y_{ip} = \alpha_i + \psi_p + \beta_1 * \textit{Consonant News}_{ip} + \beta_2 * \textit{Non-consonant News}_{ip} + \gamma \mathbf{X}_{ip} + \varepsilon_{ip} \tag{12}$$

where α_i and ψ_p are individual and posting FEs and $\mathbf{X}_{ip}$ is a vector of user- and post-level controls. Controls include the activity of the user in a five-day window around the post and some post characteristics, such as the article length article or which candidates are mentioned, interacted with the user type.[32]

[32] In the Reuters sample we scraped the text of all the articles and control for the following post characteristics alone and interact with whether the user is a Trump or Clinton supporter: the article length, whether the author of the post is a Trump or Clinton supporter, the number of mentions of Clinton and Trump in the article. For Megathreads, instead,

Equation (12) identifies the coefficients of interest, β_1 and β_2, through a diff-in-diff type of specification. The coefficient β_2 measures the average difference, between supporters of a given candidate and independent users, in the number of comments to a post containing a bad news on that candidate, relative to the difference in comments to a non-bad news post between these same two groups. The coefficient β_1 measures the same difference, but concerning bad news on the opponent of the candidate supported by partisan users. Comparing the reaction of partisans vs independents to the same post (i.e including post fixed effects) allows posts to have different relevance. Comparing the reaction of the same individual to bad news vs general news (i.e. including individual fixed effects) allows users to differ in their propensity to comment. Note that the specification with individual fixed effects is demanding, because most individuals comment on only a few posts (see Appendix Table D.1). For this reason, we also report specifications without individual fixed effects, or where we control only for whether the individual is partisan or independent.

The theory predicts that $\beta_1 - \beta_2 > 0$, and that either $\beta_2 < 0$, or $\beta_1 > 0$ or both. As explained in the previous section, partisan users may behave differently with regard to bad news vs general news (relative to independents) for three reasons: *i)* they assign different relevance to general news relative to bad news ($\chi_c^P \neq 1$ and χ_c^P differs across partisan users P); *ii)* they are better informed about their own candidate than about his/her opponent ($\sigma_c^P \neq \sigma_{c'}^P$); *iii)* they enjoy or dislike engaging with different types of news ($\lambda_c^P \neq \lambda_{c'}^P$). The sum of these three forces has an ambiguous sign, and this is why the predictions on β_1 and β_2 separately are not so sharp. Comparing the reaction of partisan users to consonant vs non-consonant bad news (relative to independents) leads to sharper predictions, because their relevance should be the same, irrespective of whether it concerns one candidate or the other. This is why we expect $\beta_1 - \beta_2 > 0$. Nevertheless, this comparison still does not enable us to separately identify mechanisms *ii)* and *iii)*. Partisan users could comment more frequently on bad news on the opponent than on the supported candidate because: (a) they are less informed about the opponent and more confident about their own candidate, or (b) they dislike uncomfortable news (or enjoy news that confirms their political preferences). To disentangle these two mechanisms, we also disaggregate bad news by their content: whether they concern a scandal, or a bad poll. Whereas on scandals both mechanisms are at work, polls are a zero sum outcome; if one candidate gains, the other loses. Hence, prior uncertainty has to be the same, irrespective of whether the bad poll concerns one candidate or the other. A finding that individuals comment more frequently on consonant bad polls than on non-consonant bad polls (i.e. that $\beta_1 - \beta_2 > 0$ on bad polls) is suggestive that mechanism (b) is at play.

Standard errors are always two-way clustered at the author and posting level. Given the large number of 0s in the dependent variable, we also estimate (12) by NLLS (using Logit when focusing on the extensive margin and Pseudo-Poisson Maximum Likelihood for the intensive margin). In the sensitivity analysis, we also replace the dummy variables BNT and BNC that classify partisan

their author is always a moderator and we do not have information on the text of the article (since we are unable to scrape the content of each article linked in the post). We thus include the following variables alone and interacted for whether the user is a Trump or Clinton supporter: the share of left-wing and right-wing sources cited in the Megathread (as described in Section 2.1) For both Reuters and Megathreads, we also control for whether the post reported a poll (alone and interacted with being a Trump or Clinton supporter).

supporters by the continuous variables defined above.

4.4 Results

Table 6 reports our results, Panel A for Reuters, Panel B for Megathreads. In Columns (1)-(4) refer to the intensive margin (i.e. the dependent variable is the count of comments by user i to post p, multiplied by 100), while Columns (5)-(8) refer to the extensive margin (i.e. the dependent variable is a dummy variable for whether user i commented post p, multiplied by 100). Columns (1) and (5) report unconditional correlations. In Columns (2) and (6) we add the controls described above, and then fixed effects. Our preferred specifications are in Columns (4) and (8).

Results for the extensive margin on Reuters show that, compared to independents, partisan users are .046 percentage points (with a SD of .022) more likely to comment consonant news and .0475 percentage points (SD .0234) less likely to comment non-consonant news. The estimated coefficients, which are almost perfectly symmetrical, imply an economically significant magnitude. At the mean, individuals are 32.6% more likely to comment a consonant news and 33.6% less likely to comment non-consonant news. On the intensive margin, we find a significant effect only for non-consonant news - cf. Column (4). Partisan users write .001446 (SD .000646)[33] fewer comments on non-consonant news, compared to independents (with an implied magnitude, at the mean, of -50.38%). The key quantity disciplined by the model is $\beta_1 - \beta_2$. This estimate is always positive and statistically significant, as expected, with a $p-$value of .0034 on the extensive margin and of .0132 on the intensive one. Thus, overall, partisan users are less likely to comment on non-consonant news on Reuters, compared to consonant ones, both on the extensive and the intensive margin.

As shown in Panel B of Table 6, results on Megathreads are similar, except that here the dominant margin is whether the news is consonant. In particular, we find that, compared to independents, partisan users are 3.33 percentage points (SD .86) more likely to comment a consonant posting and they write .0972 more comments (SD .0026). The implied magnitudes, at the mean, are of $+102.3\%$ on the extensive margin and $+66.3\%$ on the intensive one.

What mechanisms drive these results? If comments are a proxy for attention, then the model of the previous section suggests two possible reasons why partisan users comment bad news more frequently on the opponent than on their candidate. First, they have sharper priors on their own candidate than on the opponent. Second, they avoid uncomfortable news and seek pleasant ones.

Note that the estimated coefficients of the interaction between users' partisanship and candidate mentions in Panel A of Table 6 cast some doubts on the first explanation. These interactions are not statistically significant, and their algebraic sum implies that, compared to independents, partisan users do not comment more frequently any post (whether bad news or not) mentioning the opponent compared to those mentioning their candidate. If the pattern described above was due to asymmetric information, we should find that partisan users comment more frequently on the opponent than on their own candidate also for general news. Instead, they seem to do this only

[33] Note that the dependent variable in the Table is multiplied by 100.

Table 6: Activity Analysis, Reuters and Megathreads, Consonant News

	Dependent variable: Comments of User i on Post p ($\times$ 100)							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reuters								
Consonant News$_{i,p}$ (β_1)	0.2131**	0.0427	0.0415	0.0396	0.1109***	0.0475**	0.0469**	0.0460**
	(0.0964)	(0.0645)	(0.0641)	(0.0640)	(0.0397)	(0.0222)	(0.0221)	(0.0220)
Non-consonant News$_{i,p}$ (β_2)	0.0398	−0.1473**	−0.1462**	−0.1446**	0.0085	−0.0485**	−0.0483**	−0.0475**
	(0.0808)	(0.0650)	(0.0646)	(0.0646)	(0.0322)	(0.0235)	(0.0234)	(0.0234)
Trump Mentions$_p$ $\times$ Trump Supporter$_i$ (γ_1)		16.5217*	15.3140	15.5508*		−0.1380	−0.6651	−0.5543
		(9.2581)	(9.4336)	(9.4447)		(3.1552)	(3.3839)	(3.3839)
Clinton Mentions$_p$ $\times$ Clinton Supporter$_i$ (γ_2)		36.5308	33.6613	33.0646		11.3695	9.9604	9.6810
		(24.2488)	(25.0492)	(25.0686)		(7.0001)	(7.1550)	(7.1606)
Trump Mentions$_p$ $\times$ Clinton Supporter$_i$ (γ_3)		4.9541	3.8901	3.5404		4.4604	3.9876	3.8239
		(7.3889)	(6.9294)	(6.9355)		(3.0537)	(2.7951)	(2.7974)
Clinton Mentions$_p$ $\times$ Trump Supporter$_i$ (γ_4)		10.9474	8.3152	8.6587		2.3010	0.9741	1.1349
		(25.7971)	(26.0594)	(26.0583)		(7.1058)	(7.2025)	(7.1997)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value ($\beta_1 - \beta_2$)	0.0054	0.0110	0.0118	0.0132	0.0001	0.0028	0.0029	0.0034
Dep. Var Mean	0.2870	0.2870	0.2870	0.2870	0.1410	0.1410	0.1410	0.1410
Observations	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000
R2	0.0000	0.0013	0.0099	0.0110	0.0000	0.0025	0.0195	0.0212
Panel B: Megathreads								
Consonant News$_{i,p}$ (β_1)	8.7905*	10.2515***	10.2581***	9.7188***	4.4683***	3.3568***	3.3588***	3.3323***
	(5.0343)	(2.6070)	(2.6083)	(2.6426)	(1.5884)	(0.8614)	(0.8619)	(0.8602)
Non-consonant News$_{i,p}$ (β_2)	−2.7194	1.2403	1.2358	1.6064	0.1316	−0.9466	−0.9480	−0.9298
	(3.6813)	(2.8021)	(2.8015)	(2.8538)	(0.7975)	(0.5934)	(0.5933)	(0.5948)
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value ($\beta_1 - \beta_2$)	0.0018	0.0001	0.0001	0.0004	0.0009	0.0000	0.0000	0.0000
Dep. Var Mean	14.6600	14.6600	14.6600	14.6600	3.2570	3.2570	3.2570	3.2570
Observations	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942
R2	0.0001	0.0260	0.0335	0.0851	0.0015	0.0255	0.0508	0.0933

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. For Reuters, post p is Consonant News for author i if it reports a scandal or a negative poll affecting the candidate opposed by i and Non-consonant News if it reports a scandal or a negative poll affecting the candidate supported by i. For Megathreads, only scandals are considered, since negative polls are not defined. Dependent variable is multiplied by 100. Sample restricted to comments of authors classified as either Trump Supporters, Clinton Supporters or Independent. Panel A estimates in columns (2) to (4) and (6) to (8) include additional controls not reported in table: i) Post Author Trump Supporter$_p$ $\times$ Trump Supporter$_i$ ii) Post Author Clinton Supporter$_p$ $\times$ Trump Supporter$_i$ iii) Post Author Trump Supporter$_p$ $\times$ Clinton Supporter$_i$ iv) Post Author Clinton Supporter$_p$ $\times$ Clinton Supporter$_i$ v) Post reports a Poll$_p$ vi) Post reports a Poll$_p$ $\times$ Trump Supporter$_i$ vii) Post reports a Poll$_p$ $\times$ Clinton Supporter$_i$ viii) Posted Article Length$_p$ ix) Posted Article Length$_p$ $\times$ Trump Supporter$_i$ x) Posted Article Length$_p$ $\times$ Clinton Supporter$_i$ xi) Post Author Non-Classified$_p$ $\times$ Trump Supporter$_i$ xii) Post Author Non-Classified$_p$ $\times$ Clinton Supporter$_i$ xiii) Author Activity Within 5 Days from Post$_{i,p}$ Panel A estimates in columns (2),(3),(6),(7) include the following controls not reported in table: xiv) Trump Supporter$_i$ xv) Clinton Supporter$_i$ Panel A estimates in columns (2) and (6) include the following controls not reported in table: xvi) Trump Scandal$_p$ xvii) Clinton Scandal$_p$ xviii) Bad Poll Trump$_p$ xix) Bad Poll Clinton$_p$ Panel B estimates in columns (2) to (4) and (5) to (8) include the following controls not reported in table: i) Post reports a Poll$_p$ ii) Post reports a Poll$_p$ $\times$ Trump Supporter$_i$ iii) Post reports a Poll$_p$ $\times$ Clinton Supporter$_i$ iv) Right Sources Share$_p$ $\times$ Trump Supporter$_i$ v) Right Sources Share$_p$ $\times$ Clinton Supporter$_i$ vi) Left Sources Share$_p$ $\times$ Trump Supporter$_i$ vii) Left Sources Share$_p$ $\times$ Clinton Supporter$_i$ viii) Right Sources Share$_p$ ix) Left Sources Share$_p$ x) Author Activity Within 5 Days from Post$_{i,p}$ Panel B estimates in columns (2),(3),(6),(7) include the following controls not reported in table: 11. Trump Supporter$_i$ 12. Clinton Supporter$_i$ Panel B estimates in columns (2) and (6) include the following controls not reported in table: 13. Trump Scandal$_p$ 14. Clinton Scandal$_p$

when they comment on bad news.[34]

To better discriminate between these two mechanisms, Table 7 disaggregates bad news posted on Reuters in scandals and bad polls.[35] Since uncertainty on polls outcome is symmetric (if one candidate gains, the other looses), evidence that partisan users comment more frequently on the bad polls of the opponent than on those of their candidate cannot be due to asymmetric priors. Here we report directly the estimated difference $\beta_1 - \beta_2$ between consonant and non-consonant news,

[34] Specifically, consider the coefficients labelled as γ_i, $i = 1 - 4$, in Table 6. The sum $(\gamma_1 + \gamma_2) - (\gamma_3 + \gamma_4)$ is positive and not statistically signficiant—both on the intensive (36.42) and on the extensive margin (4.17).

[35] For Megathreads we cannot perform a similar disaggregation, because all polls are contained in a single Megathread.

separately for scandals and bad polls. The specification is identical to Table 6, but we only report two specifications: with no covariates and with all the FEs and controls. Columns (1) to (4) report results on the intensive margin, Columns (5) to (8) on the extensive one. For ease of comparison, Columns (1), (2) and (5), (6) report the difference between $\beta_1 - \beta_2$ estimated in Columns (1), (4) and (5), (8) of Table 6, respectively. The estimated difference $\beta_1 - \beta_2$ is always positive, as expected. On the intensive margin this difference is statistically significant only for bad polls. Users make .002985 (SD .001432) more comments on bad polls of the opponent, relative to those of their candidate, about the same magnitude as their average number of comments.[36] On the extensive margin, the difference $\beta_1 - \beta_2$ is positive and statistically significant for both scandals and bad polls. Users are .1358 percentage points (SD .061) more likely to comment bad polls on the opponent than on their candidate, again about the same magnitude as their average probability of commenting. By ruling out the channel of asymmetric uncertainties, these result thus highlight an unambiguous role of emotions in the propensity to comment pleasant vs unpleasant news. Appendix Tables D.6 and D.7 replicate Tables D.6 and D.7, respectively, using the more narrow definition of bad polls described above and show that results are similar.

Table 7: Activity Analysis, Polls and Scandals on Reuters

	Dependent variable: Comments of User i on Post p ($\times$ 100)							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\beta_1 - \beta_2$, all Bad News	0.1733***	0.1842**			0.1024***	0.0935***		
	(0.0623)	(0.0743)			(0.0260)	(0.0319)		
$\beta_1^S - \beta_2^S$, only Scandals			0.0830	0.1180			0.0662**	0.0681*
			(0.0816)	(0.0818)			(0.0329)	(0.0359)
$\beta_1^P - \beta_2^P$, only Bad Polls			0.3227***	0.2985**			0.1668***	0.1358**
			(0.1030)	(0.1432)			(0.0471)	(0.0610)
FE and Controls	No	Yes	No	Yes	No	Yes	No	Yes
Dep. Var Mean	0.2870	0.2870	0.2870	0.2870	0.1410	0.1410	0.1410	0.1410
Observations	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000
R2	0.0000	0.0110	0.0000	0.0110	0.0000	0.0212	0.0000	0.0212

Notes: OLS estimates of the difference of coefficients $\beta_1 - \beta_2$, two-way clustered standard errors at the i and p level in parenthesis. Dependent variable is multiplied by 100. Sample restricted to Reuters posts and comments of authors classified as either Trump Supporters, Clinton Supporters or Independent. "All Bad News" refers to specifications where Consonant and Non-consonant is defined using both scandals and bad polls, "only Scandals" and "only Bad Polls" are the specifications in which the effect of consonant and non-consonant scandals and bad polls is estimated separately. Controls and FEs are those defined in Table 6.

Finally, Table 8 shows that these results are robust and even stronger under different specifications and definitions. Columns (1)-(3) refer to the intensive margin, (4)-(6) to the extensive one. In Columns (2), (3), (5), and (6) we estimate $\beta_1 - \beta_2$ by NLLS — Poisson for the intensive margin, by PPMLE, and Logit for the extensive margin. This is reassuring given the sparsity of our dataset. Columns (1), (3), (4), and (6) use the continuous measure of partisanship, as defined in Section 1.1.1, instead of the discrete one, so to also includde non-classified users. The estimated difference $\beta_1 - \beta_2$ is always positive and statistically significant, as expected. Tables D.8 to D.19 in the Appendix report the estimates of β_1 and β_2 separately, along with estimates of the controls, for each one of the

[36]The coefficients β_1 and β_2, separately estimated for scandals and bad polls, are reported in Table D.12 in the Appendix.

regressions presented in Tables 6 to 8.

Table 8: Activity Analysis, Robustness

	Dependent variable: Comments of User i on Post p					
	Intensive Margin			Extensive Margin		
	OLS	Poisson		OLS	Logit	
	Continuous Tag (1)	Discrete Tag (2)	Continuous Tag (3)	Continuous Tag (4)	Discrete Tag (5)	Continuous Tag (6)
Panel A1: Reuters						
$\beta_1 - \beta_2$, all Bad News	0.1772***	0.3708**	0.3459***	0.0893***	0.4888***	0.4046***
	(0.0653)	(0.1506)	(0.0987)	(0.0272)	(0.1491)	(0.0925)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Post FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var Mean	0.2700	0.0030	0.0030	0.1330	0.0020	0.0010
R2	0.0122	0.3402	0.3506	0.0236	0.1868	0.1941
Observations	18,683,698	12,251,100	18,133,830	18,683,698	12,251,100	18,133,830
Panel A2: Reuters						
$\beta_1^S - \beta_2^S$, only Scandals	0.1511*	0.2823*	0.2911***	0.0772**	0.4325***	0.4000***
	(0.0837)	(0.1549)	(0.1006)	(0.0339)	(0.1360)	(0.0993)
$\beta_1^P - \beta_2^P$, only Bad Polls	0.2220**	0.5160*	0.4451**	0.1097**	0.5779*	0.4122**
	(0.1013)	(0.2847)	(0.2063)	(0.0447)	(0.3110)	(0.1900)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Post FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var Mean	0.2700	0.0030	0.0030	0.1330	0.0020	0.0010
R2	0.0122	0.3402	0.3506	0.0236	0.1868	0.1941
Observations	18,683,698	12,251,100	18,133,830	18,683,698	12,251,100	18,133,830
Panel B: Megathreads						
$\beta_1^S - \beta_2^S$, only Scandals	6.4276***	0.6169***	0.5047***	3.2412***	0.9248***	0.7077***
	(1.5826)	(0.1502)	(0.1229)	(0.5800)	(0.1421)	(0.0871)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Post FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var Mean	12.7770	0.1470	0.1280	3.0250	0.0330	0.0300
R2	0.0784	0.4731	0.4549	0.0871	0.1766	0.1650
Observations	5,247,118	2,995,942	5,247,118	5,247,118	2,995,942	5,247,118

Notes: OLS and NLLS estimates, two-way clustered standard errors at the i and p level in parenthesis. All controls and FEs defined in Table 6 are always included. Dependent variable is multiplied by 100 for linear models (columns (1) and (4)). For Reuters, "all Bad News" refers to specifications where Consonant and Non-consonant is defined using both scandals and bad polls, "only Scandals" and "only Bad Polls" are the specifications in which the effect of consonant and non-consonant scandals and bad polls is estimated separately. For Megathreads, "all Bad News" refers only to scandals, since negative polls are not defined. Sample restricted to comments of authors classified as either Trump Supportes, Clinton Supporters or Independent.

Overall, these estimates point to an important role of emotions in the propensity to comment political news. As we argued above, attention is likely to be an important driver of comments on Reuters post (though not the only one). Hence, these results suggest that emotions also play a role in the formation of political beliefs, as suggested by the literature on motivated cognition. Comments on Megathread are less likely to be good proxies for attention instead, because these posts concern information already in the public domain. The greater propensity to comment consonant rather than non-consonant news on Megathreads could reflect some social motives, besides an asymmetry in the allocation of attention, such as winning a debate or being approved.

5 Content Analysis

What do users write in their comments to emotionally charged news? We now address this question, with two objectives: first, to interpret our previous results on users' activity; second, to provide novel evidence on online debates over potentially emotional issues.

The theoretical model of costly attention has no specific predictions for the content of comments. Our analysis here is guided by the simple hypothesis that comments express users' true feelings and opinions.

We study three outcomes that can be inferred from the text of a comment: (i) the degree of emotionality vs. reason (Gennaro and Ash, 2021); (ii) the sentiment of the comment; (iii) whether the comment on bad news about a specific candidate speaks about a scandal of his/her opponent. In the final subsection, we also study how many likes the comment receives by other users.

The unit of observation is the comment, rather than the user-post pair. With the exception of Subsection 5.3 that studies outcome (iii), we always estimate the following specification separately for first-level (comments to posts) and higher level comments (comments to comments):

$$\begin{aligned} Y_{ipc} = \alpha_i + \psi_p + \beta_1^S * \textit{Consonant Scandal}_{ip} + \beta_1^P * \textit{Consonant Poll}_{ip} \\ + \beta_2^S * \textit{Non-consonant Scandal}_{ip} + \beta_2^P * \textit{Non-consonant Poll}_{ip} + \gamma \mathbf{X}_{ipc} + \varepsilon_{ipc} \end{aligned} \tag{13}$$

where i indicates the author of comment c and p the post to which the comment refers. Y_{ipc} is the outcome of interest, α and ψ are individual and post FEs, and $\mathbf{X}_{ipc}$ is a vector of controls. Post-author level controls are identical to those employed in the activity analysis and described in footnote 32, except that here we do not control for user's activity in a 5-day window around the post. For higher level comments, we also control for the outcome of the "parent" comment (i.e. the Y_{ipc^0} of the comment c^0 to which c is replying). Standard errors are again clustered at the i and p level and reported in parentheses. As above, we report the $p-$value against a null that the difference between $\beta_1 - \beta_2$ is zero. Since independents are always included in the sample, $\beta_1 - \beta_2$ measures the difference in the outcome variable of comments of partisan users between consonant vs non-consonant posts, compared to the difference by independents beteween these same posts. As in Section 4.4, in the Megathreads sample we only consider scandals, since polls cannot be classified as consonant or non-consonant.

5.1 Emotion vs Reason

To measure the relative use of emotion vs reason in a comment, we follow Gennaro and Ash (2021), and compute the ratio of the distance of a comment from two set of words: one relating to emotionality and affection (in the numerator), and one relating to rationality (in the denominator).[37] A

[37]The sets of words comes from two lexicons validated by linguistic psychologists (Pennebaker et al., 2015). As described by Gennaro and Ash (2021), the lexicon for rationality is made of 799 words, phrases and wildcard expressions

value of 1 means that the text is equally distant from emotional words and from rational ones, a higher value means that the text displays relatively more emotionality than reason. We then estimate equation (13) using this indicator as a dependent variable.

Table 9 reports the results. Columns (1) to (4) refer to the sample of first level comments, while columns (5) to (8) refer to higher level comments. Panel A is restricted to Reuters and Panel B to Megathreads. Columns (1) and (5) report the unconditional correlation with the variables of interest. Columns (2) and (6) add all controls. We then add post fixed effects in columns (3) and (7), and individual fixed effects in (4) and (8).

Consider first higher level comments (column 8). Compared to independents, partisan users, are more emotional when they comment a consonant scandal on Reuters, and less emotional when they comment non-consonant scandals on Megathreads, relative to the difference between partisan and independents when commenting a general news. The estimated difference $\beta_1^S - \beta_2^S$ between comments on consonant and non-consonant scandals is always positive and significant, in both samples and both for higher level and first level comments (columns 4 and 8). Thus, partisan users are more emotional when commenting consonant rather than non-consonant scandals, compared to how independents comment on the same news. Note however that the magnitudes of the estimated coefficients of interest, although statistically significant, are not large. The estimated coefficient of 0.0081 in column 8 in the Reuters sample implies that the affection/cognition ratio of partisan comments on a consonant scandal is higher by 15% of a standard deviation compared to comments by independents on the same post, relative to the difference between partisan vs independents on general news.

A plausible interpretation of this finding is that, when confronted with a scandal by his/her candidate, a partisan user tries to protect its self-identity, rationalizing the candidate's behavior, finding excuses for it, or attenuating its relevance. When instead the scandal concerns the opponent, partisan users react more emotionally than independents, because they don't need to find excuses or explanations and are free to express their feelings. The idea that users react to unpleasant news with more cognitive content in order to protect their identity is in line with other results in the literature on motivated beliefs (see in particular Kahan, 2015).

Finally, there is no evidence that the emotionality of comments on polls depends on whether the news is consonant or not, nor that it differs from that of independent users. This suggests that polls are occasions for discussing information, rather than for lively debate.

5.2 Sentiment

To capture whether a comment expresses positive or negative opinons or feelings, we classified the sentiment of a comment. Sentiment analysis differs from measurement of emotion vs reason, because it aims to classify the polarity of a text, as positive or negative. Even cognitive and rational

entailing concepts of insight, causation, discrepancy, certainty, inhibition, inclusion, and exclusion. The 1,445 elements lexicon for affection relates to positive (joy, gratitude) and negative (anxiety, anger, sadness) emotions. For the specific procedure to construct their measure, see the method outlined in Gennaro and Ash (2021), which we follow in its entirety. We are grateful to them for making the code available to us.

Table 9: Emotionality Analysis

	Dependent variable: Affection/Cognition Ratio of Comment c of User i on Post p							
	First Level Comments				Higher Level Comments			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reuters								
Consonant Scandal$_{i,p}$ (β_1^S)	0.0081**	0.0015	0.0064	0.0119	0.0067***	0.0079***	0.0087***	0.0081**
	(0.0040)	(0.0050)	(0.0052)	(0.0093)	(0.0022)	(0.0018)	(0.0018)	(0.0039)
Non-consonant Scandal$_{i,p}$ (β_2^S)	0.0025	0.0000	-0.0007	-0.0191^{*}	-0.0003	-0.0035	-0.0030	-0.0058
	(0.0044)	(0.0051)	(0.0057)	(0.0102)	(0.0024)	(0.0023)	(0.0023)	(0.0035)
Consonant Poll$_{i,p}$ (β_1^P)	-0.0079	-0.0143	-0.0144	-0.0252	0.0043	-0.0030	-0.0038	-0.0207
	(0.0053)	(0.0185)	(0.0187)	(0.0282)	(0.0028)	(0.0122)	(0.0093)	(0.0166)
Non-consonant Poll$_{i,p}$ (β_2^P)	-0.0127^{**}	-0.0188	-0.0171	-0.0324	0.0040	-0.0089	-0.0058	-0.0185
	(0.0064)	(0.0186)	(0.0189)	(0.0285)	(0.0050)	(0.0124)	(0.0094)	(0.0166)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value ($\beta_1^S - \beta_2^S$), Scandals	0.3770	0.8179	0.2957	0.0320	0.0373	0.0001	0.0001	0.0137
p-value ($\beta_1^P - \beta_2^P$), Polls	0.4747	0.5579	0.7591	0.6071	0.9557	0.1978	0.6657	0.7555
Dep. Var Mean	0.9379	0.9379	0.9379	0.9379	0.9216	0.9216	0.9216	0.9216
Observations	6,785	6,785	6,785	6,785	30,612	28,494	28,494	28,494
R2	0.0015	0.0216	0.2460	0.7664	0.0007	0.0889	0.1459	0.4714
Panel B: Megathreads								
Consonant Scandal$_{i,p}$ (β_1^S)	-0.0147^{***}	0.0095**	0.0048	0.0011	-0.0058^{**}	0.0016	0.0003	-0.0004
	(0.0038)	(0.0039)	(0.0032)	(0.0032)	(0.0025)	(0.0014)	(0.0013)	(0.0012)
Non-consonant Scandal$_{i,p}$ (β_2^S)	-0.0214^{***}	-0.0019	-0.0063^{**}	-0.0075	-0.0101^{***}	-0.0025	-0.0035^{**}	-0.0049^{***}
	(0.0050)	(0.0031)	(0.0025)	(0.0051)	(0.0029)	(0.0018)	(0.0016)	(0.0011)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value ($\beta_1^S - \beta_2^S$), Scandals	0.1158	0.0042	0.0012	0.0627	0.0114	0.0071	0.0199	0.0002
Dep. Var Mean	0.9665	0.9665	0.9665	0.9665	0.9388	0.9388	0.9388	0.9388
Observations	139,283	139,283	139,283	139,283	297,542	272,514	272,514	272,514
R2	0.0012	0.0122	0.0278	0.1712	0.0010	0.0783	0.0847	0.2221

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. For Reuters, post p is Consonant Scandal or Consonant Poll for author i if it reports a scandal or a negative poll affecting the candidate opposed by i and Non-consonant Scandal or Non-consonant Poll if it reports a scandal or a negative poll affecting the candidate supported by i. For Megathreads, only scandals are considered, since negative polls are not defined. Dependent variable is the ratio of the affection and cognition score. Sample restricted to comments of authors classified as either Trump Supporters, Clinton Supporters or Independent. Panel A estimates in columns (2) to (4) and (6) to (8) include additional controls not reported in table: i) Comment Author Trump Supporter$_i$ ii) Comment Author Clinton Supporter$_i$ iii) Trump Scandal$_p$ iv) Clinton Scandal$_p$ v) Bad Poll Trump$_p$ vi) Bad Poll Clinton$_p$ vii) Post Author Trump Supporter$_p$ viii) Post Author Clinton Supporter$_p$ ix) Post Author Non-Classified$_p$ x) Post Author Trump Supporter$_p$ $\times$ Trump Supporter$_i$ xi) Post Author Clinton Supporter$_p$ $\times$ Trump Supporter$_i$ xii) Post Author Trump Supporter$_p$ $\times$ Clinton Supporter$_i$ xiii) Post Author Clinton Supporter$_p$ $\times$ Clinton Supporter$_i$ xiv) Post reports a Poll$_p$ xv) Post reports a Poll$_p$ $\times$ Trump Supporter$_i$ xvi) Post reports a Poll$_p$ $\times$ Clinton Supporter$_i$ xvii) Posted Article Length$_p$ xviii) Posted Article Length$_p$ $\times$ Trump Supporter$_i$ xix) Posted Article Length$_p$ $\times$ Clinton Supporter$_i$ xx) Post Author Non-Classified$_p$ $\times$ Trump Supporter$_i$ xxi) Post Author Non-Classified$_p$ $\times$ Clinton Supporter$_i$ xxii) Post Trump Mentions$_p$ xxiii) Post Clinton Mentions$_p$ xxiv) Post Trump Mentions$_p$ $\times$ Trump Supporter$_i$ xxv) Post Trump Mentions$_p$ $\times$ Clinton Supporter$_i$ xxvi) Post Clinton Mentions$_p$ $\times$ Trump Supporter$_i$ xxvii) Post Clinton Mentions$_p$ $\times$ Clinton Supporter$_i$

Panel A estimates in columns (6) to (8) also include the following controls: i) Outcome of Parent Comment$_c$ ii) Comment Level$_c$ iii) Comment Level$_c$ $\times$ Scandal Trump$_p$ iv) Comment Level$_c$ $\times$ Scandal Clinton$_p$ v) Comment Level$_c$ $\times$ Bad Poll Trump$_p$ vi) Comment Level$_c$ $\times$ Bad Poll Clinton$_p$

Panel B estimates in columns (2) to (4) and (6) to (8) include the following controls not reported in table: i) Comment Author Trump Supporter$_i$ ii) Comment Author Clinton Supporter$_i$ iii) Trump Scandal$_p$ iv) Clinton Scandal$_p$ v) Post reports a Poll$_p$ vi) Post reports a Poll$_p$ $\times$ Trump Supporter$_i$ vii) Post reports a Poll$_p$ $\times$ Clinton Supporter$_i$ viii) Right Sources Share$_p$ $\times$ Trump Supporter$_i$ ix) Right Sources Share$_p$ $\times$ Clinton Supporter$_i$ x) Left Sources Share$_p$ $\times$ Trump Supporter$_i$ xi) Left Sources Share$_p$ $\times$ Clinton Supporter$_i$ xii) Right Sources Share$_p$ xiii) Left Sources Share$_p$

Panel B estimates in columns (6) to (8) also include the following controls: i) Outcome of Parent Comment$_c$ ii) Comment Level$_c$ iii) Comment Level$_c$ $\times$ Scandal Trump$_p$ iv) Comment Level$_c$ $\times$ Scandal Clinton$_p$

statements can contain positive or negative content. Our prior is hypothesis is quite simple: comments to consonant news are more likely to have positive sentiment, those to non-consonant news are more likely to be negative.

To measure sentiment, we use the classifier provided by Heitmann et al. (2020), which builds on a document-embedding representation of each comment using the RoBERTA model by Liu et al. (2019). This classifier enables reliable binary sentiment analysis by tagging each comment has having either positive (1) or negative (0) sentiment. Although the lack of a neutral class is undesirable, it is outweighed by the reliability of the classifier and its performance compared to other alternatives.

Sentiment classification is still a difficult task, no matter how advanced the classifier. To assess the extent of measurement error, we inspected 500 comments and manually classified their sentiment. Compared to our manual classification, measurement error by the model is within reasonable bounds. Appendix Table E.1 reports the confusion matrix, which cross-tabulates our manual classification with that of the model. Appendix Table E.2 reports the accuracy, precision, and the F1-score of the model, which are 76.6%, 89.4%, and 81.2%, respectively.[38] As the matrix shows, most mistakes are on negative comments that get misclassified as positive. This is mainly because the model fails to recognize sarcasm.

We estimate equation (13), using our measure of sentiment as a dependent variable. Results are presented in Table 10, which again follows the usual structure.

Our main finding concerns Megathreads. As expected, compared to independents, partisan users are significantly more likely to express a positive sentiment in their higher level comments to consonant scandals than on general news, and to express negative sentiment on comments of all levels if the scandal is non-consonant. The estimated difference $\beta_1^S - \beta_2^S$ between comments on consonant and non-consonant scandals is always positive and significant, for comments of all levels. Thus, partisan users are more positive when commenting consonant rather than non-consonant scandals on Megathreads, compared to how independents comment on the same news.

The magnitudes are not trivial. Higher level partisan comments are 2 percentage points more likely to have positive content if the scandal is consonant, and 1.9 percentage points less likely if the scandal is non-consonant, than partisan comments on general news, compared to the same difference for independents. This corresponds to 6-7% of the average probability that the comment expresses positive sentiment.

In the Reuters sample, instead, we do not see any significant effect, neither for scandals nor for polls. Perhaps this is due to the much smaller sample, which increases the relevance of measurement error. Another interpretation, however, comes from the difference in the two samples. As anticipated, Megathreads are occasions for lively discussion, where the debate can become "heated". Reuters, on the other hand, features posts with fewer comments and a calmer debate, where the tones are more likely to be less elastic.

[38]The relatively low accuracy is due to the fact that forcing a binary classification is a strong restriction. Indeed, when restricting the manual sample to comments judged as non-neutral (373 out of 500, considering the classification of both human coders), accuracy rises to 83.1%. The confusion matrix for such types of comments is reported in the right panel of Table E.1.

Table 10: Sentiment Analysis

	Dependent variable: Sentiment of Comment c of User i on Post p							
	First Level Comments				Higher Level Comments			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reuters								
Consonant Scandal$_{i,p}$ (β_1^S)	-0.0876^{***}	-0.0852^{**}	-0.0647^{*}	-0.0106	-0.0171	0.0102	0.0052	0.0166
	(0.0238)	(0.0351)	(0.0349)	(0.0676)	(0.0204)	(0.0216)	(0.0225)	(0.0309)
Non-consonant Scandal$_{i,p}$ (β_2^S)	-0.0325	-0.0132	0.0079	0.0284	-0.0326	-0.0079	-0.0121	-0.0340
	(0.0481)	(0.0443)	(0.0411)	(0.0605)	(0.0199)	(0.0261)	(0.0275)	(0.0388)
Consonant Poll$_{i,p}$ (β_1^P)	0.1669^{***}	0.0230	-0.0118	0.0422	0.1157^{***}	0.0968	0.1678	0.1991
	(0.0540)	(0.1562)	(0.1284)	(0.2010)	(0.0248)	(0.1071)	(0.1195)	(0.1607)
Non-consonant Poll$_{i,p}$ (β_2^P)	0.1095^{**}	-0.0334	-0.0670	0.2027	0.0791^{***}	0.0658	0.1304	0.1382
	(0.0490)	(0.1462)	(0.1252)	(0.1951)	(0.0272)	(0.1107)	(0.1263)	(0.1624)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value ($\beta_1^S - \beta_2^S$), Scandals	0.3427	0.2216	0.1523	0.6503	0.6223	0.5906	0.6243	0.3394
p-value ($\beta_1^P - \beta_2^P$), Polls	0.3703	0.4588	0.5475	0.2036	0.2956	0.4323	0.3672	0.2346
Dep. Var Mean	0.2359	0.2359	0.2359	0.2359	0.2489	0.2489	0.2489	0.2489
Observations	6,805	6,805	6,805	6,805	30,729	28,666	28,666	28,666
R2	0.0042	0.0182	0.2229	0.7470	0.0021	0.0114	0.0505	0.3518
Panel B: Megathreads								
Consonant Scandal$_{i,p}$ (β_1^S)	-0.0770^{***}	0.0071	0.0206	0.0177	-0.0553^{***}	0.0303^{**}	0.0211^{*}	0.0204^{**}
	(0.0161)	(0.0276)	(0.0246)	(0.0245)	(0.0088)	(0.0129)	(0.0126)	(0.0097)
Non-consonant Scandal$_{i,p}$ (β_2^S)	-0.1019^{***}	-0.0536^{***}	-0.0421^{**}	-0.0408^{*}	-0.0831^{***}	-0.0044	-0.0067	-0.0191^{*}
	(0.0158)	(0.0206)	(0.0189)	(0.0231)	(0.0085)	(0.0117)	(0.0122)	(0.0100)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value ($\beta_1^S - \beta_2^S$), Scandals	0.2832	0.0336	0.0247	0.0183	0.0190	0.0162	0.0436	0.0002
Dep. Var Mean	0.2753	0.2753	0.2753	0.2753	0.3032	0.3032	0.3032	0.3032
Observations	139,491	139,491	139,491	139,491	299,684	275,117	275,117	275,117
R2	0.0007	0.0075	0.0143	0.1404	0.0013	0.0145	0.0170	0.1372

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. For Reuters, post p is Consonant Scandal or Consonant Poll for author i if it reports a scandal or a negative poll affecting the candidate opposed by i and Non-consonant Scandal or Non-consonant Poll if it reports a scandal or a negative poll affecting the candidate supported by i. For Megathreads, only scandals are considered, since negative polls are not defined. Dependent variable is the binary sentiment score. Sample restricted to comments of authors classified as either Trump Supporters, Clinton Supporters or Independent. Panel A estimates in columns (2) to (4) and (6) to (8) include additional controls not reported in table: i) Comment Author Trump Supporter$_i$ ii) Comment Author Clinton Supporter$_i$ iii) Trump Scandal$_p$ iv) Clinton Scandal$_p$ v) Bad Poll Trump$_p$ vi) Bad Poll Clinton$_p$ vii) Post Author Trump Supporter$_p$ viii) Post Author Clinton Supporter$_p$ ix) Post Author Non-Classified$_p$ x) Post Author Trump Supporter$_p$ × Trump Supporter$_i$ xi) Post Author Clinton Supporter$_p$ × Trump Supporter$_i$ xii) Post Author Trump Supporter$_p$ × Clinton Supporter$_i$ xiii) Post Author Clinton Supporter$_p$ × Clinton Supporter$_i$ xiv) Post reports a Poll$_p$ xv) Post reports a Poll$_p$ × Trump Supporter$_i$ xvi) Post reports a Poll$_p$ × Clinton Supporter$_i$ xvii) Posted Article Length$_p$ xviii) Posted Article Length$_p$ × Trump Supporter$_i$ xix) Posted Article Length$_p$ × Clinton Supporter$_i$ xx) Post Author Non-Classified$_p$ × Trump Supporter$_i$ xxi) Post Author Non-Classified$_p$ × Clinton Supporter$_i$ xxii) Post Trump Mentions$_p$ xxiii) Post Clinton Mentions$_p$ xxiv) Post Trump Mentions$_p$ × Trump Supporter$_i$ xxv) Post Trump Mentions$_p$ × Clinton Supporter$_i$ xxvi) Post Clinton Mentions$_p$ × Trump Supporter$_i$ xxvii) Post Clinton Mentions$_p$ × Clinton Supporter$_i$
Panel A estimates in columns (6) to (8) also include the following controls: i) Outcome of Parent Comment$_c$ ii) Comment Level$_c$ iii) Comment Level$_c$ × Scandal Trump$_p$ iv) Comment Level$_c$ × Scandal Clinton$_p$ v) Comment Level$_c$ × Bad Poll Trump$_p$ vi) Comment Level$_c$ × Bad Poll Clinton$_p$
Panel B estimates in columns (2) to (4) and (6) to (8) include the following controls not reported in table: i) Comment Author Trump Supporter$_i$ ii) Comment Author Clinton Supporter$_i$ iii) Trump Scandal$_p$ iv) Clinton Scandal$_p$ v) Post reports a Poll$_p$ vi) Post reports a Poll$_p$ × Trump Supporter$_i$ vii) Post reports a Poll$_p$ × Clinton Supporter$_i$ viii) Right Sources Share$_p$ × Trump Supporter$_i$ ix) Right Sources Share$_p$ × Clinton Supporter$_i$ x) Left Sources Share$_p$ × Trump Supporter$_i$ xi) Left Sources Share$_p$ × Clinton Supporter$_i$ xii) Right Sources Share$_p$ xiii) Left Sources Share$_p$
Panel B estimates in columns (6) to (8) also include the following controls: i) Outcome of Parent Comment$_c$ ii) Comment Level$_c$ iii) Comment Level$_c$ × Scandal Trump$_p$ iv) Comment Level$_c$ × Scandal Clinton$_p$

5.3 Similarity

After analyzing *how* users discuss scandals, we now ask *what* is discussed. To capture whether users discuss different topics across emotionally vs. not emotionally charged posts, we start by employing a χ^2 test that highlights words that are most common in the sample of partisan vs. independent users when discussing scandals. Specifically, in Appendix Figure E.1 we plot the most distinctive bigrams by partisan supporters when they comment non-consonant scandals (i.e. scandals on their candidate), compared to independents when they comment scandals on the same candidate. The most distinctive tokens that distinguish Trump supporters from independents are those that relate to scandals on Clinton. That is, compared to independents, Trump supporters respond to scandals on their candidate by highlighting topics that cast doubts on the valence of his opponent. The pattern is less pronounced for Clinton supporters, although they too, compared to independents, seem to talk less about Clinton scandals.

Motivated by this pattern, we investigate whether partisans are more likely to discuss scandals of the opponent when commenting consonant vs non-consonant scandals. To do so, we construct a measure that, for each comment to a scandal concerning a candidate x, reports the "similarity" of that comment to any scandal concerning x's opponent. The measure is constructed as follows. First, we start from the text of all Reuters articles in our sample. For each candidate x, we estimate a χ^2 test (as in Gentzkow and Shapiro, 2010) of the uni- and bigrams that are most distinctive of scandals of x vs. all other news (general news and scandals on $x' \neq x$). Armed with this token-level measure of distinctiveness, we project it at the comment level by taking the weighted average of the χ^2 statistics of each token in the comment, weighted by the occurrence of each token in the comment. This yields two comment level measures that describe the similarity of each comment to scandals on Trump and on Clinton. Note that this measure is only available for scandals, because general news don't concern a specific candidate (i.e. similarity of the comment to a scandal of his/her opponent cannot be computed for comments on general news, because the opponent is not well defined). Thus, the analysis that follows is restricted to scandals, and (when including individual FE) we can only identify $\beta_2^S - \beta_1^S$ in equation (13) above, namely the difference between Non-consonant vs Consonant scandals.[39]

Specifically, let Y_{ipc} be our measure of similarity of comment c to a scandal of the opposite candidate.[40] We estimate the following specification:

$$Y_{ipc} = \alpha_i + \psi_p + \beta * Non - consonantScandal_{ip} + \delta \mathbf{X}_c + \varepsilon_{ipc}$$

where α_i and ψ_p are individual and poll fixed effects and $\mathbf{X}_c$ a vector of controls that includes a polynomial of order three in the comment length and a dummy indicating the level of the comment. β is our coefficient of interest. It measures the average difference of Y_{ipc} in the comments of partisan users between non-consonant vs consonant scandals, relative to the comments on the same scandals by independents. Standard errors are always two-way clustered at the post and individual level.

Table 11 reports the results. The first set of four columns focuses on the Reuters sample, the last four on Megathreads. Within each set of columns, the first two report results when using word counts of unigrams, the last two those using bigrams. Columns (1), (3), (5), and (7) report the

[39]Since the Megathreads scandals are a subset of the Reuters scandal, this measure of similarity is also available in the Megathread sample.

[40]That is, given a scandal on x, the similarity to a scandal of the opposite candidate is the similarity of comment c to the a Reuters article discussing a scandal on $x' \neq x$.

Table 11: Similarity Analysis

	Dependent variable: Similarity to BN opposite of the one commented							
	Reuters				Megathreads			
	1-gram		2-grams		1-gram		2-grams	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-consonant Scandal$_{i,p}$	37.36***	24.78	1.302***	$-$0.3477	7.902***	8.734***	0.4784***	0.2639*
	(7.133)	(27.348)	(0.107)	(0.870)	(1.466)	(2.281)	(0.103)	(0.124)
Trump Supporter$_i$	7.588		0.1874		3.954***		0.04765	
	(5.159)		(0.218)		(1.247)		(0.069)	
Clinton Supporter$_i$	$-$18.52		$-$0.8072**		$-$3.211**		$-$0.2157**	
	(14.437)		(0.385)		(1.491)		(0.102)	
Trump Scandal$_p$	33.94***		0.6413*		$-$2.856		0.01225	
	(8.358)		(0.377)		(3.097)		(0.112)	
Post FE	No	Yes	No	Yes	No	Yes	No	Yes
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
Polynomial in Comment's Length	No	Yes	No	Yes	No	Yes	No	Yes
Controlling for Comments' level	No	Yes	No	Yes	No	Yes	No	Yes
Dep. Var Mean	29.975	29.975	0.652	0.652	11.039	11.039	0.298	0.298
Observations	6,629	6,629	6,629	6,629	64,423	64,423	64,423	64,423
R2	0.029	0.569	0.009	0.466	0.003	0.240	0.001	0.234

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Post p is a Non-consonant Scandal for author i if it reports a scandal affecting the candidate supported by i. The dependent variable is the similarity to the news opposite to the one commented. The sample is restricted to comments to scandals on Trump or Clinton by authors classified as either Trump Supporters, Clinton Supporters or Independent.

correlations without controls and fixed effects, which we add in the remaining columns. The results show that partisans are significantly more likely to talk of scandals of the opposite candidate when they comment scandals of their candidate (i.e. non-consonant scandals), compared to when they comment scandals on his/her opponent. That is, a Trump supporter is much more likely to talk about Clinton scandals when commenting a scandal on Trump, compared to how much he/she is likely to talk of Trump scandals when commenting a scandal on Clinton. As above, the results are stronger and more robust in the Megathreads sample.

This evidence is in line with the idea of supporters shifting the focus of the comment away from emotionally discomforting news, towards comforting ones.

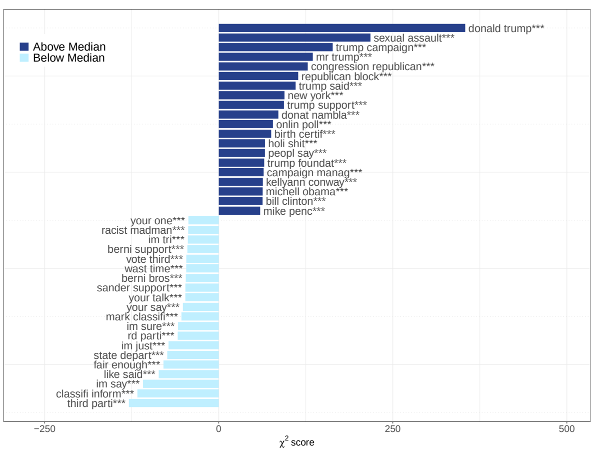
5.4 Comments' Score

Finally, we study to what extent comments by partisan users to emotional news are endorsed by others, as measured by the net "likes" received. As described above, the majority of users in `r/politics` cannot be easily classified in terms of their political preferences. Hence, a comment is more likely to be approved if it conforms with the views of non-partisan users. If the comments of partisan users reflect their true feelings, this in turn is more likely to happen when a partisan user comments on a scandal of the opponent (a consonant scandal), and less likely for scandals on his/her own preferred candidate (a non-consonant scandal). Asymmetric attention of partisan users to consonant vs non-consonant news reinforces this effect. When commenting a consonant news, a partisan user's comment may reach more like-minded individuals, since the news is consonant to them too and thus they pay more attention to it. The opposite happens with non-consonant news.

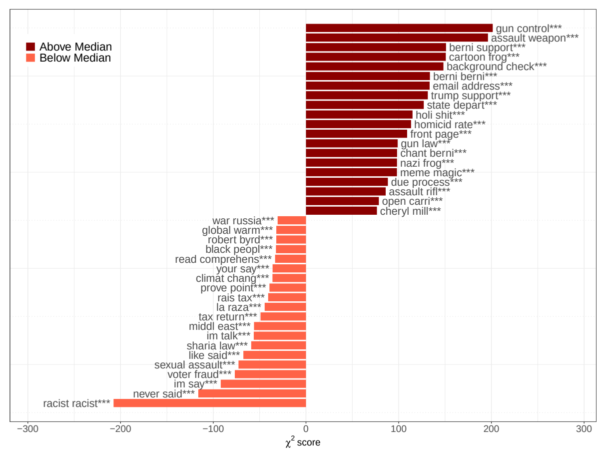
We observe the score of a comment, which measures how many "likes" (net of "dislikes") a comment receives.[41] Consider two samples of comments: those with a score respectively above or below the overall median. Figure 7 plots the words that that are most distinctive of each partisan group, in each sample. For both types of supporters, words that refer to the scandal of the opponent (i.e. consonant scandals) are those that are most characteristics of high-score comments. For Trump supporters, bigrams such as “email address” and “state department” (which are related to Clinton’s email controversy and the Benghazi attack, respectively) are among the words most distinctive of above median scoring comments. For Clinton, we find words such as “sexual assault” and “Trump foundation”.

Figure 7: χ^2 Test Statistics of Relative Words Frequencies Across Comments in `r/politics` with an Above Median versus Below Median Score, by Affiliation of the Author

(a) Clinton supporters



(b) Trump supporters



Next, we formally investigate this pattern in the entire sample, and ask whether comments receive more or less approval depending on the consonance of the news they are commenting. Here comments on general news are also included, so the analysis and interpretation is like in Subsections 5.1 and 5.2. Table 12 reports the results, with the usual format. The dependent variable is the “score” of the comment. As expected, higher level partisan comments on consonant scandals receive higher scores than those on general news, compared to the same difference for independents. Moreover, the difference between consonant vs non-consonant scandals and polls (the estimate of $\beta_1 - \beta_2$) is always positive and significant for higher level comments. The results are much more robust for scandals than for polls, and the estimates are more precise in the Megathreads sample than for Reuters, as in some of the previous subsections. On Megathreads there is also evidence that first-level comments receive relatively higher scores if they concern consonant rather than non-

[41] Users on Reddit can “upvote” a comment (an equivalent concept to what other social media call “likes”) or “downvote” it, and the score is defined as the number of upvotes minus that of downvotes. We don’t observe the identity of who posts the upvotes.

consonant scandals (the $p-$value of the hypothesis that $\beta_1 - \beta_2 = 0$ is .059). The magnitudes are also large: higher level comments by partisan users on consonant scandals receive about twice as many likes than their comments on general news (122% more on Reuters, 82% more on Megathreads), compared to the same difference for independents.

Table 12: Score Analysis

	Dependent variable: Comment Score of Comment c of User i on Post p							
	First Level Comments				Higher Level Comments			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reuters								
Consonant Scandal$_{i,p}$ (β_1^S)	0.7366	-1.9262	1.0180	4.8823	2.4616***	3.5221***	3.8664***	5.5778***
	(3.1958)	(4.8556)	(5.9011)	(13.7041)	(0.9002)	(0.6968)	(0.6792)	(1.7050)
Non-consonant Scandal$_{i,p}$ (β_2^S)	-4.6411	-13.7710^{*}	-21.4280^{**}	-16.3319	-2.1048^{***}	-2.2381^{***}	-2.1863^{***}	-0.3165
	(3.9853)	(8.2272)	(9.2287)	(14.4472)	(0.6570)	(0.7631)	(0.7700)	(1.8914)
Consonant Poll$_{i,p}$ (β_1^P)	-1.8573	-10.7622^{*}	-15.4899^{**}	2.1080	0.8304	-0.5359	-1.4602	-0.5003
	(2.4434)	(6.1196)	(6.7132)	(14.1264)	(1.0341)	(1.6949)	(1.8468)	(2.4618)
Non-consonant Poll$_{i,p}$ (β_2^P)	-11.8228^{***}	-17.6115^{***}	-23.5688^{***}	28.1058	-2.9329^{**}	-2.9651	-2.4379	-3.8011
	(2.5830)	(6.3221)	(7.7448)	(35.5549)	(1.4864)	(1.9277)	(2.1507)	(2.4035)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value ($\beta_1^S - \beta_2^S$), Scandals	0.2691	0.1133	0.0076	0.1788	0.0005	0.0000	0.0000	0.0033
p-value ($\beta_1^P - \beta_2^P$), Polls	0.0031	0.1803	0.1617	0.5249	0.0169	0.1283	0.5471	0.0466
Dep. Var Mean	9.3640	9.3640	9.3640	9.3640	4.5577	4.5577	4.5577	4.5577
Observations	6,805	6,805	6,805	6,805	30,732	28,669	28,669	28,669
R2	0.0005	0.0088	0.0370	0.7343	0.0008	0.0576	0.0657	0.3617
Panel B: Megathreads								
Consonant Scandal$_{i,p}$ (β_1^S)	36.6264***	7.1360	11.2881	8.7147	6.6524***	2.5056**	2.6721**	3.6991**
	(9.8746)	(10.5150)	(10.3724)	(10.7672)	(2.0973)	(1.2662)	(1.2315)	(1.5718)
Non-consonant Scandal$_{i,p}$ (β_2^S)	22.5280***	-14.3881^{*}	-12.1362^{*}	-9.3559	0.5389	-4.1023^{**}	-3.7363^{**}	-2.1403^{*}
	(8.5682)	(7.4150)	(7.0215)	(9.3274)	(1.7646)	(1.8834)	(1.8740)	(1.2629)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value ($\beta_1^S - \beta_2^S$), Scandals	0.4206	0.1429	0.0846	0.0588	0.0856	0.0024	0.0029	0.0018
Dep. Var Mean	9.1477	9.1477	9.1477	9.1477	4.5273	4.5273	4.5273	4.5273
Observations	139,496	139,496	139,496	139,496	299,717	275,165	275,165	275,165
R2	0.0030	0.0121	0.0196	0.4444	0.0015	0.0371	0.0388	0.1910

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. For Reuters, post p is Consonant Scandal or Consonant Poll for author i if it reports a scandal or a negative poll affecting the candidate opposed by i and Non-consonant Scandal or Non-consonant Poll if it reports a scandal or a negative poll affecting the candidate supported by i. For Megathreads, only scandals are considered, since negative polls are not defined. Dependent variable is the comment score. Sample restricted to comments of authors classified as either Trump Supporters, Clinton Supporters or Independent. Panel A estimates in columns (2) to (4) and (6) to (8) include additional controls not reported in table: i) Comment Author Trump Supporter$_i$ ii) Comment Author Clinton Supporter$_i$ iii) Trump Scandal$_p$ iv) Clinton Scandal$_p$ v) Bad Poll Trump$_p$ vi) Bad Poll Clinton$_p$ vii) Post Author Trump Supporter$_p$ viii) Post Author Clinton Supporter$_p$ ix) Post Author Non-Classified$_p$ x) Post Author Trump Supporter$_p$ × Trump Supporter$_i$ xi) Post Author Clinton Supporter$_p$ × Trump Supporter$_i$ xii) Post Author Trump Supporter$_p$ × Clinton Supporter$_i$ xiii) Post Author Clinton Supporter$_p$ × Clinton Supporter$_i$ xiv) Post reports a Poll$_p$ xv) Post reports a Poll$_p$ × Trump Supporter$_i$ xvi) Post reports a Poll$_p$ × Clinton Supporter$_i$ xvii) Posted Article Length$_p$ xviii) Posted Article Length$_p$ × Trump Supporter$_i$ xix) Posted Article Length$_p$ × Clinton Supporter$_i$ xx) Post Author Non-Classified$_p$ × Trump Supporter$_i$ xxi) Post Author Non-Classified$_p$ × Clinton Supporter$_i$ xxii) Post Trump Mentions$_p$ xxiii) Post Clinton Mentions$_p$ xxiv) Post Trump Mentions$_p$ × Trump Supporter$_i$ xxv) Post Trump Mentions$_p$ × Clinton Supporter$_i$ xxvi) Post Clinton Mentions$_p$ × Trump Supporter$_i$ xxvii) Post Clinton Mentions$_p$ × Clinton Supporter$_i$

Panel A estimates in columns (6) to (8) also include the following controls: i) Outcome of Parent Comment$_c$ ii) Comment Level$_c$ iii) Comment Level$_c$ × Scandal Trump$_p$ iv) Comment Level$_c$ × Scandal Clinton$_p$ v) Comment Level$_c$ × Bad Poll Trump$_p$ vi) Comment Level$_c$ × Bad Poll Clinton$_p$

Panel B estimates in columns (2) to (4) and (6) to (8) include the following controls not reported in table: i) Comment Author Trump Supporter$_i$ ii) Comment Author Clinton Supporter$_i$ iii) Trump Scandal$_p$ iv) Clinton Scandal$_p$ v) Post reports a Poll$_p$ vi) Post reports a Poll$_p$ × Trump Supporter$_i$ vii) Post reports a Poll$_p$ × Clinton Supporter$_i$ viii) Right Sources Share$_p$ × Trump Supporter$_i$ ix) Right Sources Share$_p$ × Clinton Supporter$_i$ x) Left Sources Share$_p$ × Trump Supporter$_i$ xi) Left Sources Share$_p$ × Clinton Supporter$_i$ xii) Right Sources Share$_p$ xiii) Left Sources Share$_p$

Panel B estimates in columns (6) to (8) also include the following controls: i) Outcome of Parent Comment$_c$ ii) Comment Level$_c$ iii) Comment Level$_c$ × Scandal Trump$_p$ iv) Comment Level$_c$ × Scandal Clinton$_p$

These results are also consistent with motivated reasoning. If users fail to update their priors upon receiving discomforting news, but update them when the news is comforting, then their opinion will be differentially misaligned with the content of the story, based on the type of news. When partisan users discuss consonant news, they are likely to be "right": their opinions square with those conveyed in the article. Viceversa, not consonant news put them in a situation where, if they want to defend their candidate, they will likely be on the losing side of the debate.

Finally, here too the results are much weaker or virtually absent for Reuters polls. One explanation of this finding is that, unlike for scandals, bad polls convey news that the candidate is losing, but nothing on its valence. Thus, a partisan user is, at worst, perceived to be supporting a loser—which is different to being perceived as supporting a morally questionable candidate—and might not feel as compelled to defend his/her behavior. This suggests that polls are not occasions for lively debates with high stakes. It also reinforces the interpretation that, when restricting our attention to polls, comments do approximate attention more than engagement. In other words, the results on activity analysis on polls described in the previous section are less likely to be the artifact of users searching for approval, rather than simply paying attention to a story. This argument is also corroborated by the results on emotionality and sentiment described above, since consonant vs not consonant polls do not differentially drive the content of comments of partisan users, compared to independents.

Conclusion

We have studied how users of Reddit's main political forum commented on political news during the 2016 US Electoral Campaign. We find three main results.

First, when browsing `r/politics`, partisan individuals do not differentially engage with different news sources (in line with Gentzkow and Shapiro, 2011), but they do engage with different news stories. That is, the engagement of a Trump supporter with right-wing (or left-wing) sources is not very different from that of Clinton supporter or an independent. Nevertheless, there is significant ideological segregation across single news stories within each source. Around a fourth of all articles are commented by Clinton supporters but not by Trump ones. Around a third are commented by Trump supporters but not by Clinton ones.

Second, when faced with bad news about a candidate, partisan users are less likely to comment if it concerns their candidate, and more likely if it concerns the opponent, compared with how independents comment the same news. These differences are large and symmetric (partisans are about 30% more or less likely to comment depending on whether the news is consonant or not). Moreover, they cannot be attributed to partisans being less uncertain about their candidate than about the opponent, because this different behavior is also observed on polls outcomes, where prior uncertainty is obviously the same for the two candidates.

Third, the contents of the comments are systematically correlated with the emotional implications of the news. If the news is pleasant (a scandal of the opponent), the comments of partisan users are more likely to display positive (rather than negative) sentiment and emotional (rather than rational) content, compared to unpleasant news (a scandal of the own candidate) and relative to how independents comment on the same news. Partisan comments on pleasant news are also more likely to be approved by others, compared to comments on unpleasant news. Since the majority of users cannot be classified in terms of their political preferences, this suggests that partisans reactions are more in line with unabiased political views when the news is consonant than when it isn't. Finally, when they comment a scandal, users are more likely to speak about a scandal of the opposite candidate if the scandal is not consonant than if it is.

These results paint a highly consistent picture. Partisan users seem reluctant to accept discomforting political news. They engage less with such news, and when they do they try to rationalize them or to find excuses, and they point to the sins of the opponent, as if they tried to defend their political identity. These behavioral features of online debates, together with partisan segregation across news content, can shed light on why individuals with different partisan affiliations hold starkly different beliefs on controversial issues.

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A Theoretical Appendix

A.0.1 Optimal allocation of attention

Exploiting symmetry, the first order conditions for an interior optimum of (**??**) with respect to ξ_c^i are:

$$\left\{\phi(\frac{\chi_T^i\mu_T^i - \chi_C^i\mu_C^i}{\theta^i})[1-(\frac{\chi_T^i\mu_T^i - \chi_C^i\mu_C^i}{\theta^i})^2] - \phi'(\frac{\chi_T^i\mu_T^i - \chi_C^i\mu_C^i}{\theta^i})\frac{\chi_T^i\mu_T^i - \chi_C^i\mu_C^i}{\theta^i}\right\}\frac{\partial\theta^i}{\partial\xi_c^i} = M_{\xi_c^i} \tag{14}$$

and similarly for $\xi_{c'}^i$. Note that $\phi'(x) = -\phi(x)x$, and

$$\begin{aligned} \frac{\partial\theta^i}{\partial\xi_c^i} &= \frac{1}{2\theta^i}(\chi_c^i)^2(\sigma_c^i)^2 \\ M_{\xi_c^i} &= \lambda_c^i/(1-\xi_c^i) \end{aligned}$$

Inserting these expressions in (14) and simplifying yields (6)in the text. Denote $C = \frac{\chi_T^i\mu_T^i - \chi_C^i\mu_C^v}{\theta^i}$ and rewrite the FOC for ξ_c^i as:

$$F_c(\xi_c^i, \xi_{c'}^i, \alpha) := \phi(\cdot)\frac{(\sigma_c^i)^2(\chi_c^i)^2}{2\theta^i} - \frac{\lambda_c^i}{1-\xi_c^i} = 0 \tag{15}$$

and similarly define $F_{c'}$. We want to compute the second order partial derivatives, $F_{cc}, F_{cc'}, F_{c'c}, F_{c'c'}$. Note that $\frac{\partial C}{\partial \xi_c^i} = -\frac{C}{\theta^i}\frac{\partial\theta^i}{\partial\xi_c^i}$. Then we can compute:

$$\begin{aligned} F_{cc} = &= \frac{\partial}{\partial\xi_c^i}\left[\phi(\cdot)\frac{(\sigma_c^i)^2(\chi_c^i)^2}{2\theta^i} - \frac{\lambda_c^i}{1-\xi_c^i}\right] \\ &= \left[\frac{(\sigma_c^i)^2(\chi_c^i)^2}{2(\theta^i)^2}\phi(\cdot)(-1+C^2)\right]\frac{\partial\theta^i}{\partial\xi_c^i} - \frac{\lambda_c^i}{(1-\xi_c^i)^2} \\ &= \left[\frac{(\sigma_c^i)^4(\chi_c^i)^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\right] - \frac{\lambda_c^i}{(1-\xi_c^i)^2} \end{aligned} \tag{16}$$

$$\begin{aligned} F_{cc'} = &= \frac{\partial}{\partial\xi_{c'}^i}\left[\phi(\cdot)\frac{(\sigma_c^i)^2(\chi_c^i)^2}{2\theta^i} - \frac{\lambda_c^i}{1-\xi_c^i}\right] \\ &= \left[\frac{(\sigma_c^i)^2(\chi_c^i)^2}{2(\theta^i)^2}\phi(\cdot)(-1+C^2)\right]\frac{\partial\theta^i}{\partial\xi_{c'}^i} \\ &= \left[\frac{(\sigma_c^i)^2(\sigma_{c'}^i)^2(\chi_c^i)^2(\chi_{c'}^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\right] \end{aligned} \tag{17}$$

and similarly for $F_{c'c}, F_{c'c'}$. For the SOC to hold, we have to verify that in the solution to the problem $F_{cc} < 0$, and $F_{cc'}^2 - F_{cc}F_{c'c'} < 0$. Under condition (A1) it clearly holds true that $F_{cc} < 0$, since $C^2 < 1$.

Let's consider the second condition:

$$
\begin{aligned}
0 > F_{cc'}^2 - F_{cc}F_{c'c'} = & \left[\frac{(\sigma_c^i)^2(\sigma_{c'}^i)^2(\chi_c^i)^2(\chi_{c'}^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\right] \\
& - \left[\frac{(\sigma_c^i)^2(\sigma_{c'}^i)^2(\chi_c^i)^2(\chi_{c'}^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\right] \\
& + \left[\frac{(\sigma_c^i)^4(\chi_c^i)^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\right]\frac{\lambda_{c'}^i}{(1-\xi_{c'}^i)^2} \\
& + \left[\frac{(\sigma_{c'}^i)^4(\chi_{c'}^i)^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\right]\frac{\lambda_c^i}{(1-\xi_c^i)^2} \\
& - \frac{\lambda_c^i\lambda_{c'}^i}{(1-\xi_c^i)^2(1-\xi_{c'}^i)^2}
\end{aligned}
$$

Which holds under (A1).

Proof. Proposition 1

From the first order conditions we can write the following system:

$$
\begin{cases}
F_{cc}\frac{\partial\xi_c^i}{\partial\alpha} + F_{cc'}\frac{\partial\xi_{c'}^i}{\partial\alpha} = -F_{c\alpha} \\
F_{c'c}\frac{\partial\xi_c^i}{\partial\alpha} + F_{c'c'}\frac{\partial\xi_{c'}^i}{\partial\alpha} = -F_{c'\alpha}
\end{cases}
$$

Solving it we find

$$
\frac{\partial\xi_c^i}{\partial\alpha} = \frac{F_{c\alpha}F_{c'c'} - F_{c'\alpha}F_{cc'}}{F_{c'c}F_{cc'} - F_{cc}F_{c'c'}} \tag{18}
$$

$$
\frac{\partial\xi_{c'}^i}{\partial\alpha} = \frac{F_{c'\alpha}F_{cc} - F_{c\alpha}F_{c'c}}{F_{c'c}F_{cc'} - F_{cc}f_{c'c'}} \tag{19}
$$

We have seen that under condition (A1) the denominator is less than zero, and $F_{cc} < 0, F_{cc'} < 0, F_{c'c} < 0, F_{c'c'} < 0$. We have to compute $F_{c\alpha}$ and $F_{c'\alpha}$.

Part (i):$\alpha = \lambda_c^i$

$$
F_{c\alpha} = -\frac{1}{1-\xi_c^i} < 0
$$

$$
F_{c'\alpha} = 0
$$

From this we conclude that $\frac{\partial\xi_c^i}{\partial\lambda_c^i} < 0$ and $\frac{\partial\xi_{c'}^i}{\partial\lambda_c^i} > 0$.

Part (i):$\alpha = (\sigma_c^i)^2$

$$
\begin{aligned}
F_{c\alpha} &= \frac{\phi(\cdot)(\chi_c^i)^2}{2\theta^i} + \left[\frac{(\sigma_c^i)^2(\chi_c^i)^2}{2(\theta^i)^2}\phi(\cdot)(-1+C^2)\right]\frac{\partial\theta^i}{\partial(\sigma_c^i)^2} \\
&= \frac{\phi(\cdot)(\chi_c^i)^2}{2\theta^i} + \left[\frac{(\sigma_c^i)^2(\chi_c^i)^2}{2(\theta^i)^2}\phi(\cdot)(-1+C^2)\right]\frac{(\chi_c^i)^2\xi_c^i}{2\theta^i} \\
&= \frac{\phi(\cdot)(\chi_c^i)^2}{2\theta^i}\left[1 + \frac{(\sigma_c^i)^2(\chi_c^i)^2}{2(\theta^i)^2}\xi_c^i(-1+C^2)\right] > 0
\end{aligned}
$$

$$
F_{c'\alpha} = \left[\frac{(\sigma_{c'}^i)^2(\chi_{c'}^i)^2}{2(\theta^i)^2}\phi(\cdot)(-1+C^2)\right]\frac{(\chi_c^i)^2\xi_c^i}{2\theta^i} < 0
$$

Note that $F_{c\alpha} > 0$ since $(\sigma_c^i)^2(\chi_c^i)^2\xi_c^i < 2(\theta^i)^2$, and $F_{c'\alpha} < 0$ since $C^2 < 1$. From this we conclude that $\frac{\partial\xi_c^i}{\partial(\sigma_c^i)^2} > 0$ and $\frac{\partial\xi_{c'}^i}{\partial(\sigma_c^i)^2} < 0$.

Part (ii):$\alpha = |\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|$

$$
F_{c\alpha} = -\frac{(\sigma_c^i)^2(\chi_c^i)^2}{2(\theta^i)^2}\phi(\cdot)\frac{|\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|}{\theta^i} < 0
$$

$$
F_{c'\alpha} = -\frac{(\sigma_{c'}^i)^2(\chi_{c'}^i)^2}{2(\theta^i)^2}\phi(\cdot)\frac{|\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|}{\theta^i} < 0
$$

Then we can compute the numerator of $\frac{\partial\xi_c^i}{\partial\alpha}$ and $\frac{\partial\xi_{c'}^i}{\partial\alpha}$:

$$
\frac{\partial\xi_c^i}{\partial|\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|} : \frac{(\sigma_c^i)^2(\chi_c^i)^2}{2(\theta^i)^2}\phi(\cdot)\frac{|\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|}{\theta^i}\frac{\lambda_{c'}^i}{(1-\xi_{c'}^i)^2} > 0
$$

$$
\frac{\partial\xi_{c'}^i}{\partial|\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|} : \frac{(\sigma_{c'}^i)^2(\chi_{c'}^i)^2}{2(\theta^i)^2}\phi(\cdot)\frac{|\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|}{\theta^i}\frac{\lambda_c^i}{(1-\xi_c^i)^2} > 0
$$

Since the denominator is negative, $\frac{\partial\xi_c^i}{\partial|\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|} < 0$, and $\frac{\partial\xi_{c'}^i}{\partial|\chi_T^i\mu_T^i - \chi_C^i\mu_C^i|} < 0$

Part (iii): $\alpha = \chi_c^i$

Consider now the case $c = T$ (the case with $c = C$ is analogous). Suppose that $\chi_T^i\mu_T^i < \chi_C^i\mu_C^i$, and consequently $C < 0$. Note that

$$
\frac{\partial\theta^i}{\partial\chi_T^i} = \frac{\xi_T^i\chi_T^i(\sigma_T^i)^2}{\theta^i}
$$

$$\frac{\partial C}{\partial \chi_T^i} = \frac{\mu_T^i}{\theta^i} - C\xi_T^i \frac{\chi_T^i (\sigma_T^i)^2}{(\theta^i)^2}$$
$$\frac{\partial C}{\partial \chi_C^i} = -\frac{\mu_C^i}{\theta^i} - C\xi_C^i \frac{\chi_C^i (\sigma_C^i)^2}{(\theta^i)^2}$$

Then we can compute

$$F_{T\chi_T^i} = \phi(\cdot)\frac{(\sigma_T^i)^2 \chi_T^i}{\theta^i}\left(1 - C\frac{\chi_T^i \mu_T^i}{2\theta^i}\right) + \phi(\cdot)\frac{(\sigma_T^i)^4 (\chi_T^i)^3}{2(\theta^i)^3}\xi_T^i(-1 + C^2)$$

$$F_{C\chi_T^i} = \phi(\cdot)\frac{(\sigma_T^i)^2 (\sigma_C^i)^2 (\chi_T^i)(\chi_C^i)^2}{2(\theta^i)^3}\xi_T^i(-1 + C^2) - \phi(\cdot)C\frac{(\sigma_C^i)^2 (\chi_C^i)^2 \mu_T^i}{2(\theta^i)^2}$$

Finally we compute the numerator of $\frac{\partial \xi_T^i}{\partial \chi_T^i}$:

$$\begin{aligned}\frac{\partial \xi_T^i}{\partial \chi_T^i} &: \phi^2(\cdot)\frac{(\sigma_T^i)^2 (\sigma_C^i)^4 (\chi_T^i)(\chi_C^i)^4}{4(\theta^i)^4}(-1 + C^2) \\ &+ \phi(\cdot)\frac{(\sigma_T^i)^2 \chi_T^i}{\theta^i}\frac{\lambda_C^i}{(1 - \xi_C^i)}\left(-1 + \frac{\chi_T^i \mu_T^i}{2\theta^i}C - \frac{(\sigma_T^i)^2 (\chi_T^i)^2}{2(\theta^i)^2}(-1 + C^2)\xi_T^i\right)\end{aligned}$$

The first term is negative since $C^2 < 1$, and the second term is negative since $C < 0$ and $\frac{(\sigma_T^i)^2 (\chi_T^i)^2 \xi_T^i}{2(\theta^i)^2} < 1$. Hence, we conclude $\frac{\partial \xi_T^i}{\partial \chi_T^i} > 0$.

Similarly we can compute $F_{T\chi_C^i}$ and $F_{C\chi_C^i}$, and obtain the numerator of $\frac{\partial \xi_T^i}{\partial \chi_C^i}$.

$$\begin{aligned}\frac{\partial \xi_T^i}{\partial \chi_C^i} &: -\phi(\cdot)\frac{(\sigma_T^i)^2 (\sigma_C^i)^2 (\chi_T^i)^2 (\chi_C^i)}{2(\theta^i)^3}(-1 + C^2)\frac{\lambda_C^i \xi_C^i}{(1 - \xi_C^i)^2} \\ &- \phi(\cdot)\frac{(\sigma_T^i)^2 (\chi_T^i)^2 \mu_C^i}{2(\theta^i)^2}C\frac{\lambda_C^i}{(1 - \xi_C^i)^2} \\ &- \phi^2(\cdot)\frac{(\sigma_T^i)^2 (\sigma_C^i)^4 (\chi_T^i)^2 (\chi_C^i)^3}{4(\theta^i)^4}(-1 + C^2)\end{aligned}$$

which is positive given that $C < 0$ and $C^2 < 1$. Hence, we conclude $\frac{\partial \xi_T^i}{\partial \chi_C^i} < 0$. ■

A.0.2 The model with news about negative features of candidates

Consider the following general model. Voters preferences over the features of politicians are now:

$$q_c^i = \chi_c^i g_c - b_c$$

where voter $i's$ priors over g_c and b_c are such that $g_c \sim N(\gamma^i_c, (\sigma^{gi}_c)^2)$ and $b_c \sim N(\beta^i_c, (\sigma^{bi}_c)^2)$. Voters observe signals

$$\begin{aligned} s^{bi}_c &= b_c + \varepsilon^{bi}_c \\ s^{gi}_c &= g_c + \varepsilon^{gi}_c \end{aligned}$$

and choose attention weights

$$\xi^{gi}_c = \frac{(\sigma^{gi}_c)^2}{(\sigma^{gi}_c)^2 + (\eta^{gi}_c)^2}, \quad \xi^{bi}_c = \frac{(\sigma^{bi}_c)^2}{(\sigma^{bi}_c)^2 + (\eta^{bi}_c)^2}$$

where $(\eta^{gi}_c)^2$ and $(\eta^{bi}_c)^2$ are the variances of ε^{gi}_c and of ε^{bi}_c respectively. Repeating the steps in the text, posterior means of candidates quality are normally distributed, with ex-ante mean and variances given respectively by:

$$\begin{aligned} E(Q^i_c) &= \chi^i_c \gamma^i_c - \beta^i_c \equiv \mu^i_c \\ Var(Q^i_c) &= (\chi^i_c)^2 \xi^{gi}_c (\sigma^{gi}_c)^2 + \xi^{bi}_c (\sigma^{bi}_c)^2 \equiv \zeta^i_c \end{aligned}$$

Letting λ^{gi}_c and λ^{bi}_c the attention costs on g and b respectively, and solving the voters' optimization problem, optimal attention weights are:

$$\begin{aligned} \xi^{gi}_c &= 1 - \frac{\lambda^{gi}_c}{(\chi^i_c)^2 (\sigma^{gi}_c)^2} \frac{2\theta^i}{\phi(\frac{\mu^i_T - \mu^i_C}{\theta^i})} \\ \xi^{bi}_c &= 1 - \frac{\lambda^{bi}_c}{(\sigma^{bi}_c)^2} \frac{2\theta^i}{\phi(\frac{\mu^i_T - \mu^i_C}{\theta^i})} \end{aligned}$$

where

$$\theta^i = \sqrt{\varsigma^i_T + \varsigma^i_C}$$

To derive the second order conditions and some comparative statics results, we now use the following notation: $\phi(\cdot) = \phi(\frac{\mu^i_T - \mu^i_C}{\theta^i})$ and $C = \frac{\mu^i_T - \mu^i_C}{\theta^i}$. Moreover, define $y_T = \xi^{gi}_T$, $y_C = \xi^{gi}_C$, $x_T = \xi^{bi}_T$, and $x_C = \xi^{bi}_C$ and α is a given parameter to be defined below. The FOC with respect to these four variables, that give rise to the optimal attention weights stated above, can be written as a system of four equations:

$$
\begin{aligned}
G_T(y_T, y_C, x_T, x_C, \alpha) &= \phi(\cdot)\frac{(\sigma_T^{gi})^2(\chi_T^i)^2}{2\theta^i} - \frac{\lambda_T^{gi}}{1-y_T} = 0 \\
G_C(y_T, y_C, x_T, x_C, \alpha) &= \phi(\cdot)\frac{(\sigma_C^{gi})^2(\chi_C^i)^2}{2\theta^i} - \frac{\lambda_C^{gi}}{1-y_C} = 0 \\
H_T(y_T, y_C, x_T, x_C, \alpha) &= \phi(\cdot)\frac{(\sigma_T^{bi})^2}{2\theta^i} - \frac{\lambda_T^{bi}}{1-x_T} = 0 \\
H_C(y_T, y_C, x_T, x_C, \alpha) &= \phi(\cdot)\frac{(\sigma_C^{bi})^2}{2\theta^i} - \frac{\lambda_C^{bi}}{1-x_C} = 0
\end{aligned}
$$

To compute the second order conditions, first we have to compute all second order derivatives part of the Hessian matrix, which is symmetric. The SOC can be written as conditions on the determinants of the minors of the Hessian matrix. In particular the following conditions are necessary to show that the critical point is indeed a maximum. As in the simpler case, the SOC are satisfied if $C^2 < 1$.

Now we want to understand how the optimal level of attention depend on the parameter α. From the first order conditions we write the following system of equations:

$$
\begin{cases}
G_{T,y_T}Y_{T,\alpha} + G_{T,y_C}Y_{C,\alpha} + G_{T,x_T}X_{T,\alpha} + G_{T,x_C}X_{C,\alpha} = -G_{T,\alpha} \\
G_{C,y_T}Y_{T,\alpha} + G_{C,y_C}Y_{C,\alpha} + G_{C,x_T}X_{T,\alpha} + G_{C,x_C}X_{C,\alpha} = -G_{C,\alpha} \\
H_{T,y_T}Y_{T,\alpha} + H_{T,y_C}Y_{C,\alpha} + H_{T,x_T}X_{T,\alpha} + H_{T,x_C}X_{C,\alpha} = -H_{T,\alpha} \\
H_{C,y_T}Y_{T,\alpha} + H_{C,y_C}Y_{C,\alpha} + H_{C,x_T}X_{T,\alpha} + H_{C,x_C}X_{C,\alpha} = -H_{C,\alpha}
\end{cases}
$$

We apply Cramer rule to solie the system. Hereafter we only write the numerator of the solution, since the denominator, which is the determinant of the Hessian matrix, is always positiie according to the necessary second order conditions.

$$
\begin{aligned}
Y_{T,\alpha} = -G_{T,\alpha}\Bigg[& \frac{(\sigma_C^{gi})^4(\chi_C^i)^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^b\lambda_C^b}{(1-x_T)^2(1-x_C)^2} + \frac{(\sigma_C^{bi})^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_C^g\lambda_T^b}{(1-y_C)^2(1-x_T)^2} \\
& + \frac{(\sigma_T^{bi})^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_C^g\lambda_C^b}{(1-y_C)^2(1-x_C)^2} - \frac{\lambda_C^g\lambda_T^b\lambda_C^b}{(1-y_C)^2(1-x_T)^2(1-x_C)^2}\Bigg] \\
& + G_{C,\alpha}\Bigg[\frac{(\sigma_T^{gi})^2(\sigma_C^{gi})^2(\chi_T^i)^2(\chi_C^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^b\lambda_C^b}{(1-x_T)^2(1-x_C)^2}\Bigg] \\
& + H_{T,\alpha}\Bigg[\frac{(\sigma_T^{gi})^2(\sigma_T^{bi})^2(\chi_T^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_C^g\lambda_C^b}{(1-y_C)^2(1-x_C)^2}\Bigg] \\
& + H_{C,\alpha}\Bigg[\frac{(\sigma_T^{gi})^2(\sigma_C^{bi})^2(\chi_T^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_C^g\lambda_T^b}{(1-y_C)^2(1-x_T)^2}\Bigg]
\end{aligned} \tag{20}
$$

$$
\begin{aligned}
Y_{C,\alpha} = {} & G_{T,\alpha}\left[\frac{(\sigma_T^{gi})^2(\sigma_C^{gi})^2(\chi_T^i)^2(\chi_C^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^b\lambda_C^b}{(1-x_T)^2(1-x_C)^2}\right] \\
& - G_{C,\alpha}\left[\frac{(\sigma_C^{bi})^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_T^b}{(1-y_T)^2(1-x_T)^2} + \frac{(\sigma_T^{bi})^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_C^b}{(1-y_T)^2(1-x_C)^2}\right. \\
& \left. + \frac{(\sigma_T^{gi})^4(\chi_T^i)^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^b\lambda_C^b}{(1-x_T)^2(1-x_C)^2} - \frac{\lambda_T^g\lambda_T^b\lambda_C^b}{(1-y_T)^2(1-x_T)^2(1-x_C)^2}\right] \\
& + H_{T,\alpha}\left[\frac{(\sigma_C^{gi})^2(\sigma_T^{bi})^2(\chi_C^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_C^b}{(1-y_T)^2(1-x_c)^2}\right] \\
& + H_{C,\alpha}\left[\frac{(\sigma_C^{gi})^2(\sigma_C^{bi})^2(\chi_C^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_T^b}{(1-y_T)^2(1-y_C)^2}\right]
\end{aligned} \tag{21}
$$

$$
\begin{aligned}
X_{T,\alpha} = {} & G_{T,\alpha}\left[\frac{(\sigma_T^{gi})^2(\sigma_T^{bi})^2(\chi_T^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_C^g\lambda_C^b}{(1-y_C)^2(1-x_C)^2}\right] \\
& + G_{C,\alpha}\left[\frac{(\sigma_C^{gi})^2(\sigma_T^{bi})^2(\chi_C^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_C^b}{(1-y_T)^2(1-x_C)^2}\right] \\
& - H_{T,\alpha}\left[\frac{(\sigma_T^{gi})^4(\chi_T^i)^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_C^g\lambda_C^b}{(1-y_C)^2(1-x_C)^2} + \frac{(\sigma_C^{bi})^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_C^g}{(1-y_T)^2(1-y_C)^2}\right. \\
& \left. + \frac{(\sigma_C^{gi})^4(\chi_c^i)^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_C^b}{(1-y_T)^2(1-x_C)^2} - \frac{\lambda_T^g\lambda_C^g\lambda_C^b}{(1-y_T)^2(1-y_C)^2(1-x_C)^2}\right] \\
& + H_{C,\alpha}\left[\frac{(\sigma_T^{bi})^2(\sigma_C^{bi})^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_C^g}{(1-y_T)^2(1-y_C)^2}\right]
\end{aligned} \tag{22}
$$

$$
\begin{aligned}
X_{C,\alpha} = {} & G_{T,\alpha}\left[\frac{(\sigma_T^{gi})^2(\sigma_C^{bi})^2(\chi_T^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_C^b}{(1-y_T)^2(1-x_C)^2}\right] \\
& + G_{C,\alpha}\left[\frac{(\sigma_C^{gi})^2(\sigma_C^{bi})^2(\chi_C^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_T^b}{(1-y_T)^2(1-x_T)^2}\right] \\
& + H_{T,\alpha}\left[\frac{(\sigma_T^{bi})^2(\sigma_C^{bi})^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_C^g}{(1-y_T)^2(1-y_C)^2}\right] \\
& - H_{C,\alpha}\left[\frac{(\sigma_T^{gi})^4(\chi_T^i)^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_C^g\lambda_T^b}{(1-y_C)^2(1-x_T)^2} + \frac{(\sigma_T^{bi})^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_C^g}{(1-y_T)^2(1-y_C)^2}\right. \\
& \left. + \frac{(\sigma_C^{gi})^4(\chi_c^i)^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_T^b}{(1-y_T)^2(1-x_T)^2} - \frac{\lambda_T^g\lambda_C^g\lambda_T^b}{(1-y_T)^2(1-y_C)^2(1-x_T)^2}\right]
\end{aligned} \tag{23}
$$

Now we can move to the proof of the analog of Proposition 1, which now is reformulated as follows:

Proposition 2 *Suppose that (A1) holds. Then:*
(i) Voter i pays more attention to signal s_c^{ki} , for $k = g, b$, if the cost of paying attention to that signal is lower and if prior uncertainty about the underlying feature corresponding that signal is higher:

$$\frac{\partial \xi_c^{ki}}{\partial \lambda_c^{ki}} < 0, \quad \frac{\partial \xi_c^{ki}}{\partial (\sigma_c^{ki})^2} > 0, \quad \textit{for } k = g, b$$

(ii) Voter i pays more attention to signal s_c^{ki} , for $k = g, b$, if the cost of paying attention to any other signal is higher and if prior uncertainty about any other underlying feature is lower:

$$\frac{\partial \xi_c^{ki}}{\partial \lambda_{c'}^{hi}} > 0, \quad \frac{\partial \xi_c^{ki}}{\partial (\sigma_{c'}^{hi})^2} < 0, \quad \textit{for } k, h = g, b \textit{ and for } k \neq h \textit{ and/or } c \neq c'$$

(iii) Holding constant the weight χ_c^i, voter i pays more attention to all signals if $|\mu_T^i - \mu_C^i|$ is lower:

$$\frac{\partial \xi_c^{ki}}{\partial |\mu_T^i - \mu_C^i|} < 0 \qquad \textit{for } k = g, b \textit{ and } c = T, C$$

(iv) An increase in the weight χ_c^i induces voter i to pay more attention to signal s_c^{gi} if $\mu_c^i < \mu_{c'}^i$, and it induces him to pay less attention to all other signals if $\mu_c^i > \mu_{c'}^i$ for $c' \neq c$; in the other cases, the effect of changes in χ_c^i is ambiguous:

$$\begin{aligned}
\frac{\partial \xi_c^{gi}}{\partial \chi_c^i} &> 0 \textit{ if } \mu_c^i < \mu_{c'}^i \textit{ for } c \neq c' \\
\frac{\partial \xi_c^{bi}}{\partial \chi_c^i} &< 0 \textit{ and } \frac{\partial \xi_c^{ki}}{\partial \chi_{c'}^i} < 0 \textit{ for } k = g, b \textit{ and } c \neq c' \quad \textit{if } \mu_c^i > \mu_{c'}^i \textit{ for } c \neq c'
\end{aligned}$$

Proof. Proposition 2

Part (i) and (ii):

Recall first that by assumption $C^2 < 1$. Assume for simplicity $\alpha = \lambda_T^{gi}$, then $G_{T,\alpha} = -\frac{1}{1-y_T} < 0$ and $G_{C,\alpha} = H_{T,\alpha} = H_{C,\alpha} = 0$. If we substitute in (20)-(23) we obtain $Y_{T,\alpha} < 0$ and $Y_{C,\alpha} > 0$, $X_{T,\alpha} > 0$, $X_{C,\alpha} > 0$. In the same way we can show this results for the other values of k and c. This proves the first inequality of (i) and (ii).

Now let's consider $\alpha = \sigma_T^{gi}$. Let's compute

$$\begin{aligned} G_{T,\alpha} &= \frac{\phi(\cdot)(\chi_T^i)^2}{2\theta^i} + \left[\frac{(\sigma_T^{gi})^2(\chi_T^i)^2}{2(\theta^i)^2}\phi(\cdot)(-1+C^2)\right]\frac{\partial\theta^i}{\partial(\sigma_T^{gi})^2} \\ &= \frac{\phi(\cdot)(\chi_T^i)^2}{2\theta^i} + \left[\frac{(\sigma_T^{gi})^2(\chi_T^i)^2}{2(\theta^i)^2}\phi(\cdot)(-1+C^2)\right]\frac{(\chi_T^i)^2 y_T}{2\theta^i} \\ &= \frac{(\chi_T^i)^2\phi(\cdot)}{2\theta^i}\left[1 + \frac{(\sigma_T^{gi})^2(\chi_T^i)^2}{2(\theta^i)^2} y_T(-1+C^2)\right] > 0 \end{aligned}$$

Note that $G_{T,\alpha} > 0$, since $(\sigma_T^{gi})^2(\chi_T^i)^2 y_T < 2(\theta^i)^2$. Furthermore:

$$\begin{aligned} G_{C,\alpha} &= \left[\tfrac{(\sigma_C^{gi})^2(\chi_C^i)^2}{2(\theta^i)^2}\phi(\cdot)(-1+C^2)\right]\tfrac{(\chi_T^i)^2 y_T}{2\theta^i} < 0 \\ H_{T,\alpha} &= \left[\tfrac{(\sigma_T^{bi})^2}{2(\theta^i)^2}\phi(\cdot)(-1+C^2)\right]\tfrac{(\chi_T^i)^2 y_T}{2\theta^i} < 0 \\ H_{C,\alpha} &= \left[\tfrac{(\sigma_C^{bi})^2}{2(\theta^i)^2}\phi(\cdot)(-1+C^2)\right]\tfrac{(\chi_T^i)^2 y_T}{2\theta^i} < 0 \end{aligned}$$

We can substitute in (20)-(23) and we obtain $Y_{T,\alpha} > 0$, and $Y_{C,\alpha} < 0$, $X_{T,\alpha} < 0$, $X_{C,\alpha} < 0$. In fact, $Y_{T,\alpha} > 0$ as all its terms are positive, while $Y_{C,\alpha}$, $X_{T,\alpha}$, and $X_{C,\alpha}$ have positive and negative terms. However all positive terms cancel out with some negative ones, and we are left with only negative terms. In the same way we can show this results for the other values of k and c. This proves the second inequality of (i) and (ii).

Part(iii)

Let's consider $\alpha = |\mu_T - \mu_C|$. We can compute:

$$\begin{aligned} G_{T,\alpha} &= -\tfrac{(\sigma_T^{gi})^2(\chi_T^i)^2}{2(\theta^i)^2}\phi(\cdot)\tfrac{|\mu_T-\mu_C|}{\theta^i} < 0 \\ G_{C,\alpha} &= -\tfrac{(\sigma_C^{gi})^2(\chi_C^i)^2}{2(\theta^i)^2}\phi(\cdot)\tfrac{|\mu_T-\mu_C|}{\theta^i} < 0 \\ H_{T,\alpha} &= -\tfrac{(\sigma_T^{bi})^2}{2(\theta^i)^2}\phi(\cdot)\tfrac{|\mu_T-\mu_C|}{\theta^i} < 0 \\ H_{C,\alpha} &= -\tfrac{(\sigma_C^{bi})^2}{2(\theta^i)^2}\phi(\cdot)\tfrac{|\mu_T-\mu_C|}{\theta^i} < 0 \end{aligned}$$

We substitute these values in (20)-(23) obtaining:

$$Y_{T,\alpha} = -\frac{(\sigma_T^{gi})^2(\chi_T^i)^2}{2(\theta^i)^2}\phi(\cdot)\frac{|\mu_T-\mu_C|}{\theta^i}\frac{\lambda_C^g\lambda_T^b\lambda_C^b}{(1-y_C)^2(1-x_T)^2(1-x_C)^2} < 0.$$

Similarly we obtain $Y_{C,\alpha} < 0$, $X_{T,\alpha} < 0$, $X_{C,\alpha} < 0$.

Part (iv)

Assume now $\alpha = \chi^i_T$. First notice that

$$\frac{\partial \mu^i_p}{\partial \chi^i_p} = \gamma^i_p$$
$$\frac{\partial \mu^i_p}{\partial \chi^i_{-p}} = 0$$
$$\frac{\partial \theta^i}{\partial \chi^i_p} = \frac{\chi^i_p (\sigma^{gi}_p)^2 y_p}{\theta^i}$$

Then we can compute

$$\begin{aligned}
G_{T,\alpha} &= \frac{\phi(\cdot)(\sigma^{gi}_T)^2 \chi^i_T}{\theta^i} - \frac{(\sigma^{gi}_T)^2(\chi^i_T)^2}{2\theta^i}\phi(\cdot) C \frac{\partial}{\partial \chi^i_T}\left(\frac{\mu^i_T - \mu^i_C}{\theta^i}\right) - \frac{(\sigma^{gi}_T)^2(\chi^i_T)^2}{2(\theta^i)^2}\phi(\cdot)\frac{\partial \theta^i}{\partial \chi^i_T} \\
&= \frac{\phi(\cdot)(\sigma^{gi}_T)^2 \chi^i_T}{\theta^i} - \frac{(\sigma^{gi}_T)^2(\chi^i_T)^2}{2\theta^i}\phi(\cdot) C \left[\frac{\gamma^i_T}{\theta^i} - \frac{(\mu^i_T - \mu^i_C)\chi^i_T (\sigma^{gi}_T)^2 y_T}{(\theta^i)^3}\right] \\
&- \frac{(\sigma^{gi}_T)^2(\chi^i_T)^2}{2(\theta^i)^3}\phi(\cdot)\chi^i_T (\sigma^{gi}_T)^2 y_T \\
&= \frac{\phi(\cdot)(\sigma^{gi}_T)^2 \chi^i_T}{\theta^i} - \frac{(\sigma^{gi}_T)^2(\chi^i_T)^2}{2(\theta^i)^2}\phi(\cdot) C \gamma^i_T + \frac{(\sigma^{gi}_T)^4(\chi^i_T)^3}{2(\theta^i)^3}\phi(\cdot) y_T(-1 + C^2)
\end{aligned}$$

As observed before $(\sigma^{gi}_T)^2(\chi^i_T)^2 y_T < 2(\theta^i)^2$. This implies that, if $C < 0$, then $G_{T,\alpha} > 0$.

$$G_{C,\alpha} = -\frac{(\sigma^{gi}_C)^2(\chi^i_C)^2}{2(\theta^i)^2}\phi(\cdot) C \gamma^i_T + \frac{(\sigma^{gi}_T)^2(\sigma^{gi}_C)^2(\chi^i_C)^2 \chi^i_T}{2(\theta^i)^3}\phi(\cdot) y_T(-1 + C^2)$$

$$H_{T,\alpha} = -\frac{(\sigma^{bi}_T)^2}{2(\theta^i)^2}\phi(\cdot) C \gamma^i_T + \frac{(\sigma^{gi}_T)^2(\sigma^{bi}_T)^2 \chi^i_T}{2(\theta^i)^3}\phi(\cdot) y_T(-1 + C^2)$$

$$H_{C,\alpha} = -\frac{(\sigma^{bi}_C)^2}{2(\theta^i)^2}\phi(\cdot) C \gamma^i_T + \frac{(\sigma^{gi}_T)^2(\sigma^{bi}_C)^2 \chi^i_T}{2(\theta^i)^3}\phi(\cdot) y_T(-1 + C^2)$$

We substitute in (20)-(23) and we obtain:

$$
\begin{aligned}
Y_{T,\alpha} = &-\frac{\phi(\cdot)(\sigma_T^{gi})^2\chi_T^i}{\theta^i}\Bigg[\frac{(\sigma_C^{gi})^4(\chi_C^i)^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^b\lambda_C^b}{(1-x_T)^2(1-x_C)^2} \\
&+\frac{(\sigma_C^{bi})^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_C^g\lambda_T^b}{(1-y_C)^2(1-x_T)^2}+\frac{(\sigma_T^{bi})^4}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_C^g\lambda_C^b}{(1-y_C)^2(1-x_C)^2}\Bigg] \\
&+\frac{\lambda_C^g\lambda_T^b\lambda_C^b}{(1-y_C)^2(1-x_T)^2(1-x_C)^2}\Bigg[\frac{\phi(\cdot)(\sigma_T^{gi})^2\chi_T^i}{\theta^i} \\
&-\frac{(\sigma_T^{gi})^2(\chi_T^i)^2}{2(\theta^i)^2}\phi(\cdot)C\gamma_T^i+\frac{(\sigma_T^{gi})^4(\chi_T^i)^3}{2(\theta^i)^3}\phi(\cdot)y_T(-1+C^2)\Bigg]
\end{aligned}
$$

$$
\begin{aligned}
Y_{C,\alpha} = &\frac{\phi(\cdot)(\sigma_T^{gi})^2\chi_T^i}{\theta^i}\Bigg[\frac{(\sigma_T^{gi})^2(\sigma_C^{gi})^2(\chi_T^i)^2(\chi_C^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^b\lambda_C^b}{(1-x_T)^2(1-x_C)^2}\Bigg] \\
&+\frac{\lambda_T^g\lambda_T^b\lambda_C^b}{(1-y_T)^2(1-x_T)^2(1-x_C)^2}\Bigg(-\frac{(\sigma_C^{gi})^2(\chi_C^i)^2}{2(\theta^i)^2}\phi(\cdot)C\gamma_T^i+\frac{(\sigma_T^{gi})^2(\sigma_C^{gi})^2(\chi_C^i)^2\chi_T^i}{2(\theta^i)^3}\phi(\cdot)y_T(-1+C^2)\Bigg)
\end{aligned}
$$

$$
\begin{aligned}
X_{T,\alpha} = &\frac{\phi(\cdot)(\sigma_T^{gi})^2\chi_T^i}{\theta^i}\Bigg[\frac{(\sigma_T^{gi})^2(\sigma_T^{bi})^2(\chi_T^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_C^g\lambda_C^b}{(1-y_C)^2(1-x_C)^2}\Bigg] \\
&+\frac{\lambda_T^g\lambda_C^g\lambda_C^b}{(1-y_T)^2(1-y_C)^2(1-x_C)^2}\Bigg(-\frac{(\sigma_T^{bi})^2}{2(\theta^i)^2}\phi(\cdot)C\gamma_T^i+\frac{(\sigma_T^{gi})^2(\sigma_T^{bi})^2\chi_T^i}{2(\theta^i)^3}\phi(\cdot)y_T(-1+C^2)\Bigg)
\end{aligned}
$$

$$
\begin{aligned}
X_{C,\alpha} = &\frac{\phi(\cdot)(\sigma_T^{gi})^2\chi_T^i}{\theta^i}\Bigg[\frac{(\sigma_T^{gi})^2(\sigma_C^{bi})^2(\chi_T^i)^2}{4(\theta^i)^3}\phi(\cdot)(-1+C^2)\frac{\lambda_T^g\lambda_C^b}{(1-y_T)^2(1-x_C)^2}\Bigg] \\
&+\frac{\lambda_T^g\lambda_C^g\lambda_T^b}{(1-y_T)^2(1-y_C)^2(1-x_T)^2}\Bigg(-\frac{(\sigma_C^{bi})^2}{2(\theta^i)^2}\phi(\cdot)C\gamma_T^i+\frac{(\sigma_T^{gi})^2(\sigma_C^{bi})^2\chi_T^i}{2(\theta^i)^3}\phi(\cdot)y_T(-1+C^2)\Bigg)
\end{aligned}
$$

Notice that, if $\mu_T < \mu_C$, then $C < 0$, and consequently $Y_{T,\alpha} > 0$ as we wanted. Else, if $\mu_T > \mu_C$ so that $C > 0$, it follows that $Y_{C,\alpha} < 0$, $X_{T,\alpha} < 0$, $X_{C,\alpha} < 0$. This proves point (iv). ■

Using the assumptions stated in the text about independent and partisan voters, Proposition 2 in turn implies prediction 1.

B More on Reddit

B.1 User Experience

Users of Reddit make two decisions over how to engage with the platform in two main ways (both choices are unobserved to us). First, they choose what to browse: either the "front page" or a specific subreddit of their interest. Second, within a browsing window, they choose how to sort posts. Essentially, users could decide whether to sort posts by their novelty or popularity, or a combination of both. Based on internet archives of the Reddit front page in June 1, 2016 (https://web.archive.org/web/20160601000340/https://www.reddit.com/) a user could decide to sort posts by "hot", "new", "rising", "controversial", "top", and "gilded". In essence, these all reflect different weighting schemes of novelty and the reactions received, in terms of aggregate upvotes and downvotes. For instance, "hot" posts are those that have many "upvotes", discounted by the time of posting; "top" posts, are those that have the highest number of upvotes overall, within a time period; "controversial" posts received both many upvotes and downvotes at the same time. Selecting "new" sorts posts by the time of submission, with the newest at the top of the page. "Rising" posts are those that are currently receiving a lot of activity, in terms of comments and upvotes. Finally, posts that received "awards" from other users (that is, other users spent money to highlight those posts by purchasing virtual awards and assigning them to those posts) are called "gilded".

When browsing the front page during our sample period (and, more generally, until 2017), users were presented with the most popular/newest postings (according to their sorting choice) from a random subset of subreddits to which they subscribed, without any further individual-level customization. When browsing each single subreddit, users are presented with the most popular or newest postings on that subreddit only, again according to their preferences. Notably, users also seem to often browse a subreddit denoted as `r/all`, which aggregates posts from all the subreddits on Reddit, regardless of a user's subscriptions. This serves as a common page, available to the entire site regardless of individual preferences.

Thus, until 2017, two individuals that subscribed to the same subreddits and were sorting posts in the same way were presented the same postings, on average, regardless of their individual interactions with each posting or the amount of time they spent on the different subreddits. After 2017, a changelog was implemented that customized the home feed so to give more weight to subreddits where the individual user spent relatively more time (reddit.com/r/changelog/comments/7hkvjn). Furthermore, Reddit also customized the home page so to remove posts with which the user already interacted (reddit.com/r/changelog/comments/7j5w9f).

B.2 Classification of Subreddits

As anticipated, Reddit is divided in more than 900,000 subreddits (in June, 2016). Thus, to classify the type of each subreddit, we must first define an exhaustive list of political fora and, within this list, manually inspect each subreddit to determine its slant (if any). To define a list of political fora, we start from the 1,417 biggest fora by total number of comments (during our sample period) written by users who have posted or commented at least once on `r/politics`. Together, these 1,417 fora host 90% of their comments on the platform in our period. Within these subreddits, we identify forums that discuss politics as those subreddits whose main focus is the discussion of US Politics, US politicians, and political ideologies. Subreddits that discuss topics and social issues such as gender and racial discrimination, religion, free speech, police brutality, guns, or the environment, are also classified under this label when it is clear that the political aspect of such issues is debated within the forum. Within political fora, we distinguish between independent, partisan, and ideological forum, following the discussion in Section 1.1. To distinguish between partisan (supporting a candidate) and ideological (supporting an ideology), we require that the forum is centered around a person vs. around an ideology or party. Partisan fora are then further divided in three categories: pro Trump, pro Clinton, and supporting others (Bernie Sanders, Jill Stein). Ideological fora are divided in Pro Democrats, Pro Republicans, and Others. Table B.1 reports all the political fora, along with their classification.

B.3 Figures

Figure B.1: Distribution of Trump and Clinton Partisanship

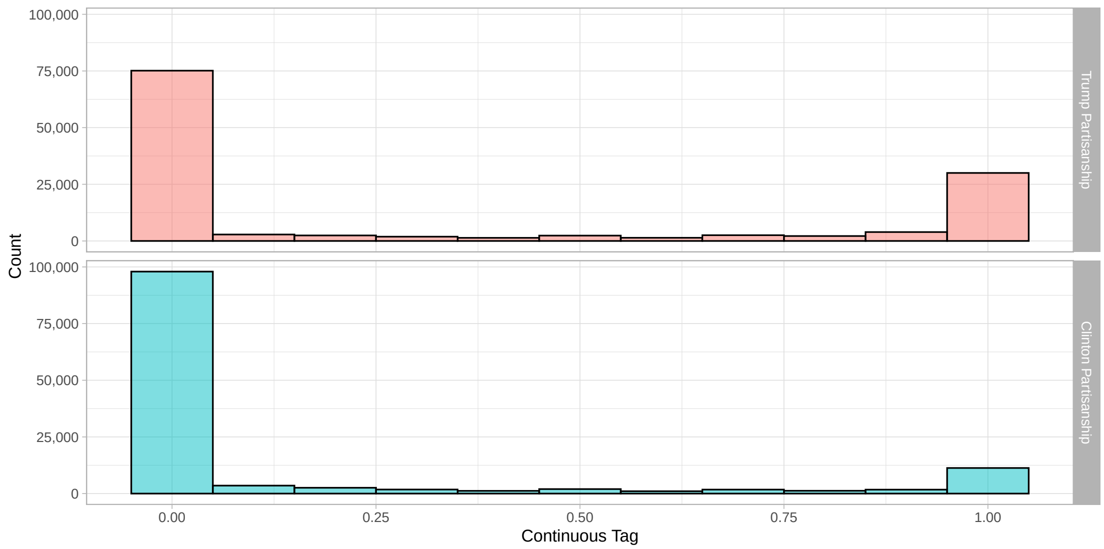
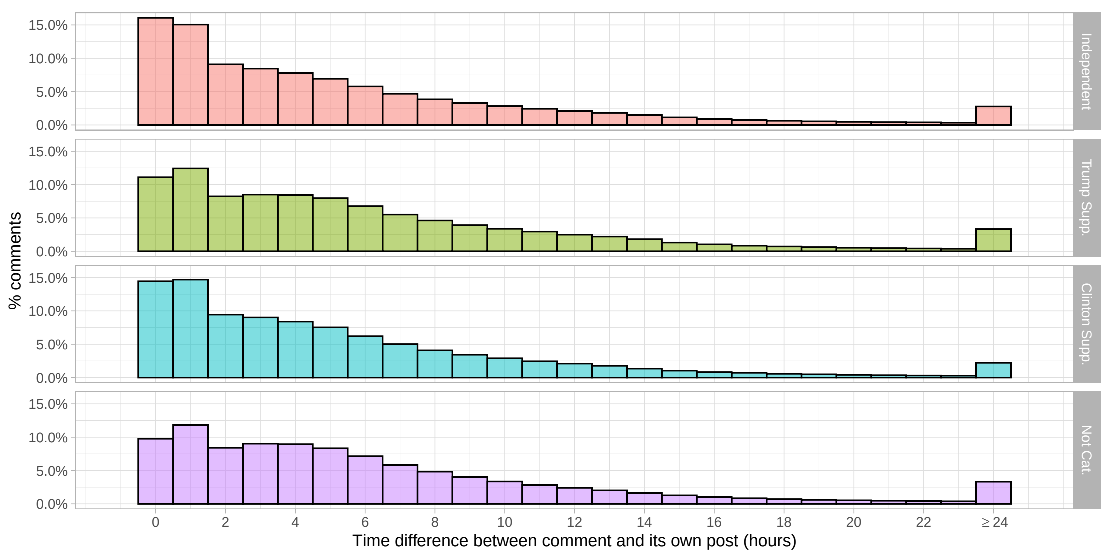


Figure B.2: % of comments by time distance from own post



B.4 Tables

Table B.1: Classification of Political Subfora

Subreddit	Classification	Subreddit	Classification
/r/againsthatesubreddits	Ideological (Others)	/r/latestagecapitalism	Ideological (Others)
/r/altright	Ideological (Rep)	/r/liberal	Ideological (Dem)
/r/anarchism	Ideological (Others)	/r/libertarian	Ideological (Others)
/r/anarcho_capitalism	Ideological (Others)	/r/lostgeneration	Ideological (Others)
/r/ask_politics	Independent	/r/menslib	Ideological (Others)
/r/askfeminists	Ideological (Others)	/r/mensrights	Ideological (Others)
/r/askhillarysupporters	Partisan (Pro Clinton)	/r/modelusgov	Ideological (Others)
/r/askthe_donald	Partisan (Pro Trump)	/r/neutralnews	Independent
/r/asktrumpsupporters	Partisan (Pro Trump)	/r/neutralpolitics	Independent
/r/bad_cop_no_donut	Ideological (Others)	/r/politic	Independent
/r/basicincome	Ideological (Others)	/r/political_revolution	Partisan (OC)
/r/bestofoutrageculture	Ideological (Others)	/r/politicaldiscussion	Independent
/r/capitalismvsocialism	Ideological (Others)	/r/politicalhumor	Independent
/r/conservative	Ideological (Rep)	/r/politicalvideo	Independent
/r/debatefascism	Ideological (Others)	/r/politics	Independent
/r/democrats	Ideological (Dem)	/r/progressive	Ideological (Dem)
/r/dncleaks	Ideological (Others)	/r/progun	Ideological (Others)
/r/energy	Independent	/r/republican	Ideological (Rep)
/r/enough_sanders_spam	Ideological (Others)	/r/sandersforpresident	Partisan (OC)
/r/enoughlibertarianspam	Ideological (Others)	/r/sargonofakkad	Ideological (Others)
/r/enoughsandersspam	Ideological (Others)	/r/shitamericanssay	Ideological (Others)
/r/enoughtrumpspam	Partisan (Pro Clinton)	/r/shitliberalssay	Ideological (Others)
/r/environment	Independent	/r/shitpoliticssays	Ideological (Others)
/r/feminism	Ideological (Others)	/r/shitredditsays	Ideological (Others)
/r/femradebates	Ideological (Others)	/r/shitstatistssay	Ideological (Others)
/r/forwardsfromgrandma	Ideological (Others)	/r/sjwhate	Ideological (Others)
/r/fullcommunism	Ideological (Others)	/r/socialism	Ideological (Others)
/r/garyjohnson	Partisan (OC)	/r/socialjusticeinaction	Ideological (Others)
/r/geopolitics	Independent	/r/the_donald	Partisan (Pro Trump)
/r/goldandblack	Ideological (Others)	/r/the_meltdown	Ideological (Others)
/r/gunpolitics	Ideological (Others)	/r/topmindsofreddit	Ideological (Others)
/r/gunsarecool	Ideological (Others)	/r/tumblrinaction	Ideological (Others)
/r/hillaryclinton	Partisan (Pro Clinton)	/r/uncensorednews	Ideological (Others)
/r/hillaryforamerica	Partisan (Pro Clinton)	/r/wayofthebern	Partisan (OC)
/r/hillaryforprison	Partisan (Pro Trump)	/r/wikileaks	Ideological (Others)
/r/jillstein	Partisan (OC)	/r/worldpolitics	Independent
/r/kossacks_for_sanders	Partisan (OC)		

Notes: Rep = "Republican Party/Conservative Ideology", Dem = "Democratic Party", OC = "Other Candidate"

Table B.2: Use of different online platforms by demographic groups

	YouTube	Facebook	Instagram	Pinterest	LinkedIn	Snapchat	Twitter	WhatsApp	Reddit
U.S. adults	73%	69%	37%	28%	27%	24%	22%	20%	11%
Men	78	63	31	15	29	24	24	21	15
Women	68	75	43	42	24	24	21	19	8
White	71	70	33	33	28	22	21	13	12
Black	77	70	40	27	24	28	24	24	4
Hispanic	78	69	51	22	16	29	25	42	14
Ages 18-29	91	79	67	34	28	62	38	23	22
18-24	90	76	75	38	17	73	44	20	21
25-29	93	84	57	28	44	47	31	28	23
30-49	87	79	47	35	37	25	26	31	14
50-64	70	68	23	27	24	9	17	16	6
65+	38	46	8	15	11	3	7	3	1
<$30,000	68	69	35	18	10	27	20	19	9
$30,000 - $74,999	75	72	39	27	26	26	20	16	10
$75,000+	83	74	42	41	49	22	31	25	15
High school or less	64	61	33	19	9	22	13	18	6
Some college	79	75	37	32	26	29	24	14	14
College+	80	74	43	38	51	20	32	28	15
Urban	77	73	46	30	33	29	26	24	11
Suburban	74	69	35	30	30	20	22	19	13
Rural	64	66	21	26	10	20	13	10	8

Notes: % of U.S. adults who say they ever use the following online platforms or messaging apps. (Pew Research Center, 2019)

Table B.3: **Top 50 News Media Websites in Reddit and Comscore**

News Source	`r/politics` shares (%)	All media shares (%)	Political sources shares (%)
thehill	9.92	2.10	15.26
washingtonpost	9.19	5.53	
politico	9.12	2.04	12.79
cnn	5.92	11.36	19.19
huffpost	4.74	2.70	2.14
vox	3.30	1.76	
nytimes	3.24	5.80	
nbcnews	2.74	5.51	4.56
theguardian	2.54	2.58	0.13
abcnews	2.21	1.79	
salon	2.19	0.23	2.23
thedailybeast	2.14	1.00	
youtube	1.97		
fox	1.93	7.45	7.89
businessinsider	1.78	4.51	
latimes	1.70	2.19	
talkingpointsmemo	1.70	0.07	
dailycaller	1.58	0.31	
cbsnews	1.54	3.81	
usatoday	1.53	4.41	
thinkprogress	1.53	0.13	
slate	1.51	0.95	
politifact	1.46	0.17	0.54
cnbc	1.39	4.13	
washingtonexaminer	1.27	0.58	2.65
washingtontimes	1.26	0.46	
ap	1.23	0.09	
buzzfeed	1.20	3.58	
bloomberg	1.18	2.03	
reuters	1.17	1.60	
nydailynews	1.13	1.21	0.43
breitbart	1.09	0.45	
msnbc	1.02	0.52	8.20
nymag	1.00	1.04	
time	0.99	1.85	
motherjones	0.99	0.24	1.01
dailymail.co.uk	0.94		
nypost	0.91	3.35	
commondreams	0.86	0.06	
independent.co.uk	0.82		
yahoo	0.80		

News Source	`r/politics` shares (%)	All media shares (%)	Political sources shares (%)
fivethirtyeight	0.74		
npr	0.65	2.68	
theintercept	0.64	0.07	
theatlantic	0.64	1.51	
thenation	0.60	0.08	0.22
fortune	0.57	0.61	
chicagotribune	0.50	0.96	
esquire	0.49		
vice	0.42	1.67	

C Supplementary Appendix to Section 2

C.1 Notes on the Construction of the Isolation Index

Our adaptation of the isolation index used in Gentzkow and Shapiro (2011) is the result of certain methodological choices that we deem consistent with the context we study. This section further clarifies our measure of segregation and it outlines alternative ways to construct the index. Results displayed in section C.2 show that results are qualitatively unchanged when these alternative measures are adopted.

Selection of Sources: When studying the segregation across sources, we follow Gentzkow and Shapiro (2011) in restricting the set of sources we consider to national political news and opinion websites. We thus exclude local news and opinion websites, websites devoted exclusively to non-political topics and general news aggregation websites and platforms (such as Yahoo! News and Youtube). We consider only sources with at least 100 comments from June 1 to November 7, 2016. About 7.8% of the sources with at least 100 comments is not accessible anymore, nor it is possible to recover any useful information regarding their scope. For this reason, they have been excluded from the set of sources used to compute the Isolation Index. The final number of websites included amounts to 855.

Margin of Segregation: Our main results focus on the intensive margin of segregation, given by the total number of comments on each outlet. Instead, the index reported in Gentzkow and Shapiro (2011) captures the margin of segregation, given by the daily visits to each outlet. A user *visits* an outlet if she comments that outlet at least once. We aggregate visits at the daily level to increase comparability of our results with those of Gentzkow and Shapiro (2011).[42] Since postings and sources are different in nature – each post is posted only once, while sources are posted multiple times – we use two distinct definitions of daily visits. For sources, we measure the extensive margin using the average daily number of visits. We define the number of visits to a source in a given day as the number of users that commented that source in that day. We then take the average of this number in the period for each source to obtain the average daily visits to the source. TS_j^F and CS_j^F in Eq. (1) are thus defined as the average daily number of visits to source j by Trump and Clinton supporters, respectively. For posts, we use the total number visits to the post. TS_j^F and CS_j^F in Eq. (1) are then given by the total number of visits to post j by Trump and Clinton supporters. It would not be reasonable to use the average daily visits for postings since they are observed for a much more limited time period compared to sources. Indeed, the activity on posts lasts approximately one day, as shown in Figure B.2. However, exactly for this reason the idea of average daily visits to sources and total visits to posts are strictly comparable in terms of the temporal granularity that we consider. Similarly, total visits should not be used for sources since, especially in the aggregate period, the probability that a user will comment, and thus visit, a given source increases considerably and the index would not properly capture the extent of segregation in the fora.

Treatment of Non-Partisan Users: In our construction of the isolation index, we drop non-partisan users. That is, we consider only the activity of Trump and Clinton supporters, dropping Independents and non-classified users from the sample. An alternative approach, preferred by Gentzkow and Shapiro (2011), is to impute the ideology of these users. To do this, we need to assume that every user has a true ideology that is either Pro Clinton or Pro Trump. Let $Indep_j$ be the number of comments by Independents to outlet j. We impute the unobserved ideology of $Indep_j$ by assuming that the share of Trump (Clinton) supporters among them is equal to the share of comments by Trump (Clinton) supporters among partisan users who

[42] For a deeper discussion on time aggregation, see Section VI.A in Gentzkow and Shapiro (2011).

commented outlet j. For Trump supporters, this is equal to the share conservative of outlet j. We impute in the same way the share of Trump and Clinton supporters among Not Classified users. We then replace TS_j^F and CS_j^F in Eq. (1) with their respective imputed analogues. Similarly, we impute the partisanship of non-partisan users for daily visits, considering these and not the total number of comments in the imputation procedure.

Segregation of Ideological Users: So far we have only focused on the segregation of partisan users, Trump and Clinton supporters. However, the isolation index could be used to compute the segregation of ideological (Conservative vs. Liberal) users. To calculate this, we need to first classify users as Conservatives or Liberals. This is done in a similar way to the categorization of users shown in Algorithm 1. In this case, however, we replace *partisan fora* with *ideological and partisan fora*, in the specification of the algorithm. In particular, the subfora relevant to the classification of Conservative users are those classified as of Pro-Trump partisanship or of Republican ideology in table B.1. Those that define Liberals instead are those categorized as of Pro-Clinton partisanship or of Democrat ideology. This algorithm thus assigns users to four categories: Independents, Conservatives, Liberals, and Non-Classified. We can then compute the various versions of the isolation index replacing TS_j^F (CS_j^F) with the analogous term for Conservative (Liberal) users. Accordingly, when studying segregation across sources outside of `r/politics`, we include to the set of partisan fora also the Democrat and Republican subfora, as defined in table B.1.

Estimation of the Share Conservative: In Equation (1), we rely on a joint estimation of outlet's share conservatives. That is, we estimate the share conservative on a given outlet using the activity on that outlet in all subfora considered. This allows us to fix this measure across fora and to better compare the extent segregation in `r/politics` vs. partisan or ideological fora. An alternative approach is to estimate these values separately in each set of fora (e.g., using the activity only on `r/politics` to compute the share conservatives of outlets in `r/politics`). In this case, we simply modify Eq. (1), replacing TS_j and CS_j with TS_j^F and CS_j^F, respectively. Recall that each post lives only in one forum, hence this distinction is relevant only for the segregation across sources. Indeed, for posts $TS_j = TS_j^F$ and $CS_j = CS_j^F$ hold by definition. Hence, separate and joint estimation of the posts' share conservatives are equivalent and yield the same estimates of the isolation index.

C.2 Robustness Checks

Tables C.2a, and C.2b present several robustness checks, according to the possible choices defined above. These tables compare segregation across sources on `r/politics` with segregation across news in `r/politics` and with segregation across sources on partisan fora. These are reported in, respectively, the first, second and third column, within each group of three columns.

As anticipated, we perform the following robustness checks:

i. Extensive vs. Intensive Margin of Segregation. In both Tables, this is reported in Columns (1) to (6) (intensive margin) vs. Columns (7) to (12) (extensive margin).

ii. Including Democrats and Republicans, in addition to Trump and Clinton Supporters. In all Tables, this is reported in Panels B vs. Panels A, respectively.

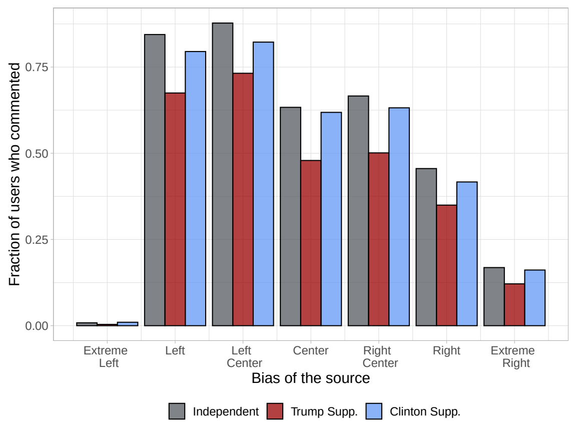
iii. Dropping vs. imputing Independents and Non-Classified. In all Tables, this is reported in Columns (1) to (3), and (7) to (9) vs. (4) to (6), and (10) to (12), respectively.

iv. Jointly vs. separately estimating the Share Conservative of sources. Table C.2a vs. C.2b, respectively. As this variation does not affect the measure of segregation across postings, those estimates are left unchanged, as seen comparing the respective columns in Tables C.2a and C.2b.

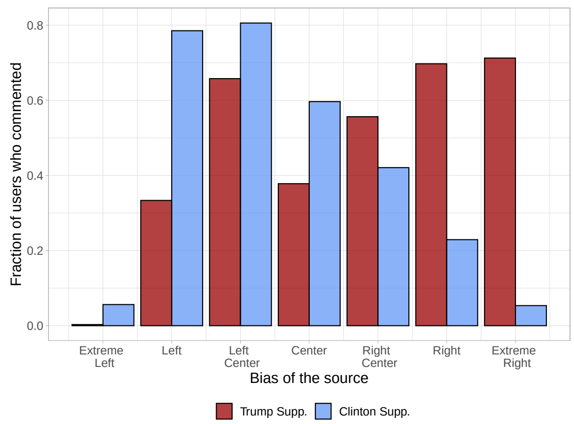
C.3 Figures

Figure C.1: Extensive Margin of Activity, by Bias of the Source

(a) Activity of `r/politics` users on `r/politics`



(b) Activity of `r/politics` Users on PF



Notes: The set of partisan fora includes only pro-Trump and pro-Clinton partisan fora, as defined in Table B.1. The figure reports $S_E = \text{User}_{pb}/\text{User}_p$, where User_{pb} is the number of users with affiliation p that commented posts sharing news from sources with a bias of b and User_p is the number of users with affiliation p on `r/politics`. Since users can comment multiple sources, this index does not sum to one across the different b. On the extreme example in which all users of affiliation p comment all type of sources, the sum of the index across b equals the number of media bias categories (seven). Throughout, we consider activity restricted to our sample window (June 1–November 7, 2016).

C.4 Tables

Table C.1: Isolation Index

(a) Share Conservative Jointly Estimated

Margin	Intensive (# of Comments)						Extensive (Daily Visits)					
Strategy	Dropped			Imputed			Dropped			Imputed		
Subreddit	`r/politics`		PF	`r/politics`		PF	`r/politics`		PF	`r/politics`		PF
Across	Sources (1)	News (2)	Sources (3)	Sources (4)	News (5)	Sources (6)	Sources (7)	News (8)	Sources (9)	Sources (10)	News (11)	Sources (12)
Panel A: Trump Supp. vs Clinton Supp.												
2016-06	0.031	0.244	0.269	0.034	0.245	0.271	0.026	0.220	0.275	0.035	0.223	0.285
2016-07	0.018	0.162	0.322	0.019	0.171	0.311	0.021	0.177	0.281	0.027	0.179	0.291
2016-08	0.015	0.215	0.380	0.017	0.234	0.377	0.016	0.224	0.421	0.022	0.234	0.427
2016-09	0.024	0.200	0.339	0.025	0.218	0.337	0.030	0.233	0.365	0.035	0.246	0.373
2016-10	0.013	0.219	0.381	0.014	0.229	0.380	0.009	0.238	0.419	0.012	0.241	0.428
2016-11	0.029	0.207	0.397	0.028	0.227	0.393	0.024	0.241	0.410	0.028	0.257	0.414
Aggregate	0.016	0.240	0.315	0.017	0.255	0.309	0.018	0.276	0.322	0.019	0.283	0.320
Panel B: Conservatives vs Liberals												
2016-06	0.030	0.241	0.262	0.033	0.241	0.261	0.025	0.215	0.274	0.032	0.219	0.281
2016-07	0.018	0.159	0.319	0.020	0.167	0.309	0.017	0.172	0.278	0.021	0.174	0.292
2016-08	0.014	0.211	0.362	0.015	0.229	0.358	0.015	0.219	0.401	0.021	0.229	0.405
2016-09	0.024	0.199	0.332	0.024	0.215	0.332	0.029	0.230	0.361	0.033	0.242	0.371
2016-10	0.012	0.212	0.359	0.012	0.222	0.356	0.008	0.231	0.399	0.011	0.234	0.407
2016-11	0.027	0.201	0.380	0.027	0.221	0.375	0.021	0.234	0.392	0.024	0.249	0.398
Aggregate	0.016	0.234	0.305	0.016	0.248	0.299	0.017	0.268	0.312	0.018	0.274	0.310

(b) Share Conservative Separately Estimated

Margin	Intensive (# of Comments)						Extensive (Daily Visits)					
Strategy	Dropped			Imputed			Dropped			Imputed		
Subreddit	`r/politics`		PF	`r/politics`		PF	`r/politics`		PF	`r/politics`		PF
Across	Sources (1)	News (2)	Sources (3)	Sources (4)	News (5)	Sources (6)	Sources (7)	News (8)	Sources (9)	Sources (10)	News (11)	Sources (12)
Panel A: Trump Supp. vs Clinton Supp.												
2016-06	0.033	0.244	0.546	0.038	0.245	0.562	0.027	0.220	0.538	0.038	0.223	0.564
2016-07	0.017	0.162	0.475	0.019	0.171	0.487	0.018	0.177	0.497	0.025	0.179	0.526
2016-08	0.016	0.215	0.615	0.019	0.234	0.626	0.019	0.224	0.623	0.028	0.234	0.643
2016-09	0.020	0.200	0.600	0.021	0.218	0.610	0.026	0.233	0.608	0.034	0.246	0.626
2016-10	0.020	0.219	0.629	0.022	0.229	0.639	0.023	0.238	0.647	0.033	0.241	0.664
2016-11	0.042	0.207	0.600	0.044	0.227	0.619	0.047	0.241	0.608	0.055	0.257	0.625
Aggregate	0.012	0.240	0.522	0.013	0.255	0.531	0.014	0.276	0.510	0.015	0.283	0.515
Panel B: Conservatives vs Liberals												
2016-06	0.033	0.241	0.506	0.038	0.241	0.514	0.027	0.215	0.510	0.036	0.219	0.535
2016-07	0.018	0.159	0.461	0.020	0.167	0.473	0.016	0.172	0.483	0.023	0.174	0.518
2016-08	0.015	0.211	0.564	0.017	0.229	0.575	0.019	0.219	0.587	0.027	0.229	0.609
2016-09	0.020	0.199	0.566	0.021	0.215	0.576	0.024	0.230	0.580	0.031	0.242	0.599
2016-10	0.020	0.212	0.569	0.021	0.222	0.575	0.021	0.231	0.598	0.031	0.234	0.614
2016-11	0.041	0.201	0.544	0.042	0.221	0.554	0.044	0.234	0.566	0.050	0.249	0.588
Aggregate	0.011	0.234	0.488	0.013	0.248	0.495	0.013	0.268	0.481	0.014	0.274	0.488

Notes: Partisan Fora include only pro-Clinton, pro-Trump partisan fora, as defined in Table B.1. The month of November includes only comments to posts up to November 7. In columns with strategy Dropped, Independents and Non-Classified users are excluded from the sample. They are included and their ideology is imputed as in Gentzkow and Shapiro (2011) in the other columns. For the extensive margin of segregation, the average daily number of visits to each source is used to compute the segregation across sources and the total number of visits to each post for the one across news. In Panel A, the share conservative of each outlet was estimated using jointly the activity of `r/politics` users on `r/politics` and Partisan Fora. In Panel B, the share conservative was estimated separately for each set of fora.

Table C.2: Phrases Associated with Share Conservative of the Post

Panel A: Phrases More Associated with Above Median Share Conservative

One-Word Phrases

gun	brexit	muslim	nra	sitin	racist
dnc	white	terrorist	cop	black	israel
convent	elizabeth	shooter	american	attack	fbi
orlando	ban	deleg	mass	dept	kill
shoot	obama	eu	wasserman	cleveland	loretta
email	dalla	violenc	san	classifi	
warren	control	lynch	pneumonia	nation	
terror	jose	speech	schultz	refuge	
polic	protest	us	matter	live	

Two-Word Phrases

gun control	brexit vote	attack judg
elizabeth warren	second amend	dnc chair
dnc email	gun law	democrat convent
san jose	convent speech	russia hack
nation convent	hack dnc	donor feder
democrat nation	gop convent	gun right
wasserman schultz	baton roug	orlando massacr
live matter	debbi wasserman	jimmi fallon
black live	background check	plan reward
mass shoot	gun violenc	reward big
orlando shoot	orlando shooter	show plan
clinton email	muhammad ali	obama administr
state dept	immun deal	hous democrat
clinton aid	state depart	muslim ban
loretta lynch	vote leav	watch list
republican convent	polic shoot	trump nomin
leak dnc	republican nation	

Table C.3: Phrases Associated with Share Conservative of the Post

Panel B: Phrases More Associated with Below Median Share Conservative

One-Word Phrases

trump	sexual	earli	women	kellyann	donald
stein	conway	ryan	accus	battleground	alleg
jill	lead	campaign	hanniti	lose	assang
debat	wikileak	vote	florida	rudi	sex
tape	giuliani	christi	billi	gari	cathol
green	win	mccain	mcmullin	presidenti	
elect	grope	lepag	point	mic	
poll	breitbart	penc	apprentic	manafort	
lewd	paul	utah	voter	chairman	

Two-Word Phrases

jill stein	trump lose	eric trump
green parti	trump say	nomine jill
poll clinton	john mccain	trump spokeswoman
earli vote	parti jill	debat delet
trump tape	trump surrog	trump apolog
trump foundat	presidenti debat	elect result
trump campaign	paul ryan	central park
clinton lead	lewd remark	lewd comment
elect day	main governor	evan mcmullin
sexual assault	paul manafort	trump grope
billi bush	poll place	accept elect
lead trump	vote jill	trump tv
kellyann conway	parti presidenti	chris christi
trump lewd	gari johnson	taco truck
paul lepag	order trump	mccain withdraw
rudi giuliani	sean hanniti	nuclear war
candid jill	manafort resign	

D Supplementary Appendix to Section 4

D.1 Figures

Figure D.1: Distribution of Number of comments by Author

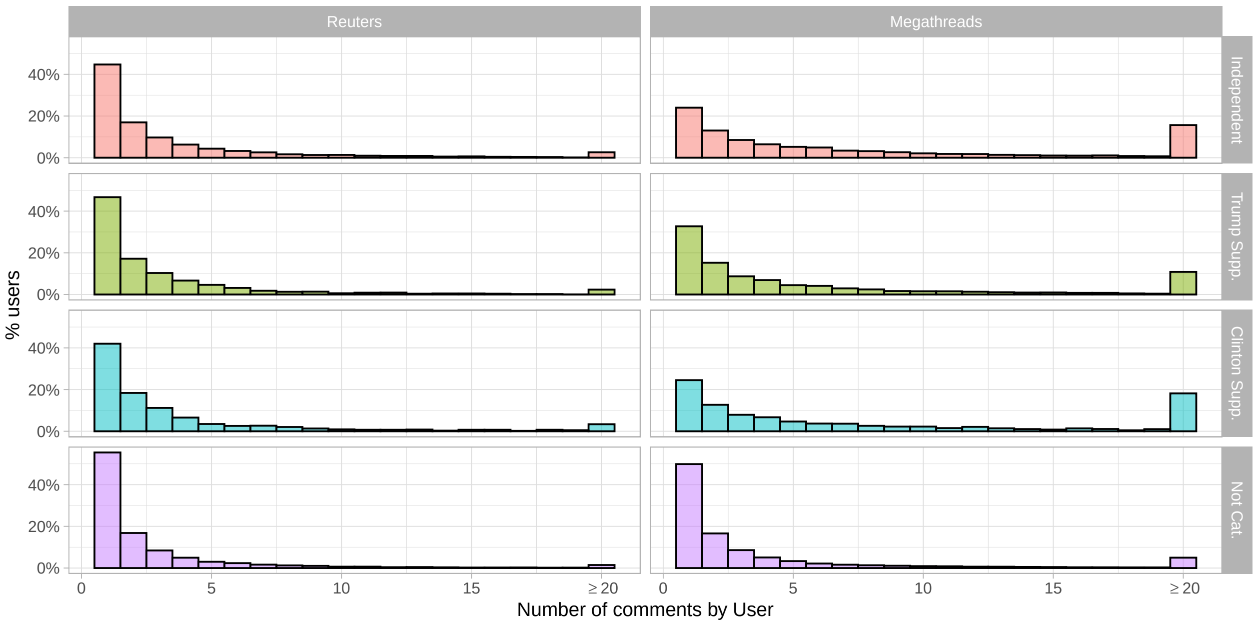
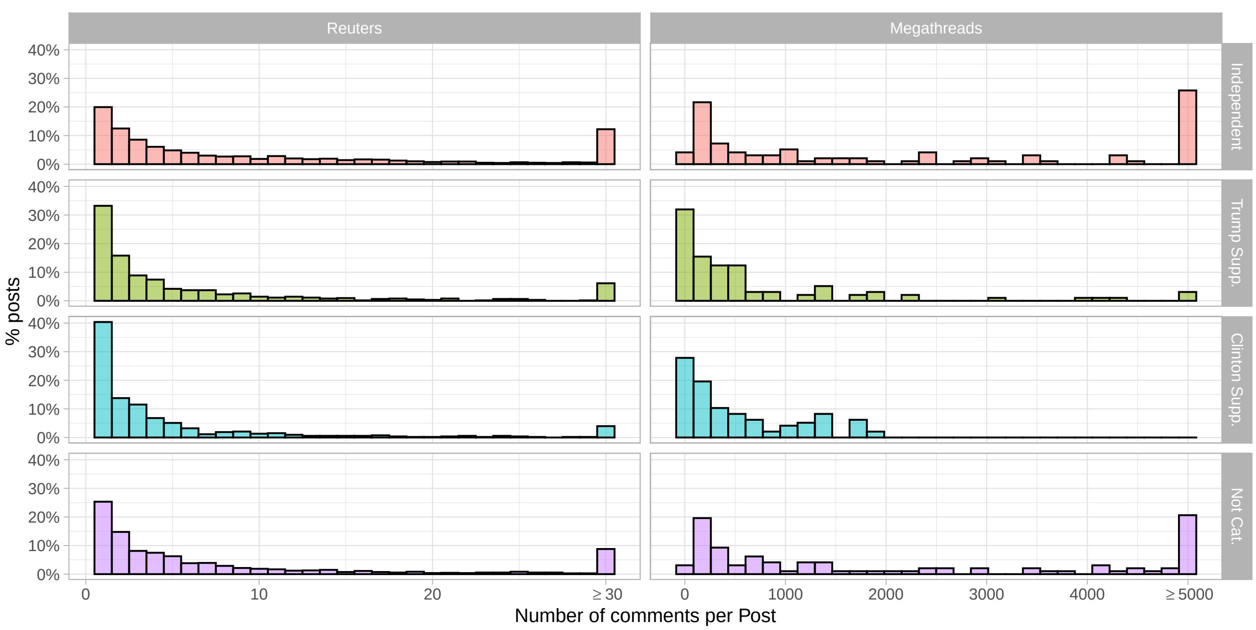


Figure D.2: Distribution of Number of comments Per Post



D.2 Tables

Table D.1: Features of the debate: average number of comments per post by affiliation

	Set of posts:						
		Reuters			Megathreads		
	All	All	BNT	BNC	All	BNT	BNC
Trump Supporters	7.31	5.02	7.78	8.07	792.00	459.40	1,571.00
Clinton Supporters	4.70	3.01	4.69	3.09	544.09	789.40	577.38
Independents	30.11	19.77	33.22	29.30	3,191.88	3,219.80	3,202.62
Non-classified	26.26	16.42	27.42	27.43	2,752.76	2,525.40	4,502.12
Total number of comments	8,301,495	59,704	5,264	7,060	706,231	34,970	78,825
Total number of posts	121,411	1,350	72	104	97	5	8
Average number of comments per post	68.38	44.23	73.11	67.88	7,280.73	6,994.00	9,853.12

Notes: Comments appearing in Megathreads and reported above refer to the whole Megathread, not to individual posts collected within each Megathread.

Table D.2: Number of Active Authors on r/politics

	Set of Posts		
	r/politics	Reuters	Megathreads
Trump Supporters	20,725	1,842	7,019
Clinton Supporters	5,740	974	2,948
Independents	44,879	6,884	20,919
Total Classified	71,344	9,700	30,886
Not Classified	215,243	7,722	47,188

Table D.3: All Scandals on Megathreads

Type	Title	Url
Bad News Clinton	Comey: FBI recommends no indictment re: Clinton emails	`https://www.reddit.com/r/politics/comments/4rd7ly/`
Bad News Clinton	DNC Email Leak Megathread	`https://www.reddit.com/r/politics/comments/4u5ztv/`
Bad News Clinton	Debbie Wasserman Schultz Resignation Megathread	`https://www.reddit.com/r/politics/comments/4uewdj/`
Bad News Clinton	DNC Email Leak Megathread	`https://www.reddit.com/r/politics/comments/4uive8/`
Bad News Trump	Trump campaign chairman Paul Manafort resigns megathread	`https://www.reddit.com/r/politics/comments/4yj7po/`

Bad News Clinton	FBI Releases Documents in Hillary Clinton E-Mail Investigation Megathread	https://www.reddit.com/r/politics/comments/50utmo/
Bad News Clinton	Megathread - Clinton Campaign releases additional medical records	https://www.reddit.com/r/politics/comments/52sps2/
Bad News Trump	Megathread - Trump Foundation ordered to stop fundraising in NY	https://www.reddit.com/r/politics/comments/55oth1/
Bad News Trump	Megathread: Donald Trump leaked comments from 2005 re:women	https://www.reddit.com/r/politics/comments/56dqes/
Bad News Trump	Megathread 2: Donald Trump Leaked Video and Campaign Statement; GOP Statements	https://www.reddit.com/r/politics/comments/56fgfr/
Bad News Trump	Megathread 3: Donald Trump Leaked Video & Statement; GOP/RNC Reactions incl. defunding of Victory Project, cancelled events, and unendorsements	https://www.reddit.com/r/politics/comments/56igk9/
Bad News Clinton	Megathread: FBI reopens investigation into Clinton emails	https://www.reddit.com/r/politics/comments/59vuny/
Bad News Clinton	Megathread II: FBI / Clinton Emails	https://www.reddit.com/r/politics/comments/59y2ct/

Table D.4: Examples of Reuters Scandals and Bad Polls

Type	Title (URL)	Article Leading Paragraph
Bad News Clinton	'Lone hacker' claims responsibility for cyber attack on Democrats http://www.reuters.com/article/us-usa-election-hack-idUSKCN0Z209Q	A "lone hacker" has taken responsibility for a cyber attack on the U.S. Democratic National Committee, which the DNC and a cyber-security firm have blamed on the Russian government.
Bad News Trump	Ruling against ex-AIG boss Greenberg raises stakes in Trump University case http://www.reuters.com/article/us-usa-election-trumpuniversity-idUSKCN0YT2M2	A ruling by New York's highest court in a fraud case against former American International Group Inc AIG.N Chief Executive Maurice "Hank" Greenberg could affect the state's case against Republican presidential candidate Donald Trump and his defunct Trump University.
Bad Poll Clinton	Clinton's lead over Trump slips after Florida shooting: Reuters/Ipsos poll http://www.reuters.com/article/us-usa-election-poll-idUSKCN0Z32BX	Donald Trump chipped away at Hillary Clinton's lead in the presidential race this week, according to a Reuters/Ipsos poll released on Friday, as the candidates clashed over how to respond to the worst mass shooting in modern U.S. history.
Bad Poll Trump	Clinton opens up double-digit lead over Trump nationwide: Reuters/Ipsos poll http://www.reuters.com/article/us-usa-election-poll-idUSKCN0YP2EX?	Democratic presidential contender Hillary Clinton has opened up a double-digit lead over Republican rival Donald Trump, regaining ground after the New York billionaire briefly tied her last month, according to a Reuters/Ipsos poll released on Friday.

Table D.5: i, p **Level Dataset Summary Statistics**

Panel A: Balanced Dataset

	Reuters		Megathreads	
	Mean	St. Dev.	Mean	St. Dev.
Number of Comments	0.287	13.317	14.660	189.428
Comments Dummy	0.141	3.757	3.257	17.752
Number of First Level Comments	0.052	2.309	4.656	82.230
First Level Comments Dummy	0.051	2.267	1.385	11.687

Panel B: Unbalanced Dataset

	Reuters		Megathreads	
	Mean	St. Dev.	Mean	St. Dev.
Number of Comments	202.804	290.505	450.078	951.661
Number of First Level Comments	36.766	49.216	142.947	433.385
First Level Comments Dummy	36.366	48.107	42.519	49.437

Notes: Variables are all multiplied by 100.

Table D.6: Activity Analysis of News on Reuters and Megathreads, Robustness to Using the Narrow Definition of Polls

	Dependent variable: Comments of User i on Post p ($\times$ 100)							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reuters								
Consonant News$_{i,p}$ (β_1)	0.2091**	0.0482	0.0478	0.0461	0.1034**	0.0475**	0.0473**	0.0465**
	(0.1050)	(0.0628)	(0.0624)	(0.0623)	(0.0430)	(0.0225)	(0.0223)	(0.0223)
Non-consonant News$_{i,p}$ (β_2)	0.0690	-0.1179^{**}	-0.1152^{*}	-0.1137^{*}	0.0201	-0.0347	-0.0336	-0.0329
	(0.0959)	(0.0595)	(0.0596)	(0.0596)	(0.0384)	(0.0223)	(0.0224)	(0.0224)
Trump Mentions$_p$ $\times$ Trump Supporter$_i$ (γ_1)		15.5384*	14.3265	14.5741		-0.6863	-1.2190	-1.1031
		(9.2726)	(9.4534)	(9.4646)		(3.1920)	(3.4262)	(3.4264)
Clinton Mentions$_p$ $\times$ Clinton Supporter$_i$ (γ_2)		34.0205	31.1246	30.5390		10.1704	8.7336	8.4595
		(23.8751)	(24.7575)	(24.7782)		(6.9009)	(7.0745)	(7.0807)
Trump Mentions$_p$ $\times$ Clinton Supporter$_i$ (γ_3)		5.6073	4.5972	4.2358		4.8651	4.4155	4.2463
		(7.3924)	(6.9373)	(6.9438)		(3.0602)	(2.8029)	(2.8054)
Clinton Mentions$_p$ $\times$ Trump Supporter$_i$ (γ_4)		10.7189	8.1401	8.4632		2.4266	1.1118	1.2630
		(25.6302)	(25.8996)	(25.8984)		(7.0768)	(7.1712)	(7.1684)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value ($\beta_1 - \beta_2$)	0.0454	0.0230	0.0257	0.0284	0.0037	0.0120	0.0135	0.0152
Dep. Var Mean	0.2870	0.2870	0.2870	0.2870	0.1410	0.1410	0.1410	0.1410
Observations	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000
R2	0.0000	0.0013	0.0099	0.0110	0.0000	0.0025	0.0195	0.0212
Panel B: Megathreads								
Consonant News$_{i,p}$ (β_1)	8.7905*	10.2515***	10.2581***	9.7188***	4.4683***	3.3568***	3.3588***	3.3323***
	(5.0343)	(2.6070)	(2.6083)	(2.6426)	(1.5884)	(0.8614)	(0.8619)	(0.8602)
Non-consonant News$_{i,p}$ (β_2)	-2.7194	1.2403	1.2358	1.6064	0.1316	-0.9466	-0.9480	-0.9298
	(3.6813)	(2.8021)	(2.8015)	(2.8538)	(0.7975)	(0.5934)	(0.5933)	(0.5948)
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value ($\beta_1 - \beta_2$)	0.0018	0.0001	0.0001	0.0004	0.0009	0.0000	0.0000	0.0000
Dep. Var Mean	14.6600	14.6600	14.6600	14.6600	3.2570	3.2570	3.2570	3.2570
Observations	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942
R2	0.0001	0.0260	0.0335	0.0851	0.0015	0.0255	0.0508	0.0933

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. For Reuters, post p is Consonant News for author i if it reports a scandal or a negative poll affecting the candidate opposed by i and Non-consonant News if it reports a scandal or a negative poll affecting the candidate supported by i. For Megathreads, only scandals are considered, since negative polls are not defined. Dependent variable is multiplied by 100. Sample restricted to comments of authors classified as either Trump Supporters, Clinton Supporters or Independent. Panel A estimates in columns (2) to (4) and (6) to (8) include additional controls not reported in table: i) Post Author Trump Supporter$_p$ $\times$ Trump Supporter$_i$ ii) Post Author Clinton Supporter$_p$ $\times$ Trump Supporter$_i$ iii) Post Author Trump Supporter$_p$ $\times$ Clinton Supporter$_i$ iv) Post Author Clinton Supporter$_p$ $\times$ Clinton Supporter$_i$ v) Post reports a Poll$_p$ vi) Post reports a Poll$_p$ $\times$ Trump Supporter$_i$ vii) Post reports a Poll$_p$ $\times$ Clinton Supporter$_i$ viii) Posted Article Length$_p$ ix) Posted Article Length$_p$ $\times$ Trump Supporter$_i$ x) Posted Article Length$_p$ $\times$ Clinton Supporter$_i$ xi) Post Author Non-Classified$_p$ $\times$ Trump Supporter$_i$ xii) Post Author Non-Classified$_p$ $\times$ Clinton Supporter$_i$ xiii) Author Activity Within 5 Days from Post$_{i,p}$ Panel A estimates in columns (2),(3),(6),(7) include the following controls not reported in table: xiv) Trump Supporter$_i$ xv) Clinton Supporter$_i$ Panel A estimates in columns (2) and (6) include the following controls not reported in table: xvi) Trump Scandal$_p$ xvii) Clinton Scandal$_p$ xviii) Bad Poll Trump$_p$ xix) Bad Poll Clinton$_p$ Panel B estimates in columns (2) to (4) and (5) to (8) include the following controls not reported in table: i) Post reports a Poll$_p$ ii) Post reports a Poll$_p$ $\times$ Trump Supporter$_i$ iii) Post reports a Poll$_p$ $\times$ Clinton Supporter$_i$ iv) Right Sources Share$_p$ $\times$ Trump Supporter$_i$ v) Right Sources Share$_p$ $\times$ Clinton Supporter$_i$ vi) Left Sources Share$_p$ $\times$ Trump Supporter$_i$ vii) Left Sources Share$_p$ $\times$ Clinton Supporter$_i$ viii) Right Sources Share$_p$ ix) Left Sources Share$_p$ x) Author Activity Within 5 Days from Post$_{i,p}$ Panel B estimates in columns (2),(3),(6),(7) include the following controls not reported in table: 11. Trump Supporter$_i$ 12. Clinton Supporter$_i$ Panel B estimates in columns (2) and (6) include the following controls not reported in table: 13. Trump Scandal$_p$ 14. Clinton Scandal$_p$

Table D.7: Activity Analysis, Polls and Scandals on Reuters, Robustness to Using Narrow Definition of Polls

	Dependent variable: Comments of User i on Post p ($\times$ 100)							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\beta_1 - \beta_2$, all Bad News	0.1401**	0.1598**			0.0833***	0.0795**		
	(0.0700)	(0.0729)			(0.0287)	(0.0327)		
$\beta_1^S - \beta_2^S$, only Scandals			0.0830	0.1172			0.0662**	0.0675*
			(0.0816)	(0.0819)			(0.0329)	(0.0359)
$\beta_1^P - \beta_2^P$, only Bad Polls			0.2964**	0.2582*			0.1335**	0.1072
			(0.1401)	(0.1444)			(0.0624)	(0.0670)
FE and Controls	No	Yes	No	Yes	No	Yes	No	Yes
Dep. Var Mean	0.2870	0.2870	0.2870	0.2870	0.1410	0.1410	0.1410	0.1410
Observations	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000
R2	0.0000	0.0110	0.0000	0.0110	0.0000	0.0212	0.0000	0.0212

Notes: OLS estimates of the difference of coefficients $\beta_1 - \beta_2$, two-way clustered standard errors at the i and p level in parenthesis. Dependent variable is multiplied by 100. Sample restricted to Reuters posts and comments of authors classified as either Trump Supporters, Clinton Supporters or Independent. "All Bad News" refers to specifications where Consonant and Non-consonant is defined using both scandals and bad polls, "only Scandals" and "only Bad Polls" are the specifications in which the effect of consonant and non-consonant scandals and bad polls is estimated separately. Controls and FEs are those defined in Table 6.

Table D.8: Activity Analysis, Reuters Sample, Baseline: OLS with Discrete Classification

	Dependent variable: Comments of User i on post p							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant News$_{i,p}$ (β_1)	0.2131**	0.0427	0.0415	0.0396	0.1109***	0.0475**	0.0469**	0.0460**
	(0.0964)	(0.0645)	(0.0641)	(0.0640)	(0.0397)	(0.0222)	(0.0221)	(0.0220)
Non-consonant News$_{i,p}$ (β_2)	0.0398	−0.1473**	−0.1462**	−0.1446**	0.0085	−0.0485**	−0.0483**	−0.0475**
	(0.0808)	(0.0650)	(0.0646)	(0.0646)	(0.0322)	(0.0235)	(0.0234)	(0.0234)
Post Clinton Mentions$_p$		62.6904				23.3522*		
		(39.2590)				(13.7038)		
Post Trump Mentions$_p$		−22.1774				−4.5730		
		(18.8484)				(7.8643)		
Post Trump Mentions$_p$ × Trump Supporter$_i$		16.5217*	15.3140	15.5508*		−0.1380	−0.6651	−0.5543
		(9.2581)	(9.4336)	(9.4447)		(3.1552)	(3.3839)	(3.3839)
Post Trump Mentions$_p$ × Clinton Supporter$_i$		4.9541	3.8901	3.5404		4.4604	3.9876	3.8239
		(7.3889)	(6.9294)	(6.9355)		(3.0537)	(2.7951)	(2.7974)
Post Clinton Mentions$_p$ × Trump Supporter$_i$		10.9474	8.3152	8.6587		2.3010	0.9741	1.1349
		(25.7971)	(26.0594)	(26.0583)		(7.1058)	(7.2025)	(7.1997)
Post Clinton Mentions$_p$ × Clinton Supporter$_i$		36.5308	33.6613	33.0646		11.3695	9.9604	9.6810
		(24.2488)	(25.0492)	(25.0686)		(7.0001)	(7.1550)	(7.1606)
Posted Article Length$_p$ × Trump Supporter$_i$		0.0000	0.0000	0.0000		0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Posted Article Length$_p$ × Clinton Supporter$_i$		−0.0000	−0.0000	−0.0000		−0.0000	−0.0000	−0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Post Author Trump Supporter$_p$ × Trump Supporter$_i$		−0.0827	0.1027	0.1031		−0.0141	0.0655**	0.0657**
		(0.1047)	(0.0758)	(0.0758)		(0.0405)	(0.0316)	(0.0316)
Post Author Clinton Supporter$_p$ × Clinton Supporter$_i$		0.0164	0.0266	0.0271		0.0668	0.0656***	0.0657***
		(0.1077)	(0.0500)	(0.0501)		(0.0581)	(0.0245)	(0.0245)
Post Author Clinton Supporter$_p$ × Trump Supporter$_i$		−0.1167	−0.1065	−0.1070		−0.0243	−0.0256	−0.0259
		(0.1140)	(0.0772)	(0.0772)		(0.0437)	(0.0351)	(0.0351)
Post Author Trump Supporter$_p$ × Clinton Supporter$_i$		−0.1885**	−0.0036	−0.0019		−0.0665	0.0130	0.0137
		(0.0896)	(0.0443)	(0.0443)		(0.0425)	(0.0198)	(0.0198)
Post Author Not Classified$_p$ × Trump Supporter$_i$		−0.0995	0.0021	0.0030		−0.0278	0.0204	0.0208
		(0.0992)	(0.0684)	(0.0684)		(0.0357)	(0.0265)	(0.0265)
Post Author Not Classified$_p$ × Clinton Supporter$_i$		−0.0590	0.0427	0.0428		−0.0352	0.0130	0.0131
		(0.0941)	(0.0382)	(0.0383)		(0.0409)	(0.0147)	(0.0147)
Poll$_p$ × Trump Supporter$_i$		0.0151	0.0281	0.0261		−0.0135	−0.0070	−0.0079
		(0.0876)	(0.0875)	(0.0874)		(0.0307)	(0.0311)	(0.0311)
Poll$_p$ × Clinton Supporter$_i$		−0.0302	−0.0158	−0.0139		−0.0006	0.0064	0.0073
		(0.0726)	(0.0746)	(0.0746)		(0.0297)	(0.0293)	(0.0293)
Author Activity Within 5 Days around Post$_{i,p}$		0.0114***	0.0115***	0.0142***		0.0044***	0.0044***	0.0057***
		(0.0010)	(0.0010)	(0.0012)		(0.0003)	(0.0003)	(0.0003)
Trump Supporter$_i$		−0.0632	−0.1286			−0.0379	−0.0680**	
		(0.0842)	(0.0829)			(0.0298)	(0.0334)	
Clinton Supporter$_i$		−0.1043	−0.1704***			−0.0583*	−0.0885***	
		(0.0643)	(0.0384)			(0.0314)	(0.0193)	
Bad News Trump$_p$		0.2711				0.1059		
		(0.2732)				(0.1159)		
Bad News Clinton$_p$		−0.0093				−0.0021		
		(0.1726)				(0.0630)		
Poll$_p$		−0.3252**				−0.1192**		
		(0.1424)				(0.0541)		
Posted Article Length$_p$		−0.0000				−0.0000		
		(0.0000)				(0.0000)		
Bad Poll Trump$_p$		0.3308***				0.1610***		
		(0.0982)				(0.0494)		
Bad Poll Clinton$_p$		0.3641***				0.1447***		
		(0.1159)				(0.0529)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value $(\beta_1 - \beta_2)$	0.0054	0.0110	0.0118	0.0132	0.0001	0.0028	0.0029	0.0034
Dep. Var Mean	0.2870	0.2870	0.2870	0.2870	0.1410	0.1410	0.1410	0.1410
Observations	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000
R2	0.0000	0.0013	0.0099	0.0110	0.0000	0.0025	0.0195	0.0212

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to comments of authors classified as either Trump Supportes, Clinton Supporters or Independent.

Table D.9: Activity Analysis, Reuters Sample, Robustness: OLS with Continuous Classification

	Dependent variable: Comments of User i on post p $\times 100$							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant News$_{i,p}$	0.2858***	0.0950	0.0936	0.0910	0.1434***	0.0540**	0.0525**	0.0514**
	(0.1059)	(0.0784)	(0.0796)	(0.0795)	(0.0429)	(0.0228)	(0.0234)	(0.0233)
Non-consonant News$_{i,p}$	0.1119	-0.0849	-0.0869	-0.0862	0.0416	-0.0368^{*}	-0.0383^{*}	-0.0380^{*}
	(0.0905)	(0.0771)	(0.0764)	(0.0764)	(0.0358)	(0.0205)	(0.0202)	(0.0202)
Post Clinton Mentions$_p$		70.3421				29.3089		
		(45.8140)				(18.0765)		
Post Trump Mentions$_p$		-35.1229^{*}				-11.7165		
		(20.7701)				(8.8108)		
Post Trump Mentions$_p$ $\times$ Trump Supporter$_i$		19.8385**	19.6795**	19.7028**		4.6796	4.7340*	4.7444*
		(8.8546)	(8.1558)	(8.1606)		(3.0604)	(2.7250)	(2.7257)
Post Trump Mentions$_p$ $\times$ Clinton Supporter$_i$		18.0286**	17.8143**	17.2275**		12.9239***	12.9815***	12.7207***
		(8.7480)	(8.4672)	(8.4635)		(3.0436)	(2.9279)	(2.9228)
Post Clinton Mentions$_p$ $\times$ Trump Supporter$_i$		23.5838	22.7983	23.0009		4.6597	4.2257	4.3158
		(30.3574)	(30.3827)	(30.3792)		(8.0454)	(8.0347)	(8.0329)
Post Clinton Mentions$_p$ $\times$ Clinton Supporter$_i$		52.4932	51.7463	51.1674		8.1467	7.6986	7.4412
		(36.9399)	(37.0065)	(37.0160)		(7.7927)	(7.7663)	(7.7652)
Posted Article Length$_p$ $\times$ Trump Supporter$_i$		0.0000	0.0000	0.0000		0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Posted Article Length$_p$ $\times$ Clinton Supporter$_i$		-0.0000	-0.0000	-0.0000		-0.0000	-0.0000	-0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Poll$_p$ $\times$ Trump Supporter$_i$		-0.0243	-0.0128	-0.0132		0.0012	0.0073	0.0071
		(0.0757)	(0.0768)	(0.0768)		(0.0248)	(0.0254)	(0.0254)
Poll$_p$ $\times$ Clinton Supporter$_i$		-0.0309	-0.0197	-0.0168		0.0374	0.0436	0.0448
		(0.0959)	(0.0964)	(0.0964)		(0.0319)	(0.0309)	(0.0309)
Post Author Trump Supporter$_p$ $\times$ Trump Supporter$_i$		0.0651	-0.0081	-0.0083		0.0302	0.0048	0.0047
		(0.1136)	(0.0768)	(0.0769)		(0.0496)	(0.0253)	(0.0253)
Post Author Clinton Supporter$_p$ $\times$ Clinton Supporter$_i$		0.1874	0.0885	0.0884		0.1166*	0.0620***	0.0619***
		(0.1425)	(0.0569)	(0.0569)		(0.0702)	(0.0226)	(0.0226)
Post Author Clinton Supporter$_p$ $\times$ Trump Supporter$_i$		0.0537	-0.0443	-0.0445		0.0313	-0.0229	-0.0230
		(0.0977)	(0.0523)	(0.0523)		(0.0404)	(0.0238)	(0.0238)
Post Author Trump Supporter$_p$ $\times$ Clinton Supporter$_i$		0.0699	-0.0038	-0.0024		0.0262	0.0006	0.0013
		(0.1500)	(0.0724)	(0.0724)		(0.0538)	(0.0236)	(0.0235)
Author Activity Within 5 Days around Post$_{i,p}$		0.0107***	0.0108***	0.0139***		0.0041***	0.0041***	0.0055***
		(0.0010)	(0.0010)	(0.0013)		(0.0003)	(0.0002)	(0.0003)
Trump Supporter$_i$		-0.1091^{*}	-0.0785^{*}			-0.0503^{**}	-0.0363^{***}	
		(0.0600)	(0.0409)			(0.0233)	(0.0138)	
Clinton Supporter$_i$		-0.1453^{**}	-0.1148^{**}			-0.0732^{***}	-0.0591^{***}	
		(0.0659)	(0.0497)			(0.0199)	(0.0134)	
Trump Scandal$_p$		0.3101				0.1285		
		(0.2940)				(0.1266)		
Clinton Scandal$_p$		-0.0185				0.0049		
		(0.1972)				(0.0782)		
Poll$_p$		-0.2711^{*}				-0.1151^{*}		
		(0.1536)				(0.0596)		
Posted Article Length$_p$		-0.0000				-0.0000		
		(0.0000)				(0.0000)		
Bad Poll Trump$_p$		0.2154*				0.1170**		
		(0.1194)				(0.0536)		
Bad Poll Clinton$_p$		0.2362*				0.0994*		
		(0.1306)				(0.0556)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
Dep. Var Mean	0.2700	0.2700	0.2700	0.2700	0.1330	0.1330	0.1330	0.1330
Observations	21,429,900	18,683,698	18,683,698	18,683,698	21,429,900	18,683,698	18,683,698	18,683,698
R2	0.0000	0.0012	0.0110	0.0122	0.0001	0.0022	0.0218	0.0236

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to comments of authors with more than 5 comments in political subreddits.

Table D.10: Activity Analysis, Reuters Sample, Robustness: NLLS with Discrete Classification

	Dependent variable: Comments of User i on post p $\times 100$							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant News$_{i,p}$	0.5632***	0.0677	0.1624	0.1449	0.5896***	0.2429**	0.2831**	0.2708**
	(0.1985)	(0.1700)	(0.1551)	(0.1475)	(0.1606)	(0.1220)	(0.1242)	(0.1204)
Non-consonant News$_{i,p}$	0.1276	$-$0.3211*	$-$0.3017**	$-$0.2258*	0.0573	$-$0.1809	$-$0.2254*	$-$0.2180*
	(0.2435)	(0.1738)	(0.1459)	(0.1332)	(0.2105)	(0.1436)	(0.1232)	(0.1199)
Post Clinton Mentions$_p$		190.3102**				149.0514**		
		(92.1257)				(72.1688)		
Post Trump Mentions$_p$		$-$69.8367				$-$25.4636		
		(68.8139)				(57.0695)		
Post Trump Mentions$_p$ $\times$ Trump Supporter$_i$		56.1540	46.9012	59.9884		$-$8.3277	$-$22.2223	$-$19.5429
		(37.8800)	(41.7275)	(43.1350)		(26.4613)	(32.2884)	(32.0051)
Post Trump Mentions$_p$ $\times$ Clinton Supporter$_i$		69.0874**	82.2509**	46.5931*		43.3852**	66.8108***	59.0329***
		(32.6158)	(33.3287)	(25.2471)		(21.0747)	(22.4010)	(20.6928)
Post Clinton Mentions$_p$ $\times$ Trump Supporter$_i$		50.5457	11.6122	49.2222		49.0952	48.2348	52.9110
		(62.6404)	(59.8430)	(62.6449)		(46.6755)	(50.5714)	(50.4253)
Post Clinton Mentions$_p$ $\times$ Clinton Supporter$_i$		97.8527***	69.2015	63.4132		76.5498**	69.4671*	63.6743*
		(36.8460)	(43.2470)	(41.4559)		(33.7135)	(38.6360)	(35.8453)
Posted Article Length$_p$ $\times$ Trump Supporter$_i$		0.0000	0.0000	0.0000		0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Posted Article Length$_p$ $\times$ Clinton Supporter$_i$		$-$0.0000	$-$0.0000	$-$0.0000		$-$0.0000	$-$0.0000	$-$0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Post Author Trump Supporter$_p$ $\times$ Trump Supporter$_i$		$-$0.2858	0.4589**	0.4997**		$-$0.1166	0.4845**	0.5067**
		(0.3399)	(0.2160)	(0.2208)		(0.3064)	(0.2233)	(0.2174)
Post Author Clinton Supporter$_p$ $\times$ Clinton Supporter$_i$		0.2022	0.0823	0.1017		0.3893	0.3130**	0.3070**
		(0.3314)	(0.1742)	(0.1411)		(0.3119)	(0.1292)	(0.1204)
Post Author Clinton Supporter$_p$ $\times$ Trump Supporter$_i$		$-$0.4395	$-$0.5381***	$-$0.3689		$-$0.2006	$-$0.2435	$-$0.2210
		(0.4112)	(0.2018)	(0.2366)		(0.3625)	(0.2324)	(0.2335)
Post Author Trump Supporter$_p$ $\times$ Clinton Supporter$_i$		$-$0.9151**	$-$0.1529	$-$0.1640		$-$0.6303*	$-$0.0670	0.0070
		(0.3645)	(0.2588)	(0.2550)		(0.3334)	(0.2201)	(0.1973)
Post Author Not Classified$_p$ $\times$ Trump Supporter$_i$		$-$0.3676	0.0257	0.0408		$-$0.2428	0.1033	0.1055
		(0.3134)	(0.1935)	(0.1945)		(0.2700)	(0.1756)	(0.1760)
Post Author Not Classified$_p$ $\times$ Clinton Supporter$_i$		$-$0.1962	0.0885	0.1304		$-$0.2577	0.0122	0.0254
		(0.2838)	(0.1322)	(0.1288)		(0.2618)	(0.1085)	(0.0999)
Poll$_p$ $\times$ Trump Supporter$_i$		$-$0.0623	0.0302	$-$0.1424		$-$0.1529	$-$0.1402	$-$0.1489
		(0.2327)	(0.2602)	(0.2388)		(0.2024)	(0.2202)	(0.2186)
Poll$_p$ $\times$ Clinton Supporter$_i$		$-$0.2279	$-$0.2081	$-$0.1251		$-$0.1179	$-$0.1703	$-$0.1413
		(0.1726)	(0.2098)	(0.1720)		(0.1327)	(0.1539)	(0.1460)
Author Activity Within 5 Days around Post$_{i,p}$		0.0067***	0.0070***	0.0096***		0.0072***	0.0080***	0.0111***
		(0.0003)	(0.0002)	(0.0005)		(0.0003)	(0.0003)	(0.0005)
Trump Supporter$_i$		$-$0.1436	$-$0.3544			$-$0.2404	$-$0.4354**	
		(0.2873)	(0.2369)			(0.2300)	(0.2109)	
Clinton Supporter$_i$		$-$0.2663	$-$0.4957***			$-$0.2821	$-$0.5165***	
		(0.2539)	(0.1765)			(0.2289)	(0.1486)	
Trump Scandal$_p$		0.7992				0.6362		
		(0.6065)				(0.5534)		
Clinton Scandal$_p$		$-$0.0175				$-$0.0035		
		(0.4246)				(0.3513)		
Poll$_p$		$-$1.3368**				$-$0.9748**		
		(0.6076)				(0.4929)		
Posted Article Length$_p$		$-$0.0001				$-$0.0001		
		(0.0001)				(0.0001)		
Bad Poll Trump$_p$		1.3826***				1.1914***		
		(0.4928)				(0.4260)		
Bad Poll Clinton$_p$		1.4531***				1.1154**		
		(0.5133)				(0.4463)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
Dep. Var Mean	0.0030	0.0030	0.0030	0.0030	0.0010	0.0010	0.0020	0.0020
Observations	13,095,000	13,095,000	12,251,100	12,251,100	13,095,000	13,095,000	12,251,100	12,251,100
McFadden R2	0.0010	0.0609	0.2962	0.3402	0.0009	0.0430	0.2082	0.1868

Notes: Logit and Poisson estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to comments of authors with more than 5 comments in political subreddits.

Table D.11: Activity Analysis, Reuters Sample, Robustness: NLLS with Continuous Classification

	Dependent variable: Comments of User i on post p ×100							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant News$_{i,p}$	0.7573***	0.0845	0.1347	0.1434	0.7716***	0.1402	0.1866**	0.1851**
	(0.2121)	(0.1403)	(0.0869)	(0.0949)	(0.1721)	(0.0905)	(0.0737)	(0.0759)
Non-consonant News$_{i,p}$	0.3543	−0.2341	−0.2144**	−0.2026**	0.2790	−0.1940*	−0.2170***	−0.2196***
	(0.2461)	(0.1576)	(0.0836)	(0.1011)	(0.2095)	(0.1092)	(0.0771)	(0.0782)
Post Clinton Mentions$_p$		211.7493**				181.2129**		
		(102.9295)				(88.2129)		
Post Trump Mentions$_p$		−125.4501				−78.3653		
		(78.4066)				(67.3606)		
Post Trump Mentions$_p$ × Trump Supporter$_i$		86.2737**	112.3496***	123.1539***		35.8105	46.4710*	49.6704**
		(36.0816)	(30.2103)	(32.4428)		(25.9466)	(23.8640)	(24.0849)
Post Trump Mentions$_p$ × Clinton Supporter$_i$		109.5604***	155.7536***	139.6226***		97.0336***	138.6805***	136.7992***
		(25.5211)	(22.7456)	(22.7545)		(19.2402)	(17.0986)	(16.9550)
Post Clinton Mentions$_p$ × Trump Supporter$_i$		43.5419	30.1522	47.4253		32.6714	36.1909	36.7895
		(54.5933)	(44.1356)	(46.5048)		(37.4625)	(36.9210)	(37.9114)
Post Clinton Mentions$_p$ × Clinton Supporter$_i$		79.0733*	60.3439*	63.4499		25.4990	9.7201	8.6217
		(43.2977)	(34.9936)	(40.0616)		(31.0834)	(29.7427)	(30.1171)
Posted Article Length$_p$ × Trump Supporter$_i$		0.0000	0.0000	0.0000		0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Posted Article Length$_p$ × Clinton Supporter$_i$		−0.0000	0.0000	−0.0000		−0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Post Author Trump Supporter$_p$ × Trump Supporter$_i$		0.2015	−0.1312	−0.1510		0.2071	0.0087	0.0020
		(0.3542)	(0.2506)	(0.2580)		(0.3322)	(0.1790)	(0.1890)
Post Author Clinton Supporter$_p$ × Clinton Supporter$_i$		0.5212	−0.0175	−0.0488		0.6263**	0.1231*	0.1159
		(0.3331)	(0.0985)	(0.1059)		(0.3084)	(0.0735)	(0.0747)
Post Author Clinton Supporter$_p$ × Trump Supporter$_i$		0.2041	−0.2795**	−0.2654*		0.2432	−0.1845	−0.1873
		(0.3261)	(0.1386)	(0.1428)		(0.2866)	(0.1244)	(0.1271)
Post Author Trump Supporter$_p$ × Clinton Supporter$_i$		0.2370	−0.0875	−0.1501		0.1739	−0.0596	−0.0619
		(0.4451)	(0.1819)	(0.1916)		(0.3516)	(0.1314)	(0.1311)
Poll$_p$ × Trump Supporter$_i$		−0.0526	−0.0424	−0.0930		−0.0065	−0.0136	−0.0127
		(0.1663)	(0.1668)	(0.1698)		(0.1328)	(0.1403)	(0.1433)
Poll$_p$ × Clinton Supporter$_i$		−0.0495	−0.0587	−0.0365		0.1212	0.0865	0.0931
		(0.1570)	(0.1476)	(0.1547)		(0.1213)	(0.1149)	(0.1159)
Author Activity Within 5 Days around Post$_{i,p}$		0.0066***	0.0068***	0.0097***		0.0070***	0.0079***	0.0111***
		(0.0003)	(0.0002)	(0.0004)		(0.0002)	(0.0002)	(0.0004)
Trump Supporter$_i$		−0.2609	−0.1547			−0.3164*	−0.2313**	
		(0.2373)	(0.1240)			(0.1907)	(0.1080)	
Clinton Supporter$_i$		−0.3068	−0.2968**			−0.3594**	−0.3491***	
		(0.2405)	(0.1330)			(0.1569)	(0.0931)	
Trump Scandal$_p$		0.9300				0.7946		
		(0.6357)				(0.5825)		
Clinton Scandal$_p$		0.0232				0.0815		
		(0.4503)				(0.3940)		
Poll$_p$		−1.0426				−0.8679		
		(0.6977)				(0.5390)		
Posted Article Length$_p$		−0.0001				−0.0001		
		(0.0001)				(0.0001)		
Bad Poll Trump$_p$		0.9629				0.9253*		
		(0.6169)				(0.4874)		
Bad Poll Clinton$_p$		1.0467*				0.8644*		
		(0.6309)				(0.5022)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
Dep. Var Mean	0.0030	0.0030	0.0030	0.0030	0.0010	0.0010	0.0010	0.0010
Observations	21,429,900	18,683,698	18,572,580	18,133,830	21,429,900	18,683,698	18,572,580	18,133,830
McFadden R2	0.0032	0.0587	0.3126	0.3506	0.0028	0.0414	0.2282	0.1941

Notes: Logit and Poisson estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to comments of authors with more than 5 comments in political subreddits.

Table D.12: Activity Analysis, Reuters Sample, Polls and Scandals Separately, Baseline Version: OLS with Discrete Classification

	Dependent variable: Comments of User i on post p $\times 100$							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant Poll$_{i,p}$	0.3141**	0.2720**	0.2627**	0.2642**	0.1642***	0.1003**	0.0965**	0.0972**
	(0.1245)	(0.1192)	(0.1180)	(0.1179)	(0.0574)	(0.0480)	(0.0474)	(0.0474)
Non-consonant Poll$_{i,p}$	−0.0086	−0.0317	−0.0384	−0.0343	−0.0025	−0.0375*	−0.0405*	−0.0386*
	(0.0630)	(0.0560)	(0.0565)	(0.0568)	(0.0270)	(0.0227)	(0.0228)	(0.0229)
Consonant Scandal$_{i,p}$	0.1628	−0.0051	−0.0056	−0.0080	0.0854*	0.0325	0.0322	0.0310
	(0.1241)	(0.0671)	(0.0668)	(0.0668)	(0.0508)	(0.0233)	(0.0233)	(0.0233)
Non-consonant Scandal$_{i,p}$	0.0798	−0.1294*	−0.1276*	−0.1260*	0.0192	−0.0383	−0.0378	−0.0370
	(0.1299)	(0.0751)	(0.0748)	(0.0748)	(0.0517)	(0.0272)	(0.0272)	(0.0272)
Post Clinton Mentions$_p$		61.9843				23.1729*		
		(39.1764)				(13.6736)		
Post Trump Mentions$_p$		−21.9148				−4.4907		
		(18.8773)				(7.8799)		
Post Trump Mentions$_p$ × Trump Supporter$_i$		14.3129	13.1140	13.3329		−0.9255	−1.4513	−1.3489
		(9.5010)	(9.6895)	(9.6993)		(3.3400)	(3.5682)	(3.5684)
Post Trump Mentions$_p$ × Clinton Supporter$_i$		6.5197	5.4692	5.1265		5.1266*	4.6611*	4.5007
		(7.4928)	(7.0555)	(7.0595)		(3.0750)	(2.8256)	(2.8269)
Post Clinton Mentions$_p$ × Trump Supporter$_i$		15.4897	12.7781	13.1684		3.7303	2.3754	2.5581
		(26.5099)	(26.7562)	(26.7571)		(7.2670)	(7.3538)	(7.3514)
Post Clinton Mentions$_p$ × Clinton Supporter$_i$		34.8748	31.9201	31.3284		10.4235	8.9776	8.7006
		(24.6211)	(25.4488)	(25.4683)		(7.0425)	(7.2115)	(7.2168)
Posted Article Length$_p$ × Trump Supporter$_i$		0.0000	0.0000	0.0000		0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Posted Article Length$_p$ × Clinton Supporter$_i$		−0.0000	−0.0000	−0.0000		−0.0000	−0.0000	−0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Post Author Trump Supporter$_p$ × Trump Supporter$_i$		−0.0889	0.0954	0.0957		−0.0160	0.0634**	0.0635**
		(0.1042)	(0.0750)	(0.0750)		(0.0405)	(0.0316)	(0.0315)
Post Author Clinton Supporter$_p$ × Clinton Supporter$_i$		0.0121	0.0225	0.0229		0.0653	0.0642***	0.0643***
		(0.1075)	(0.0500)	(0.0501)		(0.0581)	(0.0245)	(0.0245)
Post Author Clinton Supporter$_p$ × Trump Supporter$_i$		−0.1139	−0.1035	−0.1040		−0.0232	−0.0243	−0.0246
		(0.1143)	(0.0776)	(0.0776)		(0.0438)	(0.0353)	(0.0353)
Post Author Trump Supporter$_p$ × Clinton Supporter$_i$		−0.1857**	−0.0018	−0.0002		−0.0651	0.0141	0.0149
		(0.0899)	(0.0448)	(0.0448)		(0.0426)	(0.0199)	(0.0199)
Post Author Not Classified$_p$ × Trump Supporter$_i$		−0.0978	0.0039	0.0048		−0.0272	0.0211	0.0215
		(0.0994)	(0.0687)	(0.0687)		(0.0358)	(0.0267)	(0.0267)
Post Author Not Classified$_p$ × Clinton Supporter$_i$		−0.0612	0.0406	0.0407		−0.0360	0.0123	0.0123
		(0.0942)	(0.0384)	(0.0385)		(0.0409)	(0.0148)	(0.0148)
Poll$_p$ × Trump Supporter$_i$		−0.1161	−0.0961	−0.1006		−0.0338	−0.0245	−0.0266
		(0.1017)	(0.1031)	(0.1031)		(0.0310)	(0.0321)	(0.0321)
Poll$_p$ × Clinton Supporter$_i$		−0.2040*	−0.1825	−0.1833		−0.0365	−0.0266	−0.0270
		(0.1200)	(0.1211)	(0.1212)		(0.0431)	(0.0428)	(0.0428)
Author Activity Within 5 Days around Post$_{i,p}$		0.0114***	0.0115***	0.0142***		0.0044***	0.0044***	0.0057***
		(0.0010)	(0.0010)	(0.0012)		(0.0003)	(0.0003)	(0.0003)
Trump Supporter$_i$		−0.0632	−0.1286			−0.0378	−0.0679**	
		(0.0841)	(0.0828)			(0.0298)	(0.0334)	
Clinton Supporter$_i$		−0.1050	−0.1711***			−0.0585*	−0.0887***	
		(0.0643)	(0.0384)			(0.0314)	(0.0192)	
Bad Poll Trump$_p$		0.2858***				0.1536***		
		(0.0959)				(0.0486)		
Bad Poll Clinton$_p$		0.3092***				0.1336***		
		(0.1065)				(0.0496)		
Trump Scandal$_p$		0.2724				0.1055		
		(0.2742)				(0.1164)		
Clinton Scandal$_p$		−0.0020				−0.0003		
		(0.1716)				(0.0626)		
Poll$_p$		−0.2828**				−0.1118**		
		(0.1354)				(0.0522)		
Posted Article Length$_p$		−0.0000				−0.0000		
		(0.0000)				(0.0000)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
Dep. Var Mean	0.2870	0.2870	0.2870	0.2870	0.1410	0.1410	0.1410	0.1410
Observations	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000
R2	0.0000	0.0013	0.0099	0.0110	0.0000	0.0025	0.0195	0.0212

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to comments of authors classified as either Trump Supportes, Clinton Supporters or Independent.

Table D.13: Activity Analysis, Reuters Sample, Polls and Scandals Separately, Robustness: OLS with Continuous Classification

	Dependent variable: Comments of User i on post p ×100							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant Poll$_{i,p}$	0.3168***	0.2867***	0.2997***	0.3043***	0.1821***	0.1219***	0.1283***	0.1303***
	(0.1067)	(0.0938)	(0.0942)	(0.0943)	(0.0506)	(0.0392)	(0.0381)	(0.0381)
Non-consonant Poll$_{i,p}$	0.0487	0.0633	0.0758	0.0823	0.0355	0.0111	0.0177	0.0206
	(0.0625)	(0.0627)	(0.0627)	(0.0629)	(0.0282)	(0.0210)	(0.0198)	(0.0199)
Consonant Scandal$_{i,p}$	0.2655*	0.0670	0.0643	0.0607	0.1234**	0.0429	0.0408	0.0392
	(0.1430)	(0.0870)	(0.0882)	(0.0880)	(0.0573)	(0.0264)	(0.0269)	(0.0269)
Non-consonant Scandal$_{i,p}$	0.1556	−0.0874	−0.0909	−0.0904	0.0476	−0.0360	−0.0383*	−0.0380
	(0.1384)	(0.0880)	(0.0869)	(0.0869)	(0.0546)	(0.0237)	(0.0232)	(0.0232)
Post Clinton Mentions$_p$		69.7611				29.0991		
		(45.7686)				(18.0628)		
Post Trump Mentions$_p$		−34.8729*				−11.6233		
		(20.8020)				(8.8207)		
Post Trump Mentions$_p$ × Trump Supporter$_i$		18.7266**	18.5464**	18.5318**		4.2059	4.2506	4.2441
		(9.1237)	(8.4302)	(8.4336)		(3.1747)	(2.8546)	(2.8549)
Post Trump Mentions$_p$ × Clinton Supporter$_i$		18.3706**	18.1202**	17.5421**		13.1350***	13.1691***	12.9121***
		(8.9030)	(8.6230)	(8.6178)		(3.0832)	(2.9581)	(2.9524)
Post Clinton Mentions$_p$ × Trump Supporter$_i$		25.8185	25.0972	25.3777		5.5797	5.1784	5.3030
		(30.7032)	(30.7037)	(30.6993)		(8.2080)	(8.1882)	(8.1859)
Post Clinton Mentions$_p$ × Clinton Supporter$_i$		52.1911	51.5312	50.9482		7.8770	7.4834	7.2243
		(37.4505)	(37.5095)	(37.5180)		(7.7734)	(7.7519)	(7.7498)
Poll$_p$ × Trump Supporter$_i$		−0.1666	−0.1678	−0.1738*		−0.0463	−0.0473	−0.0499*
		(0.1023)	(0.1031)	(0.1032)		(0.0297)	(0.0290)	(0.0290)
Poll$_p$ × Clinton Supporter$_i$		−0.1898	−0.1913	−0.1945		−0.0177	−0.0185	−0.0199
		(0.1242)	(0.1244)	(0.1244)		(0.0344)	(0.0336)	(0.0336)
Posted Article Length$_p$ × Trump Supporter$_i$		0.0000	0.0000	0.0000		0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Posted Article Length$_p$ × Clinton Supporter$_i$		−0.0000	−0.0000	−0.0000		−0.0000	−0.0000	−0.0000
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Post Author Trump Supporter$_p$ × Trump Supporter$_i$		0.0642	−0.0093	−0.0096		0.0298	0.0043	0.0042
		(0.1134)	(0.0765)	(0.0765)		(0.0495)	(0.0251)	(0.0251)
Post Author Clinton Supporter$_p$ × Clinton Supporter$_i$		0.1856	0.0854	0.0853		0.1159*	0.0608***	0.0607***
		(0.1426)	(0.0572)	(0.0572)		(0.0702)	(0.0226)	(0.0226)
Post Author Clinton Supporter$_p$ × Trump Supporter$_i$		0.0532	−0.0461	−0.0463		0.0312	−0.0234	−0.0235
		(0.0980)	(0.0525)	(0.0525)		(0.0405)	(0.0238)	(0.0238)
Post Author Trump Supporter$_p$ × Clinton Supporter$_i$		0.0706	−0.0034	−0.0019		0.0266	0.0009	0.0015
		(0.1500)	(0.0725)	(0.0725)		(0.0538)	(0.0235)	(0.0235)
Author Activity Within 5 Days around Post$_{i,p}$		0.0107***	0.0108***	0.0139***		0.0041***	0.0041***	0.0055***
		(0.0010)	(0.0010)	(0.0013)		(0.0003)	(0.0002)	(0.0003)
Trump Supporter$_i$		−0.1090*	−0.0782*			−0.0502**	−0.0361***	
		(0.0598)	(0.0407)			(0.0233)	(0.0138)	
Clinton Supporter$_i$		−0.1467**	−0.1160**			−0.0737***	−0.0596***	
		(0.0658)	(0.0497)			(0.0199)	(0.0133)	
Bad Poll Trump$_p$		0.1346				0.0897*		
		(0.1174)				(0.0492)		
Bad Poll Clinton$_p$		0.1516				0.0704		
		(0.1285)				(0.0521)		
Trump Scandal$_p$		0.3164				0.1305		
		(0.2948)				(0.1269)		
Clinton Scandal$_p$		−0.0100				0.0079		
		(0.1959)				(0.0779)		
Poll$_p$		−0.1985				−0.0904		
		(0.1464)				(0.0570)		
Posted Article Length$_p$		−0.0000				−0.0000		
		(0.0000)				(0.0000)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
Dep. Var Mean	0.2700	0.2700	0.2700	0.2700	0.1330	0.1330	0.1330	0.1330
Observations	21,429,900	18,683,698	18,683,698	18,683,698	21,429,900	18,683,698	18,683,698	18,683,698
R2	0.0000	0.0012	0.0110	0.0122	0.0001	0.0022	0.0218	0.0236

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to comments of authors with more than 5 comments in political subreddits.

Table D.14: Activity Analysis, Reuters Sample, Polls and Scandals Separately, Robustness: NLLS with Discrete Classification

	Dependent variable: Comments of User i on post p $\times 100$							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant Poll$_{i,p}$	0.753***	0.899***	0.785***	0.732***	0.786***	0.684***	0.572**	0.549**
	(0.231)	(0.277)	(0.287)	(0.243)	(0.204)	(0.229)	(0.242)	(0.238)
Non-consonant Poll$_{i,p}$	−0.032	0.298	0.204	0.216	−0.019	0.082	−0.005	−0.029
	(0.231)	(0.250)	(0.251)	(0.258)	(0.199)	(0.212)	(0.221)	(0.218)
Consonant Scandal$_{i,p}$	0.451*	−0.009	0.117	0.091	0.479**	0.178	0.255**	0.237*
	(0.268)	(0.182)	(0.157)	(0.155)	(0.218)	(0.127)	(0.128)	(0.124)
Non-consonant Scandal$_{i,p}$	0.239	−0.277	−0.281*	−0.191	0.124	−0.131	−0.211*	−0.195*
	(0.340)	(0.180)	(0.151)	(0.139)	(0.309)	(0.151)	(0.121)	(0.117)
Post Clinton Mentions$_p$		189.101**				148.200**		
		(91.986)				(72.005)		
Post Trump Mentions$_p$		−69.568				−25.246		
		(68.870)				(57.079)		
Post Trump Mentions$_p$ × Trump Supporter$_i$		51.838	44.227	57.029		−12.725	−23.941	−21.514
		(38.342)	(42.426)	(43.497)		(27.075)	(32.660)	(32.373)
Post Trump Mentions$_p$ × Clinton Supporter$_i$		74.358**	83.155**	47.976*		48.003**	67.445***	60.009***
		(32.208)	(33.047)	(25.322)		(20.732)	(22.326)	(20.582)
Post Clinton Mentions$_p$ × Trump Supporter$_i$		58.955	15.425	53.975		56.427	51.097	56.456
		(63.876)	(60.669)	(63.372)		(47.328)	(51.263)	(51.058)
Post Clinton Mentions$_p$ × Clinton Supporter$_i$		96.270**	67.062	60.143		73.759**	68.225*	61.669*
		(37.431)	(42.802)	(41.298)		(34.197)	(37.950)	(35.179)
Posted Article Length$_p$ × Trump Supporter$_i$		0.000	0.000	0.000		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Posted Article Length$_p$ × Clinton Supporter$_i$		−0.000	−0.000	−0.000		−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Poll$_p$ × Trump Supporter$_i$		−0.741**	−0.498*	−0.623**		−0.468*	−0.374	−0.361
		(0.341)	(0.277)	(0.294)		(0.270)	(0.252)	(0.247)
Poll$_p$ × Clinton Supporter$_i$		−1.018***	−0.795**	−0.670**		−0.522**	−0.437*	−0.395
		(0.331)	(0.316)	(0.278)		(0.265)	(0.259)	(0.253)
Post Author Trump Supporter$_p$ × Trump Supporter$_i$		−0.300	0.430*	0.468**		−0.128	0.471**	0.490**
		(0.336)	(0.225)	(0.225)		(0.305)	(0.231)	(0.224)
Post Author Clinton Supporter$_p$ × Clinton Supporter$_i$		0.195	0.074	0.091		0.381	0.308**	0.301**
		(0.331)	(0.175)	(0.141)		(0.311)	(0.129)	(0.120)
Post Author Clinton Supporter$_p$ × Trump Supporter$_i$		−0.428	−0.530***	−0.361		−0.192	−0.241	−0.217
		(0.414)	(0.202)	(0.239)		(0.365)	(0.234)	(0.235)
Post Author Trump Supporter$_p$ × Clinton Supporter$_i$		−0.910**	−0.141	−0.148		−0.623*	−0.061	0.016
		(0.366)	(0.267)	(0.261)		(0.335)	(0.226)	(0.204)
Post Author Not Classified$_p$ × Trump Supporter$_i$		−0.364	0.024	0.038		−0.239	0.103	0.105
		(0.315)	(0.192)	(0.193)		(0.272)	(0.175)	(0.175)
Post Author Not Classified$_p$ × Clinton Supporter$_i$		−0.200	0.091	0.132		−0.262	0.012	0.025
		(0.284)	(0.133)	(0.129)		(0.262)	(0.108)	(0.100)
Author Activity Within 5 Days around Post$_{i,p}$		0.007***	0.007***	0.010***		0.007***	0.008***	0.011***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Trump Supporter$_i$		−0.146	−0.353			−0.241	−0.434**	
		(0.289)	(0.237)			(0.231)	(0.210)	
Clinton Supporter$_i$		−0.268	−0.503***			−0.282	−0.520***	
		(0.254)	(0.176)			(0.228)	(0.148)	
Bad Poll Trump$_p$		1.196**				1.102***		
		(0.481)				(0.398)		
Bad Poll Clinton$_p$		1.234**				1.008**		
		(0.492)				(0.414)		
Trump Scandal$_p$		0.801				0.637		
		(0.606)				(0.552)		
Clinton Scandal$_p$		−0.007				0.004		
		(0.423)				(0.350)		
Poll$_p$		−1.148**				−0.885*		
		(0.574)				(0.458)		
Posted Article Length$_p$		−0.000				−0.000		
		(0.000)				(0.000)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
Dep. Var Mean	0.003	0.003	0.003	0.003	0.001	0.001	0.002	0.002
Observations	13,095,000	13,095,000	12,251,100	12,251,100	13,095,000	13,095,000	12,251,100	12,251,100
McFadden R2	0.001	0.061	0.296	0.340	0.001	0.043	0.208	0.187

Notes: Logit and Poisson estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to comments of authors classified as either Trump Supportes, Clinton Supporters or Independent.

Table D.15: Activity Analysis, Reuters Sample, Polls and Scandals Separately, Robustness: NLLS with Continuous Classification

	Dependent variable: Comments of User i on post p $\times 100$							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant Poll$_{i,p}$	0.831***	0.697**	0.690**	0.726**	0.924***	0.463**	0.460**	0.482**
	(0.229)	(0.328)	(0.333)	(0.336)	(0.198)	(0.195)	(0.182)	(0.191)
Non-consonant Poll$_{i,p}$	0.185	0.272	0.258	0.281	0.262	0.044	0.050	0.070
	(0.223)	(0.331)	(0.330)	(0.338)	(0.192)	(0.187)	(0.171)	(0.179)
Consonant Scandal$_{i,p}$	0.705***	0.039	0.096	0.099	0.686***	0.105	0.174**	0.171**
	(0.268)	(0.142)	(0.083)	(0.094)	(0.226)	(0.095)	(0.076)	(0.078)
Non-consonant Scandal$_{i,p}$	0.453	−0.221	−0.209**	−0.193*	0.306	−0.176	−0.226***	−0.229***
	(0.317)	(0.166)	(0.086)	(0.107)	(0.295)	(0.119)	(0.084)	(0.085)
Post Clinton Mentions$_p$		210.739**				180.576**		
		(102.811)				(88.129)		
Post Trump Mentions$_p$		−125.178				−78.190		
		(78.454)				(67.352)		
Post Trump Mentions$_p$ $\times$ Trump Supporter$_i$		83.601**	109.913***	120.360***		33.509	45.617*	48.728**
		(36.222)	(30.256)	(32.337)		(25.949)	(23.974)	(24.211)
Post Trump Mentions$_p$ $\times$ Clinton Supporter$_i$		112.111***	155.838***	139.859***		99.077***	138.208***	136.265***
		(25.070)	(22.822)	(22.802)		(19.057)	(17.010)	(16.824)
Post Clinton Mentions$_p$ $\times$ Trump Supporter$_i$		48.118	32.903	50.689		36.321	36.892	37.595
		(55.125)	(43.680)	(46.199)		(37.971)	(37.206)	(38.203)
Post Clinton Mentions$_p$ $\times$ Clinton Supporter$_i$		78.108*	58.903*	61.485		23.984	9.886	8.803
		(43.908)	(35.173)	(40.470)		(31.315)	(29.556)	(29.890)
Posted Article Length$_p$ $\times$ Trump Supporter$_i$		0.000	0.000	0.000		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Posted Article Length$_p$ $\times$ Clinton Supporter$_i$		−0.000	0.000	−0.000		−0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Poll$_p$ $\times$ Trump Supporter$_i$		−0.568	−0.514	−0.582*		−0.258	−0.268	−0.289
		(0.375)	(0.331)	(0.339)		(0.218)	(0.186)	(0.193)
Poll$_p$ $\times$ Clinton Supporter$_i$		−0.619	−0.572*	−0.573		−0.174	−0.173	−0.188
		(0.380)	(0.341)	(0.353)		(0.225)	(0.192)	(0.200)
Post Author Trump Supporter$_p$ $\times$ Trump Supporter$_i$		0.198	−0.145	−0.166		0.204	0.004	−0.003
		(0.354)	(0.250)	(0.258)		(0.332)	(0.178)	(0.188)
Post Author Clinton Supporter$_p$ $\times$ Clinton Supporter$_i$		0.517	−0.022	−0.054		0.623**	0.121	0.113
		(0.333)	(0.099)	(0.106)		(0.309)	(0.073)	(0.075)
Post Author Clinton Supporter$_p$ $\times$ Trump Supporter$_i$		0.205	−0.280**	−0.266*		0.244	−0.187	−0.190
		(0.327)	(0.139)	(0.143)		(0.287)	(0.125)	(0.128)
Post Author Trump Supporter$_p$ $\times$ Clinton Supporter$_i$		0.238	−0.088	−0.150		0.175	−0.063	−0.065
		(0.445)	(0.181)	(0.190)		(0.351)	(0.131)	(0.131)
Author Activity Within 5 Days around Post$_{i,p}$		0.007***	0.007***	0.010***		0.007***	0.008***	0.011***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Trump Supporter$_i$		−0.262	−0.155			−0.316*	−0.232**	
		(0.237)	(0.122)			(0.190)	(0.107)	
Clinton Supporter$_i$		−0.310	−0.303**			−0.362**	−0.350***	
		(0.240)	(0.132)			(0.157)	(0.092)	
Bad Poll Trump$_p$		0.665				0.775		
		(0.682)				(0.489)		
Bad Poll Clinton$_p$		0.738				0.708		
		(0.685)				(0.498)		
Trump Scandal$_p$		0.938				0.799		
		(0.633)				(0.581)		
Clinton Scandal$_p$		0.034				0.088		
		(0.449)				(0.393)		
Poll$_p$		−0.757				−0.723		
		(0.723)				(0.531)		
Posted Article Length$_p$		−0.000				−0.000		
		(0.000)				(0.000)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
Dep. Var Mean	0.003	0.003	0.003	0.003	0.001	0.001	0.001	0.001
Observations	21,429,900	18,683,698	18,572,580	18,133,830	21,429,900	18,683,698	18,572,580	18,133,830
McFadden R2	0.003	0.059	0.313	0.351	0.003	0.041	0.228	0.194

Notes: Logit and Poisson estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to comments of authors with more than 5 comments in political subreddits.

Table D.16: Activity Analysis, Megathreads Sample, Baseline Version: OLS with Discrete Classification

	Dependent variable: Comments of User i on post p							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant Scandal$_{i,p}$ (β_1)	8.7905*	10.2515***	10.2581***	9.7188***	4.4683***	3.3568***	3.3588***	3.3323***
	(5.0343)	(2.6070)	(2.6083)	(2.6426)	(1.5884)	(0.8614)	(0.8619)	(0.8602)
Non-consonant Scandal$_{i,p}$ (β_2)	−2.7194	1.2403	1.2358	1.6064	0.1316	−0.9466	−0.9480	−0.9298
	(3.6813)	(2.8021)	(2.8015)	(2.8538)	(0.7975)	(0.5934)	(0.5933)	(0.5948)
Poll$_p$ × Trump Supporter$_i$		−0.0601	−0.0533	−0.6144		−0.0606	−0.0585	−0.0861
		(1.7492)	(1.7495)	(1.8492)		(0.3462)	(0.3464)	(0.3475)
Poll$_p$ × Clinton Supporter$_i$		−1.6032	−1.5982	−2.0111		0.0582	0.0597	0.0394
		(1.8567)	(1.8574)	(1.9337)		(0.2685)	(0.2686)	(0.2710)
Poll$_p$		−13.2041***				−2.1352***		
		(3.4822)				(0.5580)		
Author Activity Within 5 Days around Post$_{i,p}$		0.9122***	0.9086***	1.2088***		0.0742***	0.0731***	0.0879***
		(0.1649)	(0.1640)	(0.2419)		(0.0060)	(0.0059)	(0.0069)
Trump Supporter$_i$		−9.3041***	−9.2857***			−1.7058***	−1.7002***	
		(2.1987)	(2.2008)			(0.3636)	(0.3634)	
Clinton Supporter$_i$		−8.9702**	−8.9256**			−0.6135**	−0.5999**	
		(3.5610)	(3.5498)			(0.2558)	(0.2554)	
Trump Scandal$_p$		1.6485				1.3113		
		(4.8298)				(1.3843)		
Clinton Scandal$_p$		3.5708				1.4900		
		(4.8926)				(1.2742)		
Right Sources Share$_p$ × Trump Supporter$_i$		18.8257***	18.8225***	19.0794***		4.7120***	4.7111***	4.7237***
		(6.1549)	(6.1587)	(6.1176)		(1.3786)	(1.3793)	(1.3739)
Left Sources Share$_p$ × Trump Supporter$_i$		−7.7066	−7.7096	−7.4631		−1.2954	−1.2964	−1.2842
		(4.7527)	(4.7542)	(4.7759)		(0.8670)	(0.8671)	(0.8678)
Right Sources Share$_p$ × Clinton Supporter$_i$		0.8282	0.8127	2.0920		−0.0692	−0.0740	−0.0111
		(5.2843)	(5.2870)	(5.5391)		(0.8354)	(0.8360)	(0.8424)
Left Sources Share$_p$ × Clinton Supporter$_i$		2.5334	2.5332	2.5507		0.8820	0.8820	0.8828
		(4.3507)	(4.3522)	(4.4564)		(0.6337)	(0.6343)	(0.6343)
Right Sources Share$_p$		−13.3655				−3.6184*		
		(13.8001)				(2.1532)		
Left Sources Share$_p$		−12.3311				0.4113		
		(8.0383)				(1.3806)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
p-value $(\beta_1 - \beta_2)$	0.0018	0.0001	0.0001	0.0004	0.0009	0.0000	0.0000	0.0000
Dep. Var Mean	14.6600	14.6600	14.6600	14.6600	3.2570	3.2570	3.2570	3.2570
Observations	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942
R2	0.0001	0.0260	0.0335	0.0851	0.0015	0.0255	0.0508	0.0933

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to comments of authors with more than 5 comments in political subreddits.

Table D.17: Activity Analysis, Megathreads Sample, Robustness: OLS with Continuous Classification

	Dependent variable: Comments of User i on post p $\times 100$							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant Scandal$_{i,p}$	10.3061**	9.2333***	9.2391***	8.9151***	4.7585***	2.8653***	2.8665***	2.8456***
	(4.6265)	(2.2694)	(2.2702)	(2.2522)	(1.4260)	(0.6711)	(0.6713)	(0.6693)
Non-consonant Scandal$_{i,p}$	1.7719	2.3165	2.3134	2.4875	1.3119	-0.4062	-0.4068	-0.3956
	(3.8493)	(2.0393)	(2.0391)	(2.0690)	(0.9117)	(0.4132)	(0.4133)	(0.4136)
Poll$_p$ $\times$ Trump Supporter$_i$		-2.6955	-2.6888	-3.0598^{*}		-0.1308	-0.1295	-0.1534
		(1.6729)	(1.6722)	(1.7212)		(0.2495)	(0.2496)	(0.2502)
Poll$_p$ $\times$ Clinton Supporter$_i$		-5.2044^{***}	-5.1979^{***}	-5.5613^{***}		-0.1962	-0.1949	-0.2183
		(1.8027)	(1.8020)	(1.8676)		(0.1899)	(0.1899)	(0.1919)
Poll$_p$		-9.7874^{***}				-2.0629^{***}		
		(2.3699)				(0.5409)		
Author Activity Within 5 Days around Post$_{i,p}$		0.7429***	0.7385***	0.9835***		0.0654***	0.0645***	0.0803***
		(0.1282)	(0.1268)	(0.1887)		(0.0055)	(0.0054)	(0.0072)
Trump Supporter$_i$		0.0636	0.0860			-0.6358^{***}	-0.6314^{***}	
		(1.8918)	(1.8962)			(0.2148)	(0.2148)	
Clinton Supporter$_i$		3.8189*	3.8646*			0.5197**	0.5287**	
		(2.0204)	(2.0098)			(0.2647)	(0.2638)	
Trump Scandal$_p$		-0.5131				0.6450		
		(4.0900)				(1.2879)		
Clinton Scandal$_p$		3.3360				1.7162		
		(4.1275)				(1.2679)		
Right Sources Share$_p$ $\times$ Trump Supporter$_i$		9.0766	9.0690	9.4921		2.4668**	2.4654**	2.4926**
		(6.4390)	(6.4416)	(6.3655)		(1.0407)	(1.0412)	(1.0375)
Left Sources Share$_p$ $\times$ Trump Supporter$_i$		-12.3496^{***}	-12.3526^{***}	-12.1860^{***}		-1.1169^{**}	-1.1175^{**}	-1.1067^{**}
		(4.1381)	(4.1397)	(4.0979)		(0.5255)	(0.5257)	(0.5247)
Right Sources Share$_p$ $\times$ Clinton Supporter$_i$		-7.2078	-7.2251	-6.2625		-1.7350^{**}	-1.7384^{**}	-1.6764^{**}
		(6.6666)	(6.6654)	(6.7633)		(0.7406)	(0.7407)	(0.7449)
Left Sources Share$_p$ $\times$ Clinton Supporter$_i$		-5.5952	-5.5960	-5.5487		0.7440	0.7438	0.7468
		(4.1125)	(4.1133)	(4.1339)		(0.6041)	(0.6045)	(0.6023)
Right Sources Share$_p$		-8.3834				-2.2153		
		(9.2297)				(1.9805)		
Left Sources Share$_p$		-5.6416				0.6232		
		(5.6314)				(1.2101)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
Dep. Var Mean	12.7770	12.7770	12.7770	12.7770	3.0250	3.0250	3.0250	3.0250
Observations	5,247,118	5,247,118	5,247,118	5,247,118	5,247,118	5,247,118	5,247,118	5,247,118
R2	0.0001	0.0215	0.0284	0.0784	0.0024	0.0222	0.0464	0.0871

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to comments of authors with more than 5 comments in political subreddits.

Table D.18: Activity Analysis, Megathreads Sample, Robustness: NLLS with Discrete Classification

	Dependent variable: Comments of User i on post p $\times 100$							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant Scandal$_{i,p}$	0.4737**	1.0208***	1.0034***	0.7243***	0.9306***	0.7249***	0.6606***	0.7150***
	(0.2328)	(0.1693)	(0.1932)	(0.1713)	(0.2310)	(0.1515)	(0.1570)	(0.1648)
Non-consonant Scandal$_{i,p}$	−0.2074	0.3804*	0.4649*	0.1074	0.0423	−0.1895	−0.2065	−0.2098
	(0.2992)	(0.2130)	(0.2647)	(0.1809)	(0.2509)	(0.1637)	(0.1745)	(0.1805)
Poll$_p$ × Trump Supporter$_i$		−0.1335	−0.2330	−0.2493		−0.4465***	−0.6856***	−0.6507***
		(0.1939)	(0.2272)	(0.2340)		(0.1671)	(0.1885)	(0.1914)
Poll$_p$ × Clinton Supporter$_i$		0.7853***	0.9901**	0.4563**		0.3770***	0.3720**	0.3840**
		(0.2989)	(0.4171)	(0.2251)		(0.1295)	(0.1647)	(0.1737)
Poll$_p$		−1.7370***				−1.1923***		
		(0.3107)				(0.2407)		
Author Activity Within 5 Days around Post$_{i,p}$		0.0079***	0.0076***	0.0079***		0.0104***	0.0110***	0.0153***
		(0.0004)	(0.0004)	(0.0005)		(0.0003)	(0.0003)	(0.0006)
Trump Supporter$_i$		−0.2594*	−0.2689*			−0.5165***	−0.5381***	
		(0.1483)	(0.1548)			(0.1191)	(0.1250)	
Clinton Supporter$_i$		−0.0908	−0.0610			−0.1326**	−0.1459**	
		(0.1130)	(0.1137)			(0.0656)	(0.0693)	
Trump Scandal$_p$		0.0793				0.3021		
		(0.3468)				(0.3326)		
Clinton Scandal$_p$		0.1295				0.4156		
		(0.3216)				(0.3046)		
Right Sources Share$_p$ × Trump Supporter$_i$		1.2854**	1.7240**	1.8123**		1.6783***	2.7098***	2.7894***
		(0.5251)	(0.7799)	(0.8599)		(0.4328)	(0.6242)	(0.6424)
Left Sources Share$_p$ × Trump Supporter$_i$		−1.2353***	−1.3891***	−1.0444***		−0.4831*	−0.7129**	−0.7373**
		(0.3462)	(0.3710)	(0.3482)		(0.2876)	(0.3181)	(0.3294)
Right Sources Share$_p$ × Clinton Supporter$_i$		−0.9852	−1.9318	−0.2130		−0.0247	−0.0928	−0.1382
		(0.7868)	(1.4002)	(0.6694)		(0.3350)	(0.5520)	(0.5881)
Left Sources Share$_p$ × Clinton Supporter$_i$		−0.2674	−0.2000	0.2262		0.1050	0.1711	0.1971
		(0.2806)	(0.3028)	(0.2227)		(0.1765)	(0.2035)	(0.2167)
Right Sources Share$_p$		−1.0520				−1.2464		
		(1.0523)				(0.8038)		
Left Sources Share$_p$		−0.6593				0.1501		
		(0.4623)				(0.3964)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
Dep. Var Mean	0.1470	0.1470	0.1470	0.1470	0.0330	0.0330	0.0330	0.0330
Observations	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942	2,995,942
McFadden R2	0.0009	0.1356	0.2491	0.4731	0.0038	0.0603	0.1482	0.1766

Notes: Logit and Poisson estimates, two-way clustered standard errors at the i and p level in parenthesis.Sample restricted to comments of authors classified as either Trump Supportes, Clinton Supporters or Independent.

Table D.19: Activity Analysis, Megathreads Sample, Robustness: NLLS with Continuous Classification

	Dependent variable: Comments of User i on post p ×100							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consonant Scandal$_{i,p}$	0.6131***	0.6300***	0.6793***	0.5477***	1.0525***	0.5618***	0.5266***	0.5709***
	(0.2318)	(0.1135)	(0.0000)	(0.1241)	(0.2195)	(0.1002)	(0.1024)	(0.1121)
Non-consonant Scandal$_{i,p}$	0.1387	0.0625	0.2207***	0.0430	0.4053*	−0.1316	−0.1300	−0.1368
	(0.2770)	(0.1259)	(0.0000)	(0.1468)	(0.2375)	(0.1094)	(0.1164)	(0.1268)
Poll$_p$ × Trump Supporter$_i$		0.0847	−0.0581***	−0.0294		−0.1301	−0.2686**	−0.2718**
		(0.1456)	(0.0000)	(0.1624)		(0.1203)	(0.1315)	(0.1379)
Poll$_p$ × Clinton Supporter$_i$		−2.0458	0.5060***	0.6063***		0.5148***	0.5490***	0.5334***
		(3.3787)	(0.0002)	(0.1523)		(0.0929)	(0.1097)	(0.1158)
Poll$_p$		−1.9103***				−1.4537***		
		(0.2760)				(0.2520)		
Author Activity Within 5 Days around Post$_{i,p}$		0.0020***	0.0068***	0.0083***		0.0099***	0.0104***	0.0152***
		(0.0006)	(0.0000)	(0.0005)		(0.0003)	(0.0003)	(0.0006)
Trump Supporter$_i$		0.2148**	0.1369***			−0.1906**	−0.1977**	
		(0.0998)	(0.0000)			(0.0748)	(0.0773)	
Clinton Supporter$_i$		0.5507***	0.4572***			0.1826***	0.1832***	
		(0.0813)	(0.0000)			(0.0644)	(0.0670)	
Trump Scandal$_p$		−0.0313				0.1804		
		(0.3799)				(0.3545)		
Clinton Scandal$_p$		0.2820				0.4872		
		(0.3012)				(0.3144)		
Right Sources Share$_p$ × Trump Supporter$_i$		0.7958**	1.3235***	1.2735**		0.9476***	1.5232***	1.6032***
		(0.3800)	(0.0000)	(0.5082)		(0.3294)	(0.4481)	(0.4772)
Left Sources Share$_p$ × Trump Supporter$_i$		−0.9757***	−1.1477***	−0.8849***		−0.3760**	−0.5089**	−0.5288**
		(0.2288)	(0.0000)	(0.2256)		(0.1776)	(0.2042)	(0.2153)
Right Sources Share$_p$ × Clinton Supporter$_i$		−0.2782	−0.8322***	−0.2114		−0.3736*	−0.6386*	−0.6881*
		(0.2098)	(0.0004)	(0.3737)		(0.2141)	(0.3446)	(0.3705)
Left Sources Share$_p$ × Clinton Supporter$_i$		−0.1597	−0.2287***	0.0372		0.1025	0.1909	0.2357
		(0.1587)	(0.0001)	(0.1764)		(0.1393)	(0.1554)	(0.1675)
Right Sources Share$_p$		−0.8582				−0.8540		
		(0.9359)				(0.8087)		
Left Sources Share$_p$		−0.4513				0.2227		
		(0.4616)				(0.4000)		
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	No	Yes	No	No	No	Yes
Dep. Var Mean	0.1280	0.1280	0.1280	0.1280	0.0300	0.0300	0.0300	0.0300
Observations	5,247,118	5,247,118	5,247,118	5,247,118	5,247,118	5,247,118	5,247,118	5,247,118
McFadden R2	0.0018	0.0622	0.2179	0.4549	0.0065	0.0575	0.1428	0.1650

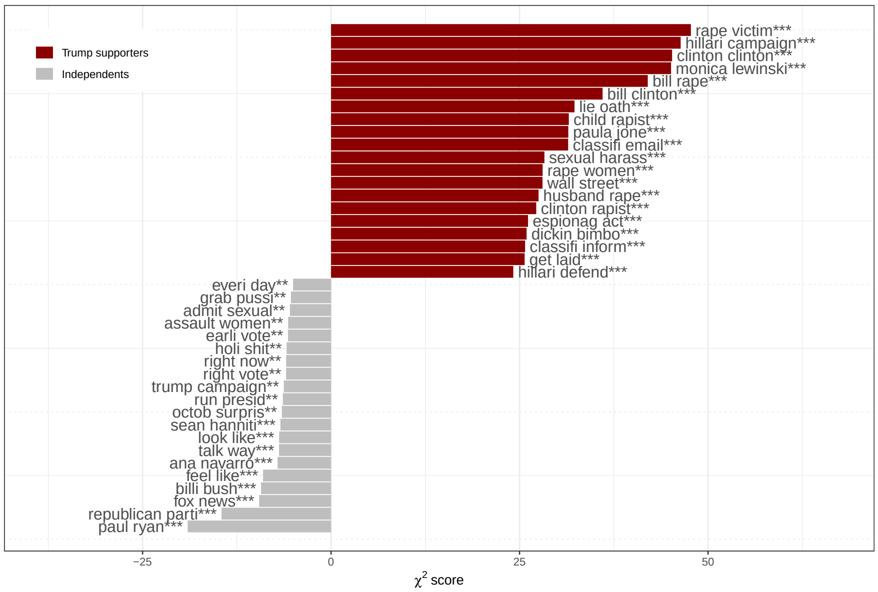
Notes: Logit and Poisson estimates, two-way clustered standard errors at the i and p level in parenthesis.Sample restricted to comments of authors with more than 5 comments in political subreddits.

E Supplementary Appendix to Section 5

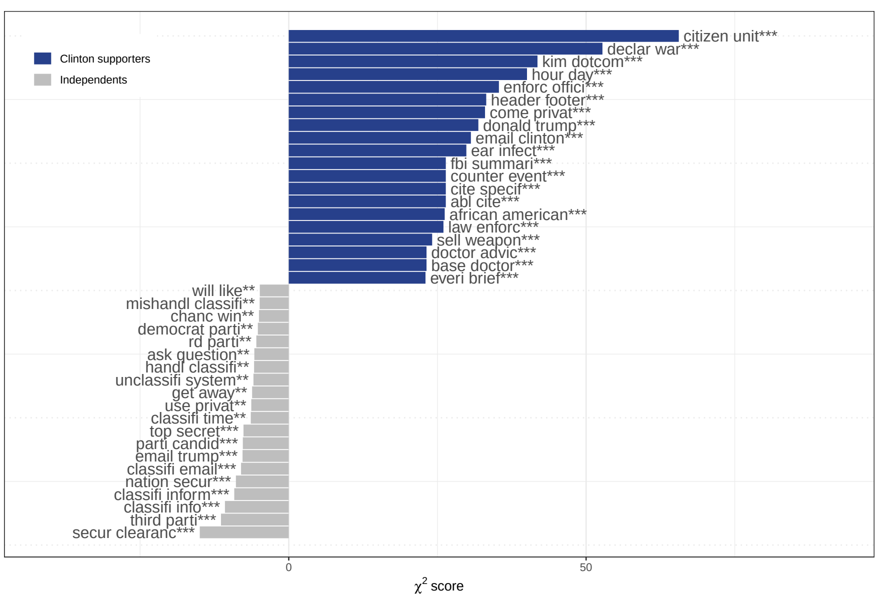
E.1 Figures

Figure E.1: χ^2 Test Statistics of Relative Words Frequencies

(a) Comments to Trump scandals, Trump Supporters vs. Independents



(b) Comments to Clinton scandals, Clinton Supporters vs. Independents



E.2 Tables

Table E.1: Sentiment Classification: Confusion Matrix

All comments - Binary Scores				Comments with Extreme Scores			
Classifier	RoBERTa			Classifier	RoBERTa		
Human	Label	Negative	Positive	Human	Label	Negative	Positive
	Negative	354	102		Negative	285	58
	Positive	15	29		Positive	5	25

Table E.2: Sentiment Classification: Performance

All comments - Binary Scores					Comments with Extreme Scores				
Label	Precision	Recall	F1-score	Support	Label	Precision	Recall	F1-score	Support
Negative	0.959	0.776	0.858	456	Negative	0.983	0.831	0.900	343
Positive	0.221	0.659	0.331	44	Positive	0.301	0.833	0.442	30
Accuracy				0.766	Accuracy				0.831
Simple avg	0.590	0.718	0.595	500	Simple avg	0.642	0.832	0.671	373
Weighted avg	0.894	0.766	0.812	500	Weighted avg	0.928	0.831	0.864	373