Disengaging from Reality

Online Behavior and Unpleasant Political News*

Leonardo D'Amico Guido Tabellini

November 2024

Abstract

Why, in the face of scandals and misbehaviors, partisan supporters don't seem to change their minds about their favored candidates? We study individuals' online engagement with negative news on candidates in the 2016 US Presidential Election. Compared to independents, partisan users avoid commenting bad news on their favorite candidate, but seek them on its opponent, a political "ostrich effect". When they do comment on bad news about their candidate, they try to rationalize them, display a more negative sentiment, and are more likely to cite scandals of the opponent. This behavior is consistent with the predictions of a model of online interactions where paying attention to non-consonant news is emotionally or psychologically costly, while paying attention to consonant ones is pleasing. Because users enjoy receiving positive feedback on their views, social media amplify intrinsic biases that drive ideological segregation.

*D'Amico: damico@g.harvard.edu, Department of Economics, Harvard University. Tabellini: guido.tabellini@unibocconi.it, Department of Economics and IGIER, Università Bocconi; CEPR; CESifo.
A previous and longer version of this paper circulated with the title "Online Political Debates". We thank Alberto Alesina, Elliott Ash, Ben Enke, Claudia Marangon, Giacomo Ponzetto, Aakaash Rao, Raphaël Raux, Jesse Shapiro, Marco Tabellini, Matthew Thaler, and workshop participants at Harvard, Bocconi, LSE, EIEF, the IOG Conference at the University of Chicago and the Zurich Political Economy Seminar Series for many insightful suggestions. We are grateful to Leonardo Bianchi, Alberto Binetti, Giampaolo Bonomi, Pietro Buri, Niccolo' Cattadori, Chiara Gardenghi, Andrew Funck, Giacomo Marcolin, Alessandro Pisa and Federico Scabbia for outstanding research assistance, and Elliot Ash and Gloria Gennaro for making available to us their code for classifying the cognitive vs emotional content in a text. Tabellini thanks ERC grant 741643.

1 Introduction

Voters' beliefs are strongly shaped by their political preferences. According to recent polls, roughly three quarters of Republicans believe that the 2024 investigations on Donald Trump's alleged crimes were unfairly conducted, against only 15% of Democrats (Ballard, 2024).[1] In 2019, just before the House hearings on President Trump hypothetical impeachement, the partisan gap on whether he should be impeached was about 80 percentage points. These sorts of contrasts are not new, but they seem larger today than in the past. In 1998, at a similar point in the process of Clinton's impeachment, the partisan gap was about half that size (40 p.p.), and the same was true in 1974 about Nixon's impeachment (Jones, 2019). Partisanship also influences factual beliefs over the features of immigrants (Alesina et al., 2023), the extent of inequality and social mobility (Alesina et al., 2018), the causes of climate change (Kahan, 2015), the risks associated with Covid (Allcott et al., 2020a). Why do views differ so much along ideological lines? And could social media play a role?

We investigate the mechanisms behind this divergence by studying how people debate political news during the 2016 Clinton vs. Trump election on a widely used web platform, Reddit. Our analysis suggests two main conclusions.

First, we document evidence of a political "ostrich effect": individuals are substantially less likely to engage with news that contradict their political preferences ("non-consonant" news), and more likely to do so if the news support them (if the news is "consonant"). For example, when a recording containing Trump's lewd comments on women was leaked during the 2016 campaign, Trump supporters decreased their political activity, relative to their total activity on the platform, by 17.5% and Clinton supporters increased it by 15.3%, compared to independents. For almost a week, partisan users shied away, in relative terms, from all political discussions (not only those strictly covering the scandal) and engaged more with non-political posts: baseball, financial news, and the likes.

Second, based on a model of online interactions, we argue that social media can amplify this "ostrich effect" because of a complementarity in news engagement: users engage more with news on which they expect other like-minded users to also be more engaged. The reason is that they enjoy receiving positive feedback on their views, and this is more likely

[1] The four crimes concern the Georgia election, the Federal election and January 6 event, the classified documents and the Hush money cases.

to come from those who share their political beliefs. If a user neglects a piece of news, for whatever intrinsic motive, and anticipates that other like-minded individuals will also do so, she is even less attracted to it because she expects fewer validations of her views. And conversely if a user is attracted to a spefic news. As users with different ideologies engage with different news, their beliefs polarize. Since social media provide more opportunities for social interactions, they amplify any intrinsic force that leads to ideological segregation in news exposure, a channel that adds to others already studied in the literature - cf. Levy and Razin (2019) and Aridor et al. (2024).

To formalize this point and guide the empirical analysis, we formulate a theoretical model where individuals choose how much attention to pay to political news on a web platform and whether to comment on it. The purpose of commenting is purely social: individuals draw utility from how many likes their comment receives, and post a comment if their expected utility is above a given random threshold. Attention is costly and has two purposes. First, an instrumental motive, namely to gather information in order to rank two competing political candidates in an imminent election. Second, a social motive, namely to engage with the news and come up with a comment. As users pay more attention to a given debate, they are also more likely to post likes or dislikes on the comments of others, because higher attention means more exposure to the post and its comments.

The model allows for various intrinsic reasons why users with different ideologies pay attention to different news. They may be more or less informed about one of the candidates (so that news convey different informational value in a Bayesian sense), they may be more or less interested in a topic, or they may find it psychologically pleasant or unpleasant to engage with different news. In this last case, 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 they are less willing to engage with uncomfortable news (Bénabou and Tirole, 2011, 2016; Flynn et al., 2017; Thaler, 2024; Lilley and Wheaton, 2024). In equilibrium, social interactions associated with news' engagement induce more ideological segregation of attention and of comments across political news, compared to a setting without social approval. In turn, this influences beliefs.

The rest of the paper provides evidence of these patterns of asymmetric engagement and sheds light on the motivations behind them. To do so, we study how users comment on political news posted on Reddit between June and November 2016. Reddit was the 7th 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 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 consistent with the online behavior of the general US population, as we show below. Two other features of the platform stand out. First, due to the rules of the forum, posts on `r/politics` approximate a flow of US political news. Each post only shows the title, the source, and the link of an article strictly related to US politics, which 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.

To study how users' behavior is influenced by the congruence of the news with their ideology, 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 or across different days.

As anticipated, our first result is that partisan users are less likely to comment any political news, compared to independents, in the days immediately following the breaking of news of a major scandal on their candidate, and more active in the days after the scandal of his / her opponent. The results we previewed around Trump's leak of lewd comments extend, symmetrically, to all three major Clinton scandals during the campaign. Except, of course, in this case it was Clinton supporters who shied away from politics and Trump ones who engaged more. As in the "ostrich effect" documented in finance by Karlsson et al. (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. This effect is driven not only by users' activity on postings that cover the scandals in question, but also by their engagement with all political news, and their substitutions into (or away from) non-political news.

Next, 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, which we manually classify by looking at all news from Reuters.com posted on the platform. 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. Moreover, as predicted by our model and in line with the social motive of news engagement, comments on consonant news receive about 70% more likes (net of dislikes) than the average comment, while comments on non-consonant news receive less likes than the average (how much less varies across samples).

The theory predicts that these patterns are amplified in absolute value by an "audience effect". When the audience is larger and debates are more lively, social complementarities are more relevant and the difference in behavior between consonant vs non-consonant news is larger. With our non-experimental data we cannot precisely identify the presence of these peer effects. However, we repeat our analysis on another sample of "mega"-posts (called Megathreads), which are created by platform moderators for hot topics that draw large discussions and aggregate many individual postings on the same topic. Megathreads attract large audiences: each one on average has about 7,000 comments, against 44 for the average Reuters post. In this sample, compared to Reuters, we find a much larger contrast in news engagement between consonant vs non-consonant news, as predicted if social motives are at play. Moreover, users remain more active on a Megathread if their previous comments on that same Megathread received more net likes, which is also in line with the social motive.

To distinguish among different intrinsic motives for news engagement, we further split the Reuters sample into scandals and negative polls. As outlined in the model, a possible explanation of our finding is that users are already more informed about their own candidate, and hence less interested in news about him/her, whether good or bad. While opposite partisan users may be differentially confident about the valence or moral character of the two candidates, the outcome of polls refers to a single underlying event: who is ahead. Hence, uncertainty is symmetric across candidates. 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.

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, still with the same diff-in-diff strategy. We find that, when partisan users comment on a scandal on the opponent, they 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 is unpleasant than if it is pleasant. That is, when a post casts doubts on the valence of their candidate, partisan users are more likely to highlight controversies on his/her opponent.

Overall, these findings are difficult to explain without invoking some form of motivated cognition. 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, nor can they explain the patterns of our event studies, where we study engagement with politics overall around scandal dates, rather than with a particular piece of news. Differences in the perceived reliability of specific news postings (Gentzkow and Shapiro, 2006) seem unlikely in the Reuters sample, where all news come from the same source, and in any case they also cannot explain the event studies. Moreover, the content of the comments reinforces the interpretation that these patterns reflect feelings of pleasure or discomfort when faced with different kinds of news. Finally, our results across samples that differ in audience size and on the number of likes received suggest that social motives are also at play and may amplify the magnitude of the psychological drivers of news engagement.

This paper is related to several strands of literature. Our motivation is tied to the ideological polarization of beliefs. A common explanation of this polarization rests on differential exposure to information across ideological lines (see the survey by Levy and Razin, 2019; Gentzkow and Shapiro, 2006, 2011; Bakshy et al., 2015; Golub and Sadler, 2016). Our paper suggests a novel explanation of why we observe political segregation in social media: because individuals enjoy receiving positive feedback on their views. Moreover, compared to the existing literature, we focus on how individuals engage with unpleasant political news, and we study the content of online debates and not just selective exposure to news.

Our theoretical model relates to the literature on rational inattention and its application to politics (see Matějka and Tabellini, 2020 and Maćkowiak et al., 2023 for a general review). By adding a social interaction block to a rational inattention model, we highlight the interplay between intrinsic and social motives of attention, and show that social approval can be an amplifying force of the intrinsic drivers covered by the literature.

Our paper is also related to the large literature on motivated beliefs, cited above and surveyed by Bénabou and Tirole (2016). Most of the existing evidence of motivated cognition is based on experiments, with the exception of Di Tella et al. (2007) and Karlsson et al. (2009). We provide non-experimental evidence of engagement with news that is consistent with motivated reasoning amplified by social motives. This complements other recent papers that have shown that the "ostrich effect" found in finance by Karlsson et al. (2009) is also present in politics (see in particular Tyler et al., 2022 and Garz et al., 2020).[2]

Our assumption that individuals enjoy receiving social approval on their views is in line with the so called "spiral of science" hypothesis, namely the idea that individuals are more likely to publicly express their opinion if they expect it to be shared by the majority (e.g., Yun and Park, 2011; Hampton et al., 2014; Matthes et al., 2017).[3]

Finally, our findings shed light on how political debates unfold on social media and relate to the literature on the effects of social media on political ideology and information acquisition (Bail et al., 2018; Sunstein, 2017; Allcott et al., 2020b; see Aridor et al., 2024

[2]Tyler et al. (2022) follow the web-browsing behavior of about 800 partisan individuals recruited on YouGov during the 2016 US presidential election. Focusing on two scandals that are also in our sample, they show that political news consumption rises in the days immediately after a scandal involving the opponent of the preferred candidate, but it does not fall if the scandal involves their preferred candidate. Garz et al. (2020) analyze Facebook posts by German news sources covering the lifting of immunity for German politicians between 2012 on 2017. They find that posts that are congenial with the outlet's ideology receive more likes, shares and comments. Compared with these papers, we focus on evidence at the individual-post level, measuring the consonance of each post with every user in our sample. Since the sample also includes non-partisan users and political news unrelated to scandals, we can perform a diff-in-diff analysis. This allows us to capture observed and unobserved individual heterogeneity (most importantly in partisanship) and to discriminate across different individual-level motives of news engagement. In addition to these papers, Kim and Kim (2021) rely on ANES survey data to show that people self-declare to be less interested in politics when the President of their preferred party is less popular.

[3]Related to this, in an online experiment on Reddit, Srinivasan (2023) finds that users increase their postings of news articles if their previous posts received more comments, suggesting that they are motivated by receiving attention from others; this effect is strong but short lived.

for a review). Acemoglu et al. (2023) discusses social complementarities in the posting of news, while we focus on commenting activities and highlight that social complementarities also influence the demand (as opposed to supply) of online news. Within this literature, we are among the first to study data on the Reddit platform and to highlight its advantages for applied economic and political analysis, following D'Amico (2018) (see also Moehring, 2022; Srinivasan, 2023).

The outline of the paper is as follows. The next section formulates a model of news engagement and derives a number of predictions. Section 2 describes our data and the context of the web platform. Section 3 studies the propensity to comment different kinds of news and the net likes received, while the content of the comments is studied in section 4. A final section concludes.

2 Theory

This section describes a simple model of news engagement that guides our empirical analysis. Individuals choose how much attention to pay to political news on a web platform and whether to comment on it. They are motivated by two goals: to rank the candidates, and to socially engage with other users. We start by outlining the social motive, which determines wether a user comments on the news. We then study the instrumental motive of ranking the candidates. Finally, we put the two together to determine equilibrium attention and discuss the empirical predictions.

2.1 Social Motive

There is a continuum of individuals composed by a discrete number of types indexed by i who differ in their political preferences. Each type has size 1. Individuals are exposed to political news indexed by p, described below. With probability $P(\xi_p^i)$ they think of something to say about the news, where ξ_p^i denotes individual attention to that news and $P(.)$ is a twice continuously differentiable increasing and concave function. Thus, attention increases the probability that the news triggers a thought or reaction that could be shared with others in a comment.

If individuals comment on the news, they draw a utility proportional to the number of likes posted on their comment by other users. Likes received are random, and reflect the attention of other users of the same type. Specifically, with a probability that increases with their attention to the news, individuals read the comments of others and can react by posting a like. We assume that individuals post a like with a positive probability only if the comment was made by the same political type (their "friend"), otherwise the probability of posting a like is zero. Implicit in this assumption is the idea that, although users are anonymous, comments reflect the true feelings and opinions of users, and likes manifest agreement with the content of the comment.

Thus, the expected utility of type i from commenting on news p can be expressed as a function of the attention of other users of the same type, namely:

$$w_p^i = W(\xi_p^{-i}; \varepsilon_p^i)$$

where $-i$ denotes other individuals of the same type as i, and $W(.)$ is an increasing, concave and continuously differentiable function of ξ_p^{-i}. The parameter ε_p^i captures variation in expected net likes received, due to factors other than users' attention. For instance, p was posted when there was a lively and emotional debate that induced others to post more likes on the comments they read. For concreteness, higher values of ε_p^i increase net likes received and hence the expected utility of commenting: $W(.)$ is also increasing in ε_p^i. To sign some comparative statics results, we assume $\partial^2 W(.)/\partial\xi\partial\varepsilon \geq 0$. We refer to ε_p^i as the size of the audience for type i who comments post p. Since individuals of the same type are identical, we let ξ_p^{-i} be a scalar. This exploits the fact that, as shown below, in equilibrium all individuals of the same type choose the same level of attention. Since we neglect dislikes, no strategic interaction occurs between individuals of different types (i.e. with different political preferences).[4]

Finally, we assume that individuals post a comment if their expected utility exceeds a random threshold, $w_p^i \geq \varpi_p$, where ϖ_p is distributed according to a uniform distribution $F(.)$.

Putting all of this together, the expected utility of individual i from commenting news

[4]In principle, dislikes could be added to the model, assuming that they are posted by users with opposite political preferences compared to the author of the comment. This would complicate the analysis, however, because attention of others would be a strategic complement for the same types, and a strategic substitute for opposite types. We also neglect higher level comments (i.e comments on the comments of others).

p can be written as:

$$v_p^i = P(\xi_p^i)F[W(\xi_p^{-i};\varepsilon_p^i)]W(\xi_p^{-i};\varepsilon_p^i) \equiv V(\xi_p^i,\xi_p^{-i};\varepsilon_p^i)$$

The first term is the probability of finding something to say in a comment. The second term is the probability of writing a comment, conditional on having something to say. Their product is the probability that the individual comments on the news. The last term is his/her expected benefit from the comment. Thus, expected utility increases with own attention, because it increases the probability of having something to say. Moreover, through likes, the marginal benefit of own attention increases with the attention of other users of the same type: $\partial^2 V(\xi_p^i,\xi_p^{-i};\varepsilon_p^i)/\partial\xi_p^i\partial\xi_p^{-i} > 0$. Thus, attention of users with the same political preferences are strategic complements. If individuals expect others of the same type to be more attentive to news p, they expect more likes on their comments. This has two effects: first it makes them more likely to comment, since $w_p^i \geq \varpi_p$ is more likely. Second, it induces them to pay more attention in order to be able to write a comment, both because their expected utility from commenting w_p^i is higher, and because they are more likely to comment conditional on their own attention ($F(.)$ is higher). Hence, as discussed more extensively below, news engagement exhibits homophily and induces segregation. Similarly, the marginal benefit of own attention is higher if the post has a larger potential audience—i.e., if ε_p^i is larger—since the probability of of receiving likes on one's comments rises with ε_p^i: $\partial^2 V(\xi_p^i,\xi_p^{-i};\varepsilon_p^i)/\partial\xi_p^i\partial\varepsilon_p^i > 0$.

But social interactions through comments is not the only reason to follow political news. Individuals are also intrinsically interested in the news for political reasons. We now turn to this second motive for attention.

2.2 Instrumental Motive

In line with our empirical setting, political news concern an imminent election. There are two political candidates indexed by subscripts c and c'. From the perspective of voter i, candidate c has quality $Q_c^i = \sum_k \chi_{kc}^i q_{kc}$, where $\{q_{kc}\}$ is a vector of true features of candidate c (eg. his/her policy position on issue k or his/her personal featues), $\chi_{kc}^i > 0$ is the weight assigned by voter i to that feature, and $k = 1,2,...K$. We assume that $\{q_{kc}\}$ are unobserved and voters' priors are drawn from independent normal distributions with prior means $\mu^i_{kc} > 0$ and prior variances $(\sigma^i_{kc})^2$. Different voter types have different political preferences ($\chi^i_{kc} \neq \chi^j_{kc}$) and / or different priors ($\mu^i_{kc} \neq \mu^j_{kc}$) for at least some k if $i \neq j$.

The news described above (the index p) refer to candidate features, kc.[5] Specifically, at any given moment in time, voters observe a noisy signal $s^i_{kc} = q_{kc} + \varepsilon^i_{kc}$ of true feature q_{kc}, where ε^i_{kc} is normally distributed with mean 0 and variance $(\eta^i_{kc})^2$. As in the literature on rational inattention (eg. Maćkowiak et al. (2023)), the choice of attention is modeled as the choice of the variance of the signals, $(\eta^i_{kc})^2$. Specifically, voters choose attention ξ^i_{kc} defined as:[6]

$$\xi^i_{kc} = \frac{(\sigma^i_{kc})^2}{(\sigma^i_{kc})^2 + (\eta^i_{kc})^2} \tag{1}$$

Voters' expectation of overall candidate' quality conditional on observing signal s^i_{kc} (i.e their posterior mean) are denoted by $\widehat{}$ and are formed according to Bayes rule, namely:

$$\hat{Q}^i_{kc} = \chi^i_{kc}\hat{q}^i_{ck} + \Lambda^i_{kc} \tag{2}$$

where $\hat{q}^i_{kc} = (1 - \xi^i_{kc})\mu^i_{kc} + \xi^i_{kc}s^i_{kc}$ and $\Lambda^i_{kc} = \sum_{h \neq k} \chi^i_{hc}\mu^i_{hc}$. The first term on the RHS of (2) is the posterior on the candidate feature on which the user receives a signal, the second term (Λ^i_{kc}) captures the posterior on all other features, which equal the prior since the news concerns kc. If voters pay more attention, their posterior means reflects observed signals more closely.[7]

Voters wish to rank the two candidates. Thus, voters' preferences from this instrumental motive of attention are $\Omega^i_{kc}(\xi^i_{kc}) = E^i Max\{\hat{Q}^i_{kc}\ ;\ Q^i_{c'}\}$, where E^i is the expectations operator over the posterior mean $\hat{Q}^i_{kc}$ described above. That is, $\Omega^i_{kc}(\xi^i_{kc})$ encodes the *ex-ante* expectation of the overall quality of the best candidate, from the perspective of i. It is *ex-ante* because it represents the expectation before attention is chosen and the signal is observed. It is from the perspective of i because it depends on i's prior beliefs. And it is

[5] That is, while in the previous subsection we indexed news with p, we will substitute subscript p with kc, to make explicit that news p discusses feature k of candidate c.

[6] We assume that the choice set is compact: $\xi^i_{kc} \in [\bar{\bar{\xi}}, 1]$ for $\bar{\bar{\xi}} \to 0$, or equivalently that $\eta^i_{kc} \in [0, \bar{\eta}]$ for $\bar{\eta} \to \infty$.

[7] The variable $\hat{Q}^i_{kc}$ refers to the overall quality of candidate c but is indexed by the subscript k as a reminder that it refers to posterior means condition on s^i_{kc}. As discussed in the appendix, before individual i chooses attention and observes the content of signal s^i_{kc}, his/her posterior mean $\hat{Q}^i_{kc}$ is also normally distributed, with known mean and variance, the latter a known function of user attention.

indexed by candidate feature kc because we are considering the choice of attention over news about that candidate feature.[8]

Finally, attention is costly, with a convex cost function $M^i_{kc}(\xi^i_{kc})$ multiplied by a shifter λ^i_{kc}. We follow the literature on costly attention and assume that the cost of attention is proportional to the relative reduction of uncertainty upon observing the signal, measured by entropy, namely:

$$\lambda^i_{kc} M^i_{kc}(\xi^i_{kc}) = -\lambda^i_{kc} \log(1 - \xi^i_{kc}) \tag{3}$$

where $\lambda^i_{kc} > 0$ reflects the attention cost for voter i from observing signal s^i_{kc} (Maćkowiak et al., 2023) . The term $-\log(1 - \xi^i_{kc})$ measures the reduction of uncertainty about candidate c upon observing the signal.[9] The parameter λ^i_{kc} reflects the material or time cost of paying attention to a particular news, other determinants of attention not captured by the model, such as the entertainment value of the post, 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, a higher value of λ^i_{kc} implies that the voter prefers a late resolution of uncertainty (it dislikes resolution of uncertainty), and viceversa if λ^i_{kc} is lower. The qualitative results discussed below would be similar for any strictly convex function of attention.

2.3 Equilibrium

Putting all this together, the objective function of user i when choosing attention to post kc is:

$$Max_{\xi^i_{kc}} [\Omega^i_{kc}(\xi^i_{kc}) - \lambda^i_{kc} M^i_{kc}(\xi^i_{kc}) + \beta V(\xi^i_{kc}, \xi^{-i}_{kc}; \varepsilon^i_{kc})] \tag{4}$$

The first term is the instrumental motive of attention, namely to rank the two candidates. As discussed above, this depends on the prior distributions on the candidates' qualities, which

[8] Voters know that they will vote for the candidate with the higher expected quality in the imminent election. Thus, when exposed to signal s^i_{kc}, they take into account that attention affects their posterior beliefs over the expected quality of candidate c. For candidate c' nothing is observed, and the voter therefore compares the updated posterior $\hat{Q}^i_{kc}$ against the prior for the other candidate, $Q^i_{c'}$.

[9] Note that the variance of posterior beliefs on q^i_{kc} (i.e the posterior variance) is: $\rho^i_{kc} = \xi^i_{kc}(\eta^i_{kc})^2$. From Equation (1), it is easy to see that the term $1 - \xi^i_{kc}$ is the ratio between the posterior variance and the prior variance $(\sigma^i_{kc})^2$ (i. the variance of prior beliefs). More attention to the signal (higher ξ^i_{kc}) thus corresponds to a reduction of uncertainty upon observing the signal. As stated in the Appendix, we assume that λ^i_{kc} is sufficiently small that optimal attention is always at an interior optimum.

in turn depend on the vector of prior means, prior variances and weights of each candidate feature. The second term is the convex cost of attention. The last term is the expected social benefit of attention, resulting from engaging with the news in a social environment. The parameter $\beta > 0$ is the relative weight assigned to this goal. In equilibrium user i chooses ξ^i_{kc} so as to maximize (4), taking as given equilibrium attention of all other users of the same type.[10]

As shown in the Appendix, equilibrium attention ξ^{i*}_{kc} is implicitly defined by first taking the FOC of (4), and then setting $\xi^{-i}_{kc} = \xi^i_{kc}$. Since $\partial^2 V(\xi^i_p, \xi^{-i}_p; \varepsilon^i_p)/\partial\xi^i_p\partial\xi^{-i}_p > 0$, the game is smooth super-modular (Vives, 2005). Hence an equilibrium exists, and the comparative statics properties of the extremal equilibria (i.e. of the equilibria with highest and lowest attention respectively) reflect those of the marginal benefits and cost of attention (eg., Amir, 2005 or Vives, 2005). The Appendix proves:

Proposition 1 *If the relative weight $\beta > 0$ assigned to social engagement is sufficiently small, the equilibrium is unique and it has the following properties: in equilibrium, users pay more attention to news concerning candidate features kc for which:*
(i) the cost of attention λ^i_{kc} is lower: $\partial\xi^{i*}_{kc}/\partial\lambda^i_{kc} < 0$
(ii) prior uncertainty σ^i_{kc} is higher: $\partial\xi^{i*}_{kc}/\partial\sigma^i_{kc} > 0$
(iii) the relevance χ^i_{kc} is higher, if candidate c is not their favored candidate: $\partial\xi^{i*}_{kc}/\partial\chi^i_{kc} > 0$ if $\sum_h \chi^i_{hc}\mu^i_{hc} < \sum_h \chi^i_{hc'}\mu^{i\prime}_{hc}$.
(iv) the potential audience, ε^i_{kc}, is larger: $\partial\xi^{i*}_{kc}/\partial\varepsilon^i_{kc} > 0$
Effects (i)-(iii) are larger in absolute value the larger is the potential audience ε^i_{kc} and the more users care about the likes to their comments (i.e. the larger is β):
$|\partial^2\xi^{i*}_{kc}/\partial x^i_{kc}\partial\varepsilon^i_{kc}|, |\partial^2\xi^{i*}_{kc}/\partial x^i_{kc}\partial\beta| > 0$ *for* $x = \lambda, \sigma$, *and for* $x = \chi$ *if* $\sum_h \chi^i_{hc}\mu^i_{hc} < \sum_h \chi^i_{hc'}\mu^{i\prime}_{hc}$*).*

For instrumental or psychological motives, users are intrinsically interested in news that reflect their political preferences: what they find entertaining or less disturbing given their ideology (low λ^i_{kc}), what they are unsure about (high σ^i_{kc}), what they find relevant (high χ^i_{kc}).[11] This explains political segregation: users with similar political views are attracted

[10] As stated in the appendix, to make sure that the second order conditions for optimal attention are satisfied, we assume that $|x^i_c| < \theta^i_{kc}$ for all levels of attention ξ^i_{kc} and all k and c, where x^i_c and θ^i_{kc} are respectively the mean and the standard deviation of the normally distributed random variable $\Delta^i_{kc} = \hat{Q}^i_{kc} - Q^i_{c'}$, for $c' \neq c$.

[11] If c is the ex-ante favored candidate (i.e. if $\sum_h \chi^i_{hc}\mu^i_{hc} > \sum_h \chi^i_{hc'}\mu^{i\prime}_{hc}$), a rise in χ^i_{kc} has an ambiguous effect because it also makes candidate c even more attractive ex-ante (it raises the prior mean of $\hat{Q}^i_{kc}$). This

by the same news. These effects are amplified by the social benefit of engaging with like-minded people, as captured by the size of the audience, ε^i_{kc}, or by the preference parameter β. Commenting the news is a social activity, and users are more attracted to it if their comments are appreciated by other users. This in turn is more likely to happen if like minded-users are also more attentive to the post (if ξ^{-i}_{kc} is higher) and if there are more of them around (i.e. if ε^i_{kc} is higher).

Note that this social aspect of news engagement that creates echo-chambers does not directly influence beliefs. Since agents are rational, their beliefs are revised only by the content of the signal s^i_{kc}, not by the comments of other users. Nevertheless, socialization induced by news engagement influences belief formation indirectly, through attention. Users pay more attention to news to which others with similar views are also attracted, while they neglect news that are also neglected by their political friends. This social aspect of online news amplifies asymmetries in beliefs of users with different political preferences, besides what would happen if individuals were exposed to the news in isolation.

2.4 Predictions

In the data we observe comments, not attention. But in equilibrium, the probability that user i comments post p is:

$$c^i_p = P(\xi^{i*}_p)F[W(\xi^{i*}_p;\varepsilon^i_p)] \tag{5}$$

which is an increasing function of (own and others') equilibrium attention, ξ^{i*}_p, and of the size of the potential audience, ε^i_p. Own attention matters through the term $P(\xi^{i*}_p)$, others' attention through the term $F[W(\xi^{i*}_p;\varepsilon^i_p)]$. Likes received are also increasing in these two variables, by assumption.

As described in the next section, we observe whether specific news are consonant (i.e. pleasant) or non-consonant (i.e unpleasant) for specific political types, depending on their content. Suppose that the cost of attention, λ^i_{kc}, is higher on non-consonant news, and lower on consonant news, compared to news that are emotionally neutral. For instance, as in our empirical setting, news reporting a scandal on the candidate that I dislike is consonant and more enjoyable, because it confirms my political beliefs, while news about a scandal on my preferred candidate is non-consonant and more costly to consider, because it contradicts my

in turn makes the news less discriminating and hence it reduces the marginal benefit of attention (see Bartoš et al., 2016 for a similar result in a different setting).

political judgement. Then Proposition 1 and equation (5) imply:

Predictions: *Users are more likely to comment on a post* p*, and receive more likes on such comments, if:*
(i) the post reports a consonant news, for which the the cost of attention, λ_p^i*, is lower, compared to non-consonant news*
(ii) the potential audience of like minded individuals on that post, ε_p^i*, is higher, compared to news on which the audience is lower.*
(iii) These two effects are interactive: the larger is the potential audience ε_p^i*, the greater is the difference in the probabilities of commenting and on the likes received, between consonant and non-consonant news.*

Predictions (i) and (iii) reflect a direct effect of costly attention, which is amplified by social interactions. On the direct effect, users pay more attention to news that they enjoy, compared to news they dislike, because the cost of attention is lower. Being more attentive makes them more likely to come up with a comment on consonant than on non-consonant news. But social interactions amplify these effects: users realize that other like minded individuals are also more attentive to consonant than to non-consonant news. Since others' attention also drives the likes received on one's comments, the expected utility from commenting is higher, and this makes it more likely to comment. Finally, the effects of social interactions are larger the greater is the expected audience of like minded individuals. Here too there is a direct effect (a larger audience increases the probability of commenting and the number of likes received), and an indirect effect (a larger audience increases the difference in the effects of consonant vs non-consonant news).

Note that the amplifying effect of a lager audience works in opposite directions on consonant vs non-consonant news: with a larger audience, I realize that more of my friends are drawn to the news if it is consonant, and this increases my probability of commenting. Symmetrically, I also realize that more of my friends are drawn away from non-consonant news, and this makes me less likely to comment a non-consonant news when many of my friends are online.

Overall, these results also imply that news engagement exhibits segregation by political preferences, because political preferences are correlated with the instrumental motives of attention. Whether a political news is consonant or not, or whether a user is interested or not in a topic, largely correlates with ideology. However, our model illustrates an additional mechanism of segregation. While the instrumental motive can be its primary cause, social media can powerfully amplify segregation because people also enjoy online validation of their views. The likelihood of receiving such validation depends on other ideologically aligned users being active on that particular news story. Because ideologically aligned users tend to like and dislike similar things, this audience effect induces even more segregation in news engagement. A democrat, for instance, will rationally expect fewer democrats to be engaged with scandals casting Clinton under a bad light, and this makes him /her even less inclined to engage with such news.

The empirical analysis mostly focuses on prediction (i), although we have something to say also about predictions (ii) and (iii).

3 Data

3.1 Reddit

Our data 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 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.[12]

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 targeting. *Ideological* fora, on the other hand, are defined by supporting a political ideology, such as conservatism, liberalism or feminism. Fora collecting supporters of a specific party, but not centered around one of the two candidates, are included in this category. For instance, `r/republican` defines itself as a "place for Republicans to discuss issues with other Republicans", and it is classified as ideological.[13] 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.2 in the Appendix reports all the political fora, along with their classification and a precise description of the classification method (in Section B.3). 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,[14] 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. 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.[15] Importantly for our purposes, users can write posts only sharing the title of the news source and the links, while their thoughts on the article are 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

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

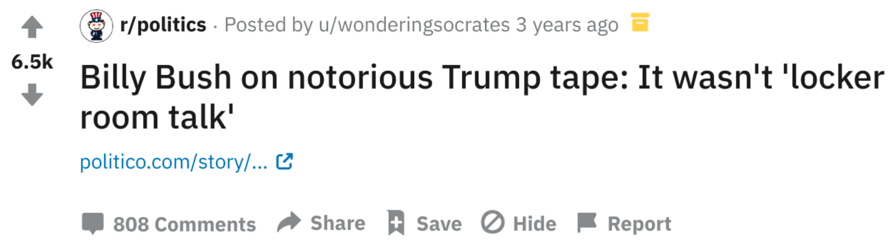
[13] Fora supporting candidates (eg. `r/The_Donald` and `r/hillaryclinton`) differ from ideological fora (eg. `r/republican`, or `r/Democrats`), because parties may have more than one candidate and users are active also in non-election periods.

[14] 8.5 million as of July 2024.

[15] See Appendix Section B.4 for a full description of the rules of the forum.

to the comments section. Thus, 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 1 shows an example of a posting related to the "Access Hollywood" scandal.

Figure 1: Example of Posting



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.1 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). Appendix Figure B.2 plots 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), restricting the comparison to all the exclusively political sources that are common to `r/politics` and Comscore.[16] Overall, the news sources attracting more comments in `r/politics` tend to be those that also attract more online page views in the Comscore sample.

[16]These are 14 out of 50, but they account for 78% of visits of the top 50 Comscore sources. The correlation coefficient across the share of comments on top 50 `r/politics` sources and the corresponding share of visits on top 50 political Comscore sources (including zeros when sources are in only one of the two samples) is 0.63. For common sources, it is 0.76.

3.1.1 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. In line with the model, our interpretation of independents is that they are not actively supporting one candidate, so that they have no emotional attachment to either campaign. But they might have a political leaning, which we do not observe and does not change the main predictions of Section 2.4.

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, we classify 61.6% of the total comments on `r/politics`. Of these, 71.5% come from independents, 11.1% from Clinton supporters, and the remaining 17.4% from Trump supporters. 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%.

In terms of number of users, Panel A of Appendix Table C.1 shows that we classify 71,344 users, of which 20,725 are Trump Supporters, 5,740 are Clinton Supporters and

Table 1: Share of classified comments per fora, by affiliation of comment author

Panel A: Discrete Classification			*Relative Activity by Fora*		
	Number of comments	% of total comments	`r/politics`	Pro-Clinton Fora	Pro-Trump Fora
By Trump Supporters	887,183	10.69	22.9	0.1	76.9
By Clinton Supporters	570,386	6.87	46.7	53.2	0.1
By Independents	3,656,287	44.04	99.6	0.2	0.2
By Non-Classified	3,187,675	38.4	80.2	7.1	12.7

Panel B: Continuous Classification	Number of comments	% of total comments
By Classified Users	7,998,970	96.4
By Non-Classified Users	302,561	3.6

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 6 comments on non partisan fora or on partisan fora: here, furthermore, we restrict the sample to authors with at least one comment on `r/politics`. 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. Comments made by moderators or bots are excluded from the counts.

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. However, as shown above, despite the large number of non-classified users, they do not account for the majority of comments.

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 shows that this larger sample accounts for practically all comments. 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 partisan preferences also to individuals whose behavior is more ambiguous. Panel B of Appendix Table C.1 reports the descriptive statistics of V_i^P, while Appendix Figure B.1 shows its distribution.

A concern with our classification is that we might be misclassifying users with multiple accounts or that we might be capturing activity by artificial users (so-called "bots") that are programmed to be active in a partisan way on online political fora. To address this concern, we repeat our analyses on two subsamples. In one we restrict to accounts that are very active, which we define with more than 10 comments in our sample period, more than three times the median number of comments. In the second we restrict to users that have an above median activity (above 64 comments) in non-political fora in our sample period, who are unlikely to be politically-targeted bots.

3.2 Classification of Political News

Finally, 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 that 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 Megathread 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.[17]

These two subsamples are representative of two types of debates that can take place on

[17]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.

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; in terms of our model, attention here is likely to largely reflect the instrumental motive of ranking the candidates. 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 likely to have a much larger active audience interested in that topic. In terms of our model, the parameter ε_p^i is presumably larger on Megathreads, implying a greater influence of the social motive on users' activity.

Coherently with these differences, the total number of comments on Megathreads is more than an order of magnitude larger than on Reuters posts. As shown in the first column of Table 2, 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 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, while Trump supporters and independents make .00035 and .00067, respectively.

Table 2: 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
Not Classified	26.25	16.42	27.42	27.43	2,752.76	2,525.40	4,502.12
Total number of comments	8,300,833	59,704	5,264	7,060	706,231	34,970	78,825
Total number of posts	121,410	1,350	72	104	97	5	8
Average number of comments per post	68.37	44.23	73.11	67.88	7,280.73	6,994.00	9,853.12
Average score per comment	6.68	5.33	8.16	5.08	6.07	17.52	9.96

Notes: Comments appearing in Megathreads and reported above refer to the each whole Megathread, not to individual posts collected within each Megathread. BNT and BNC indicate the sample of bad news (scandals or polls) for Trump and Clinton, respectively.

Panel A of Appendix Table C.1 reports the number of authors of comments, by type, 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), while Appendix Table C.2 reports their average and median number of comments. On r/politics and on Megathreads, the average is much larger than the median because there a few very prolific users, while most users make only a few comments.

Each Reuter post and each Megathread was manually classified as either a general news or as a bad news about either Trump or Clinton.[18] 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 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 interferences colluding with the Trump campaign. Examples of scandals on Clinton are email leaks or Clinton handling of the Benghazi attack.[19]

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. Appendix Section C.1 provides the precise definition of bad polls and

[18]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.

[19]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. 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.

supplementary analyses in Appendix Section C.4 show that results are robust to alternative definitions. Appendix Table C.5 provides some examples of Reuters scandals and bad polls.

On the basis of this classification, we thus construct dummy variables for scandals, bad polls, or either of the two. 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 2 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. The last line of the Table reports the average comment score (one plus the number of likes net of dislikes received by comments to that post). The average score on bad news is twice as large on Megathreads than on Reuters, again in line with the observation that Megathreads have a much larger active audience (a larger ε_p^i).

As shown in Appendix Table C.3, 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. Appendix Tables C.4 and C.5 provide some examples of scandals and bad polls, for Reuters, and the entirety of scandals posted as Megathreads. An exhaustive list of all bad news on Reuters and the links to each original article is available in supplementary material available upon request.

4 Engagement with News

Our empirical analysis starts by describing how partisan users comment on all political news in the days of four major scandals, in an event study fashion. We then study partisan comments on single postings about all the scandals that we identified in Section 3.2. We discuss our identification strategy in each context.[20]

4.1 Event Studies

As in the "ostrich effect" first studied in finance by Karlsson et al. (2009), if the cost of attention λ_{kc}^i is higher on non-consonant news and lower on consonant news, we expect

[20]Conducting event studies for all the bad news (including minor ones) that we identify is unfeasible, since they occur repeatedly, at high-frequency, and overlap.

partisan users to detach themselves from politics in days when political news are likely to focus on scandals on their own candidate, devoting instead more attention to sports, entertainment, financial news and the like. Conversely, we expect them to be attracted to political fora when the political debate is likely to focus on scandals about the opponent.

To choose the main scandals, we used the fact that all popular discussions on `r/politics` were aggregated into Megathreads. These Megathreads, which are reported in Appendix Table C.4, highlight four main controversies, three on Clinton and one on Trump: The leak of DNC emails and subsequent resignation of the DNC Chairman, discussed on July 23, 24, and 25, which received a total of 23,625 comments. The release from the FBI of documents concerning the Clinton e-mail investigation, discussed on September 2 with, 9,664 comments. The Hollywood Access Trump scandal, discussed on October 7 and 8, with 37,916 comments. Finally, the reopening of the FBI investigation on Clinton's emails, discussed on October 28 and 29, with 32,739 comments.[21]

As shown in Appendix Table C.4, the raw counts of engagement on these scandals are already quite telling of ideological segregation. In Clinton scandals, Trump supporters make twice to four time as many comments compared to Clinton supporters. The reverse is true for the Trump scandal, where Clinton supporters make 1.7 times more comments than Trump supporters.

To study these patterns more systematically, as well as dynamically, we estimate the following regression in a two-week window around each scandal:

$$Y_{it} = \alpha_i + \beta_t + \sum_{\substack{\tau=-7 \\ \tau\neq-1}}^{7} \left(\gamma_\tau^T * TS_i + \gamma_\tau^C * CS_i \right) * D_{t+\tau} + \varepsilon_{it}$$

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

[21]There was also another substantial controversy, which received 9,508 comments: the recommendation from Jim Comey (then FBI director) of no indictment over Clinton's handling of her email server, which was posted on July 5. We exclude this from our analysis since it can be interpreted as attenuating the concern of Clinton's mishandling of emails. There were also three other minor controversies covered by the Megathreads, which received less than 5,000 comments each. The resignation of the Trump campaign chairman, Paul Manafort, on August 19 (1,899 comments). The release from the Clinton campaign of medical records on September 14 (3,295 comments). The order to the Trump foundation to stop fundraising in NY on October 3 (3,496 comments). They are minor and partially overlap with other major scandals. Section 4.2, will include these scandals, as well as others, when we analyze comments across posts, rather than over time as we do here.

effects, TS_i and CS_i are dummy variables for Trump and Clinton supporters respectively, and $D_{t+\tau}$ are day dummy variables.[22] 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. Figure 2 plots the estimated coefficients γ_{τ}^{T} and γ_{τ}^{C} for all scandals, with their 95% confidence intervals (standard errors are clustered by individual). Each coefficient measures the change between day t and day $t = -1$ in the activity on political fora, as a fraction of all Reddit activity, for Trump (solid red line) and Clinton supporters (dashed blue line), compared to average independents, in the period surrounding each scandal.

As expected, Trump supporters are more active on political fora compared to independents right after the Clinton scandals, and less active after the Access Hollywood scandal, while the reverse is true for Clinton supporters. There is no obvious evidence of pre-trends. In all cases but one, effects for both groups of users vanish after one week.[23]

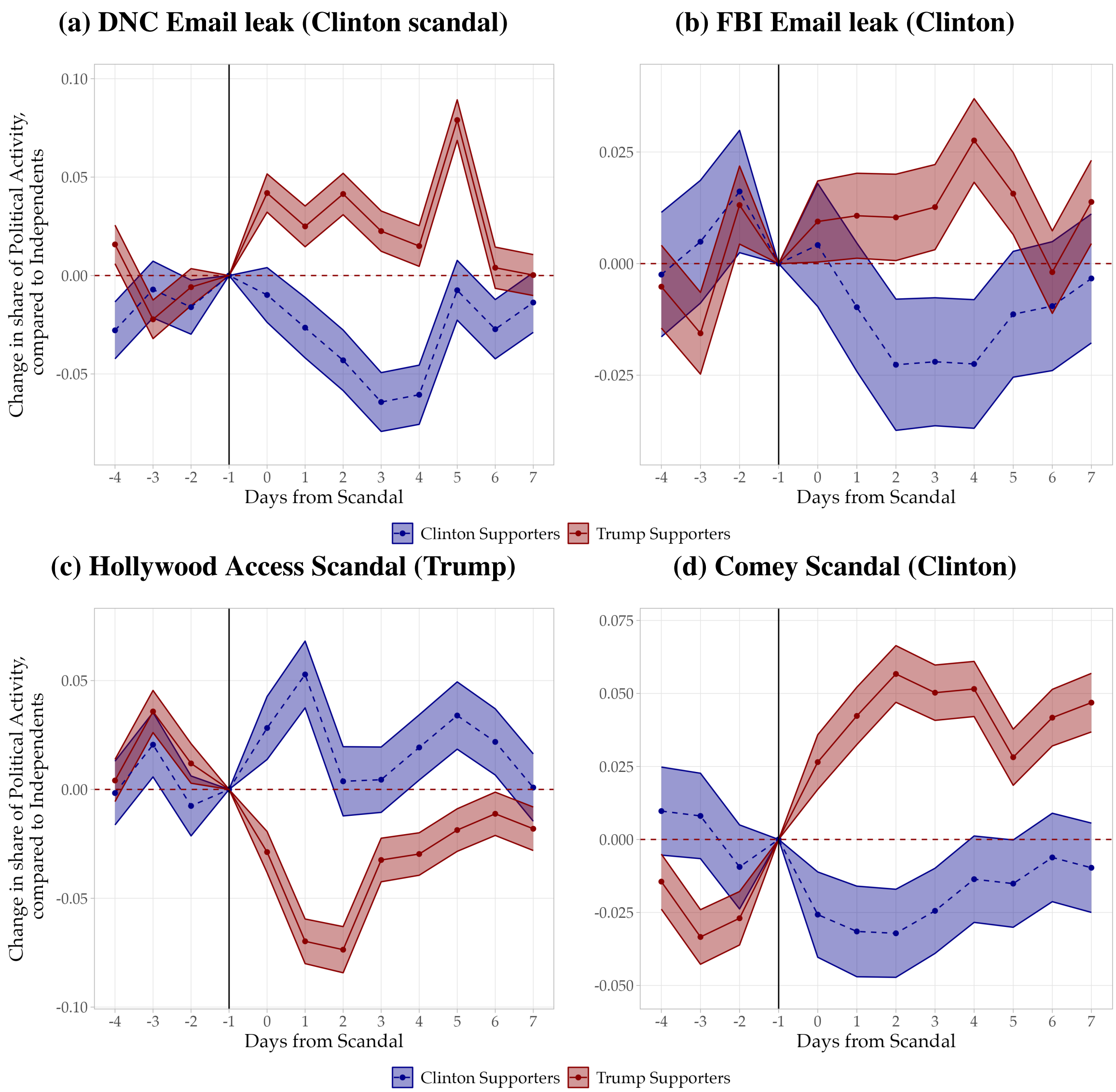
The effect of these scandals is sizable in magnitude. The day after the Access Hollywood scandal became public, Trump supporters decreased their share of comments on political fora by 7 percentage points, a 17.5% decrease compared to a mean of 40% in the 7 days before the scandal. Clinton supporters increased it by 6 percentage points, a 15.3% increase compared to the pre-period. For the Comey scandal, the pattern is similar: Clinton supporters decreased their share of comments by 3 p.p. the two days after (7% compared to the pre-period mean), while Trump supporters increased it by 6 p.p. at the peak of the effect two days after (13.3%). For the DNC scandal, in percentage terms compared to the pre-period mean, effects were of a 12% increase for Trump supporters and a 21% decrease for Clinton supporters. Around the FBI Email leak, these figures were somewhat smaller: a 3% increase for Trump supporters and an 8% decrease for Clinton supporters.

Do these patterns reflect increased/decreased engagement with all political news, or only with emotionally charged news? To answer, we used ChatGPT to tag all political posts around scandal windows, extending the manual tagging of scandals that we did on the Reuters sample described in Section 3.2. The classification exercise yields reassuring results and the prevalence of scandals increases right after the dates when they become pub-

[22] Political fora include `r/politics`, partisan fora, and all other subreddits devoted to discussions of US politics. The exhaustive list is reported in Appendix Table B.2.

[23] The only exception is engagement by Trump supporters after the Comey scandal, which seems to last longer. This might be driven by the fact that the scandal occurred shortly before the presidential election, so that later days capture additional engagement by Trump supporters.

Figure 2: Engagement with Political News Around Scandal Dates



Notes: The figure presents the average change, with respect to day $t = -1$, of the ratio of comments on political fora over total comments on the entire Reddit platform, for Trump supporters (solid red line) and Clinton supporters (dashed blue line), expressed as a difference with the same measure for independent users. The bands denote 95% confidence intervals (standard errors are clustered by user). Day $t = 0$ is the date when a scandal on either candidate became public. Panel (a) refers to the leak of DNC emails showing that the DNC favored Clinton over Sanders in the primary. Panel (b) refers to the release of FBI documents concerning the Clinton e-mail investigation. Panel (c) refers to the Access Hollywood videotape scandal, where Trump was recorded making lewd comments on women. Panel (d) refers to the declaration by James Comey that the FBI would re-open the investigation of Clinton's email controversy. The sample of political postings is restricted to posts by categorized authors' one week before and after the scandal announcement. All regressions control for individual fixed effects.

lic, as shown in Appendix Figure C.1.[24] We then repeat the event studies dropping all news tagged as bad news on either candidate, thus studying engagement only on non-scandals. Appendix Figure C.2 reports the results. The coefficients of the full sample overlap with those in this restricted sample, highlighting that asymmetric engagement concerns all political discussions, and not just those strictly covering the scandals.

If the outcome is measured by the total number of comments on political fora, rather than by the share of comments as a fraction of total Reddit comments, the patterns are similar but the estimated coefficient are smaller in absolute value. This suggests that, in the days after a scandal, users are not just less (or more) engaged with political news compared to days before the bad news, but that they substitute their activity towards (or away from) non-political news, such as financial news or sports news.

Finally, to assess robustness, we also consider the two samples that only include very active users and users who are also active in non-political fora—who are unlikely to be politically-targeted bots. Results (available upon request) are virtually identical.

Overall, it is difficult to explain these findings without recourse to some kind of motivated cognition. In particular, they cannot be explained by the argument that partisan users do not have confidence on a specific news source or posting, or that they have different prior uncertainties about different candidates, since engagement refers to all political news.

4.2 Analysis Across Political News

4.2.1 Econometric Framework

We now turn to a systematic investigation of how individuals react to the bad news about a political candidate. 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.

[24] Appendix Section C.3.1 describes the classification algorithm and reports the confusion matrices. Among 181 Reuters articles not included in the training data, the AI correctly classifies 13 scandals on Clinton out of 19 and 5 Trump scandals out of 7. Of the 155 non-scandals, the AI correctly classifies 154. No scandals on one candidate are mis-classified as scandals on the other. To further corroborate the tagging outside of Reuters, we manually classified an extra random sample of 200 posts from political fora. Within this set, the AI correctly classifies the only post covering a Trump scandal, 35 posts on Clinton scandals out of 37, as well as 151 non-scandals out of 162. Because Trump scandals are relatively less frequent, we further manually classifies 119 posts around the Hollywood scandal in all political fora excluding those of Trump supporters. We find 6 posts on Trump scandals, 4 of which are correctly classified by the AI. Both the AI and us find no Clinton scandals in this set of postings.

In line with the predictions of the theory, there are two outcomes of interest: the propensity of user i to comment post p, Y_{ip}, and the score (net likes) of his/her comments to that post, Y_{ipc} - here we have to index the dependent variable also by subscript c, because the same user could write more than one comment to the same post. For both outcomes, we study both the intensive margin (the number of comments to the post, and the numerical value of the score) and the extensive margin (whether the user commented the post, and whether his/her comment received a strictly positive score).[25]

When we study the propensity to comment, the unit of observation is the user-post pair, and 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 3.1.1. When studying the comment score, the unit of observation is the comment, and the sample consists of all comments to Reuters posts and to Megathreads (again analyzed separately) in `r/politics`. Appendix Table C.9 reports the relevant summary statistics (variables on activity 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. To gain statistical power, we assume that partisan differences in activity are symmetric across ideologies. Thus, we define two treatment variables:

$$\begin{aligned} \textit{Consonant News}_{ip} &= BNC_p * TS_i + BNT_p * CS_i \\ \textit{Non-consonant News}_{ip} &= BNT_p * TS_i + BNC_p * CS_i \end{aligned} \tag{6}$$

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 *Non-consonant News*$_{ip}$ is 1 if post p is a bad news on a candidate supported by partisan user i, and *Consonant News*$_{ip}$ is 1 if post p is a bad news on his/her opponent.

On all samples and for all dependent variables, we estimate the following regressions,

[25] A strictly positive score means that the comment received at least as many likes as dislikes (each comment automatically receives one like from the author, so it starts with a default score of 1). We don't distinguish between comments made directly to the post and comments made to comments.

for Y_{ip} and Y_{ipc} respectively :

$$\begin{aligned} Y_{ip} &= \alpha_i + \psi_p + \beta_1 * \textit{Consonant News}_{ip} + \beta_2 * \textit{Non-cons. News}_{ip} + \gamma \mathbf{X}_{ip} + \varepsilon_{ip} \quad (7) \\ Y_{ipc} &= \alpha_i + \psi_p + \beta_1 * \textit{Consonant News}_{ip} + \beta_2 * \textit{Non-cons. News}_{ip} + \gamma \mathbf{X}_{ipc} + \varepsilon_{ipc} \quad (8) \end{aligned}$$

where α_i and ψ_p are individual and posting FEs and $\mathbf{X}_{ip}$ and $\mathbf{X}_{ipc}$ are vectors of user- and post-level controls. In (7) and (8), controls include some post characteristics, such as the article length or which candidates are mentioned, alone and interacted with user type. The same controls are included in both regressions, except that in (7) we also control for user's activity in a 5-day window around the post, while in (8) we also control for the hierarchical level of the comment within the discussion thread.[26]

Equation (7) 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 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. To test prediction *i)* in section 2, we test whether $\beta_1 - \beta_2 > 0$.

Comparing the reaction of partisans vs independents to the same post (i.e. including post FE) allows posts to have different relevance, uniformly for all users (in terms of the model, $\chi^i_p \neq \chi^i_{p'}$). It might still be that partisan users are more interested in scandals compared to independents, however, and this unobserved heterogeneity would not be captured by the post FE. This is why the prediction is phrased in terms of consonant vs non-consonant news $(\beta_1 - \beta_2 > 0)$, rather than consonant and non-consonant news vs. general news $(\beta_1 > 0 > \beta_2)$. In this way, we keep the type of news constant (e.g. a scandal), and

[26] In the Reuters sample we scraped the text of all the articles and control for the following post characteristics alone and interacted with whether the user is a Trump or Clinton supporter: article length, whether the post author is a Trump or Clinton supporter, the number of mentions of Clinton and Trump in the article. For Megathreads, instead, 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 (to impute the ideology of a source, we use the so called Political Bias Index, developed by the website `mediabiasfactcheck.com`, which assigns to several media sources a score on a 7-point scale from left to right; see D'Amico and Tabellini (2022) for more details). 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).

just exploit variation coming from the fact that the same scandal is consonant for some users and non-consonant for others.

Comparing the reaction of the same individual to bad news vs general news (i.e. including individual FE) allows users to differ systematically in their propensity to comment and in the contents of their comments. Note that the specification with individual FE is demanding, because most individuals comment on only a few posts (see Appendix Table C.2). For this reason, we also report specifications without individual FE, or where we control only for whether the individual is partisan or independent.

The Reuters sample has fewer comments, but it has the advantage that all news originate from the same source. This reduces the concern that our results may be due to correlation between partisan identities and (unobserved) confidence in the news source.

Standard errors are always two-way clustered at the author and post level. Given the large number of 0s in the number of comments, we also estimate (7) 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 TS and CS that classify partisan supporters by the continuous variables defined 3.1.1.

4.2.2 Results

Main results Table 3 reports our results on the propensity to comment, 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 the fixed effects in the remaining columns. 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)[27] 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 3, 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.

The estimated values of $\beta_1 - \beta_2$ are generally much larger in the Megathreads than in the Reuters sample. This is in line with prediction *iii)* of Section 2.4, because the relevant audience is larger and more active on Megathreads than on the Reuters posts.

Table 4 repeats the same regressions, but with comment score as a dependent variable. In Columns (1)-(4) the dependent variable is the numerical value of the score, in Columns (5)-(8) it is a dummy variable for whether the comment score is strictly positive. The rest of the Table is the same as Table 3. As expected, partisan comments on consonant news receive a significantly larger score than on non-consonant news, compared to independents commenting on the same news, both on Reuter posts and in the Megathreads. Again, the more demanding specifications are in Columns (4) and (8).

Consider first the regressions with the numerical value of the score (Column 4). In the Reuters sample, the effect is driven by consonant news: the difference in score between partisan vs independent comments on consonant posts is about 75% of the average score. On Megathreads, the difference in score between partisan and independent comments is significant (and with the expected opposite sign) on both consonant and non-consonant posts. Expressed as a percentage of the average score, this difference is 77% for consonant posts and 50% for non consonant ones. Thus, in line with prediction *iii)*, the difference

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

Table 3: Activity Across Consonant and Non-consonant News

	Dependent variable: Comments of User i on Post p ($\times$100)							
	Num. of Comments (Intensive Margin)				Num. of Comments $>$ 0 (dummy, 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**	$-$0.0475**
	(0.0808)	(0.0650)	(0.0646)	(0.0646)	(0.0322)	(0.0235)	(0.0234)	(0.0234)
p-value ($\beta_1 - \beta_2$)	0.0054	0.0110	0.0118	0.0132	0.0001	0.0028	0.0029	0.0034
Dep. Var Mean	0.2870	0.2870	0.2870	0.2870	0.1410	0.1410	0.1410	0.1410
Observations	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000	13,095,000
R2	0.0000	0.0013	0.0099	0.0110	0.0000	0.0025	0.0195	0.0212
Panel B: Megathreads								
Consonant Scandal$_{i,p}$ (β_1^S)	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^S)	$-$2.7194	1.2403	1.2358	1.6064	0.1316	$-$0.9466	$-$0.9480	$-$0.9298
	(3.6813)	(2.8021)	(2.8015)	(2.8538)	(0.7975)	(0.5934)	(0.5933)	(0.5948)
p-value ($\beta_1^S - \beta_2^S$)	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
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

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: the partisan affiliation (if any) of the author of p or whether it is not classified, interacted with the partisan affiliation (if any) of i; whether p reports a poll, interacted with the affiliation of i; the length of the article shared in p, interacted with the affiliation of i; the number of Clinton and Trump mentions in the text of the article shared in p, interacted with the affiliation of i; the activity of user i in a five-day window around p. Panel B estimates in columns (2) to (4) and (6) to (8) include the following controls not reported in table: whether p reports a poll, interacted with the affiliation of i; the share of right- and left-wing sources shared in p (separately), interacted with the affiliation of i; the activity of user i in a five-day window around p. Panel A and B estimates in columns (2), (3), (6), (7) include controls for the affiliation of i. Panel A estimates in columns (2) and (6) include controls for whether the post is a Trump/Clinton scandal/bad poll. Panel B estimates in columns (2) and (6) include controls for whether p reports a Trump/Clinton scandal.

in score between consonant vs non-consonant comments is larger (in % of the dependent variable) on Megathreads where the audience is larger and more active than on Reuters posts.

Next, consider the likelihood of receiving a positive score (column 8). Here partisans differ from independents on both types of posts, consonant and non-consonant, in the expected direction. The magnitudes are similar in the Reuters and Megathreads samples. Partisans are more likely to receive a positive score compared to independents by 15 percentage point (SD of 0.03) in Reuters and 12 percentage points (SD of 0.03) in the Megathreads (corresponding to 19% and 13% of the mean respectively) if the post is consonant, and less likely by 8 or 9 percentage points (SD of 0.03 and 10% of the mean) in both samples.

Table 4: Likes net of Dislikes Across Consonant and Non-consonant News

	Dependent variable: Score of Comment c of User i on Post p							
	Comment Score				Comment Score >0			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reuters								
Consonant News$_{i,p}$ (β_1)	1.4727*	2.1936**	2.3956**	4.1692**	0.0643***	0.1428***	0.1297***	0.1504***
	(0.8087)	(1.0926)	(1.1937)	(1.7092)	(0.0211)	(0.0313)	(0.0317)	(0.0342)
Non-consonant News$_{i,p}$ (β_2)	−3.1093***	−3.7710**	−3.6747**	−0.1574	−0.1637***	−0.1087***	−0.1087***	−0.0783**
	(0.8640)	(1.4776)	(1.5674)	(1.6785)	(0.0331)	(0.0330)	(0.0362)	(0.0308)
p-value ($\beta_1 - \beta_2$)	0.0002	0.0000	0.0001	0.0106	0.0000	0.0000	0.0000	0.0000
Dep. Var Mean	5.4290	5.4290	5.4290	5.4290	0.7938	0.7938	0.7938	0.7938
Observations	37,537	37,537	37,537	37,537	37,537	37,537	37,537	37,537
R2	0.0003	0.0104	0.0213	0.2607	0.0060	0.0577	0.1135	0.4475
Panel B: Megathreads								
Consonant News$_{i,p}$ (β_1^S)	9.1325***	4.0004**	4.3568***	4.6360**	−0.0436	0.1290***	0.0993***	0.1157***
	(2.8565)	(1.7263)	(1.6484)	(2.1129)	(0.0378)	(0.0335)	(0.0349)	(0.0286)
Non-consonant News$_{i,p}$ (β_2^S)	1.8497	−4.0729**	−3.9126**	−3.0418**	−0.2002***	−0.1106***	−0.1314***	−0.0940***
	(2.1555)	(1.8333)	(1.8851)	(1.3532)	(0.0596)	(0.0415)	(0.0432)	(0.0264)
p-value ($\beta_1^S - \beta_2^S$)	0.1239	0.0037	0.0021	0.0003	0.0893	0.0000	0.0000	0.0000
Dep. Var Mean	5.9948	5.9948	5.9948	5.9948	0.8644	0.8644	0.8644	0.8644
Observations	439,213	439,213	439,213	439,213	439,213	439,213	439,213	439,213
R2	0.0010	0.0080	0.0112	0.1641	0.0058	0.0481	0.0680	0.2237
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

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample, variables, and controls are defined in Table 3, except that we don't control for user's activity in a 5-day window around the post, and instead we control for the hierarchical level of the comment.

Mechanisms What mechanisms drive these results? In terms of instrumental motives, the model of Section 2 suggests two possible reasons why partisan users are more attentive and hence comment bad news more frequently on the opponent than on their candidate. First, they could have sharper priors (lower $\sigma^i_{\kappa c}$) on their own candidate than on the opponent. Second, the cost of attention ($\lambda^i_{\kappa c}$) could be lower on consonant news and higher if it is non-consonant.

Note that the estimated coefficients of the interaction between users' partisanship and candidate mentions in the Reuters articles, which are reported in Appendix Table C.10, already cast some doubts on the first explanation. If the pattern described above was due to asymmetric information, we should find that, also for general news, partisan users comment more frequently on the opponent than on their own candidate. These interactions are instead not statistically significant, and their algebraic sum implies that, compared to independents, on average partisan users do not comment more frequently posts mentioning the opponent than those mentioning their candidate. Instead, they do this only when they comment bad news.[28]

To disentangle these two mechanisms more precisely, Table 5 disaggregates bad news posted on Reuters in scandals and bad polls. Since uncertainty on poll outcomes 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, separately for scandals and bad polls. The specification is identical to Table 3, but we only report two specifications: with no covariates and with all the FEs and controls.[29]

Ideological segregation on polls is, if anything, even stronger than on scandals. 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 3, 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.[30] 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, results on polls thus point unambiguously to a role of emotions in the propensity to comment pleasant vs unpleasant news. Appendix Tables C.11 and C.12 replicate Tables 3 and 5, respectively, using a nar-

[28] Specifically, consider the coefficients labelled as γ_i, $i = 1 - 4$, in Appendix Table C.10. 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).

[29] For Megathreads we cannot perform a similar disaggregation, because all polls are contained in a single Megathread. We only report regressions on the propensity to comment, and not on score, because the distinction between scandals and polls could affect the score in other ways, besides users' attention. For instance, comments on scandals could attract more likes or dislikes than comments on polls, because they are emotionally more charged.

[30] The coefficients β_1 and β_2, separately estimated for scandals and bad polls, are reported in separate supplementary material available upon request.

rower definition of bad polls (described in Appendix Section C.1) and show that results are similar.

Table 5: Activity Analysis, Polls and Scandals on Reuters

	Dependent variable: Comments of User i on Post p ($\times 100$)							
	Num. of Comments (Intensive Margin)				Num. of Comments > 0 (dummy, 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 3.

The model also implies that instrumental motives are amplified by social motives. Table 4 shows that comments on consonant news indeed receive more likes, in line with the model predictions. To draw a more direct link between the probability of commenting and social approval, we use our Megathreads sample to estimate whether users are more likely to be engaged in a debate when their comments are receiving more social approval. We restrict the sample to users who made at least one comment to a Megathread, and ask whether the probability that they continue to comment on that same Megathread is affected by the net likes received on their comments on that Megathread up to that point. Specifically, we estimate a survival regression at the comment-user-post level:

$$\mathbf{1}\left(\begin{array}{c}\text{User } i \text{ stops}\\ \text{commenting post } p\\ \text{after making}\\ \text{comment } c\end{array}\right) = \alpha_i + \psi_p + \xi_{t(c)} + \beta Z_{icp} + \gamma \mathbf{X}_{ipc} + \varepsilon_{ipc}$$

The dependent variable is a dummy variable that equals 0 for all comments by user i on Megathread p before his last comment, it equals 1 on his last comment. The variable of interest, Z_{icp} is the average score of all comments made by user i to Megathread p before and including comment c. Thus, the coefficient β captures whether receiving more likes to previous comments makes a user more or less likely to continue commenting. $\xi_{t(c)}$ is an hour fixed effect, measured from the time of opening the Megathread up to the 15th hour (the last hour fixed effect includes all hours from 15 and onwards), since users are more likely to abandon a debate as time goes by. Note that debates are not very long lasting: on average, more than 90% of all comments are written during the first 15 hours. Controls at the individual and post level are the same as in Table 3, but when the hours fixed effect is not included we also control for the number of hours from the opening of the Megathread. The estimated coefficient on this variable provides a benchmark against which to assess the magnitude of the coefficient of interest, β. We winsorize comments' score and hours since posting to the 99.5th percentile, which corresponds to a score of 138 and to 55 hours.[31] Because we are not exploiting partisan differences, we use all authors for this analysis, but restricting to only classified authors yields the same results.

Table 6: Social Approval and Engagement

	Dependent variable: User i Stops Commenting after Comment c ($\times 100$)					
	(1)	(2)	(3)	(4)	(5)	(6)
Average Comment Score	0.0223	-0.1051^{***}	-0.0748^{***}			
	(0.0226)	(0.0095)	(0.0092)			
Comment Score				0.0133	-0.0759^{***}	-0.0541^{***}
				(0.0155)	(0.0064)	(0.0065)
Hours from Start of Debate	0.2125^{**}	1.0402^{***}		0.2105^{**}	1.0474^{***}	
	(0.0904)	(0.0683)		(0.0913)	(0.0682)	
Controls	No	Yes	Yes	No	Yes	Yes
Post FE	No	Yes	Yes	No	Yes	Yes
Individual FE	No	Yes	Yes	No	Yes	Yes
Hour FE	No	No	Yes	No	No	Yes
Observations	659,601	659,601	659,601	659,601	659,601	659,601
R2	0.0016	0.2196	0.2221	0.0016	0.2194	0.2220

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. The dependent variable takes value 100 when the comment is the last one made by user i on a given post p, and takes value 0 otherwise. The sample is restricted to Megathreads. Controls are at the i, p level and defined in Table 3. Average comment score is the average score received by user i on its comments on post p made before comment c, including c. Comment score is the score of comment c. Hours from start of the debate is the difference in hours between the time of comment c and the time at which the posting was posted. Comment score and hours from start of the debate are winsorized at the 99.5th percentile.

Columns (2) and (3) of Table 6 show that users who are receiving many likes to the comments they just posted are significantly less likely to stop commenting, confirming that higher engagement is associated with social approval. The estimated coefficient is comparable to the effect of time. The coefficients on Average Comment Score and Hours from

[31] Results are similar without winsorizing but the relative magnitudes are affected by few extreme values in the variables.

Start of Debate in column (2) imply that receiving 10 fewer likes is equivalent to commenting an hour later. Columns (5) and (6) show a similar pattern when social approval is measured by the score of the current comment, rather than the average score of all comments up to and including comment c.[32]

Robustness In the Appendix we show that our results are robust and even stronger under different specifications and definitions. Consider first the regressions on the propensity to comment, reported in Appendix Table C.13. 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. Columns (1), (3), (4), and (6) use the continuous measure of partisanship, as defined in Section 3.1.1, instead of the discrete one, so to also include non-classified users. The estimated difference $\beta_1 - \beta_2$ is always positive and statistically significant, as expected. Moreover, it is always much larger on Megathreads than on Reuters posts, sometimes by an order of magnitude, as predicted if Megathreads have a larger audience. The fact that the results are robust to estimation by NLLS is reassuring given the sparsity of our dataset.

Next, consider Appendix Table C.14 where the dependent variable is the score. Column (1) refers to the numerical value of the score, Columns (2) to (4) to whether the score is positive. In Column (1) and (2) we estimate $\beta_1 - \beta_2$ by OLS using the continuous measure of partisanship. In Column (3) and (4) we estimate $\beta_1 - \beta_2$ by Logit, using the discrete and continuous tag, respectively. Results are robust across all models and types of author tagging. Similarly, results in Table 6 are also robust to using Logit.

Finally, Appendix Tables C.15 to C.18 replicate the main analyses in our two robustness samples where we restrict to activity by users with more than 10 comments and users that are also active in non-political fora, who are unlikely to be politically-targeted bots. Results on users with more than 10 comments are even stronger and those on users also active in non-political fora are quantitatively very similar to our main specification.

[32]The sample averages of the average comment score and current comment score are 5.06 and 4.12.

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.

As in the theory, we maintain the simple hypothesis that comments express users' true feelings and opinions. We study four outcomes that can be inferred from the text of a comment, the first of which measures *what* gets discussed, while the last three measure *how* news are discussed. The unit of observation here is the comment, rather than the user-post pair.

5.1 What Is Discussed

To capture whether users discuss different topics across emotionally vs. not emotionally charged posts, we start by highlighting words that are most distinctive of partisan vs. independent users when discussing scandals. For each bigram (two-word-phrases) in both the Reuters and Megathread samples, we compute the likelihood ratio of being used in comments by Trump (or Clinton) supporters vs independents. Appendix Figure C.4 plots the most distinctive (i.e. higher likelihood ratio measured by the χ^2 statistics) 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 tokens that are most distinctive of Trump supporters vs independents are those relating to Clinton scandals. 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, for each comment to a scandal of Trump or Clinton, we measure the "similarity" of that comment to any scandal of his/her opponent. The measure is constructed as follows, separately for the Reuters and Megathreads samples. For each candidate x, we estimate a χ^2 test (as in Gentzkow and Shapiro, 2010) of the uni- and bigrams (one and two-word phrases) 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. 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 the difference in the reaction to consonant vs. non-consonant scandals.

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

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

where α_i and ψ_p are individual and post 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 same difference for independents. Standard errors are always two-way clustered at the post and individual level.

Table 7 reports the results. We only report results on Megathreads, which has a much larger sample.[33] The first four columns report results when using word counts of unigrams, the last four those using bigrams. Columns (1) and (5) report the specification 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. The magnitudes of the estimated coefficients in the fully saturated specifications of columns (4) and (8) are also large, between 72% and 87% of the dependent variable

[33] In the Reuters sample the estimated coefficients of interest are not statistically significant in the fully saturated specification. Sample size matters if, as likely, the dependent variable is measured with error. It is also the case, as noted above, that Megathreads are the posts where most of the large debates take place, and where social motives are likely strongest.

Table 7: Similarity of Comments to Scandals of the Candidate Opposing the one Discussed

	Dependent variable: Similarity of Text of Comment i to Text of Scandal Opposite of Scandal Discussed in p							
	1-gram				2-grams			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Not Consonant Scandal$_{i,p}$	7.902***	6.443**	5.932*	8.734***	0.4784***	0.3541**	0.3162*	0.2639*
	(1.466)	(3.098)	(2.879)	(2.281)	(0.103)	(0.148)	(0.146)	(0.124)
Trump Supporter$_i$	3.954***				0.04765			
	(1.247)				(0.069)			
Clinton Supporter$_i$	−3.211**				−0.2157**			
	(1.491)				(0.1018)			
Trump Scandal$_p$	−2.856	−3.922			0.01225	−0.01318		
	(3.097)	(3.176)			(0.112)	(0.111)		
Individual FE	No	No	No	Yes	No	No	No	Yes
Post FE	No	No	Yes	Yes	No	No	Yes	Yes
Controlling for Comments' level	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Dep. Var Mean	11.039	11.039	11.039	11.039	0.298	0.298	0.298	0.298
Observations	64,423	64,423	64,423	64,423	64,423	64,423	64,423	64,423
R2	0.003	0.001522	0.008	0.240	0.001358	0.001358	0.003	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.

mean.

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

5.2 How Are News Discussed

Next, we focus on *how* scandals are discussed. We estimate equation (8) again, but now the dependent variables measure the content of the comment, rather than its score. We start with the degree of emotionality vs. reason in a text, computed as in (Gennaro and Ash, 2021), by the ratio of the distance of a comment from two sets of words: one relating to emotionality and affection (in the numerator), and one relating to rationality (in the denominator).[34] A value of 1 means that the text is equally distant from emotional and rational words, a higher value means that the text displays relatively more emotionality than reason.

The other two measures of content captures the sentiment of a comment - i.e. whether a comment expresses positive or negative opinons or feelings.[35] Our preferred measure of

[34] 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.

[35] Sentiment analysis differs from measurement of emotion vs reason, because it aims to classify the polar-

sentiment is the classifier provided by Hartmann et al. (2023), which builds on a document-embedding representation of each comment using the RoBERTA model by Liu et al. (2019), that tags each comment as having either positive or negative sentiment.[36] For robustness, we also report results on an alternative measure of sentiment developed by Gennaro and Ash (2021). Their algorithm constructs the sentiment score as the distance between the comment and sets of words representing positive and negative sentiment centroids.[37]

The specification is like in equation (8). 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 between these same posts.

Again. we only report estimated coefficients for the Megathreads sample, which is larger and where emotions presumably play a larger role.[38] Results are displayed in Table 8. For all outcome variables, in odd columns we report a specification without controls and FE, and in even columns a fully saturated specification. In Columns (1)-(2) the dependent variable is the ratio of emotionality to rationality, the remaining columns refer to the two alternative measures of sentiment.

Emotionality Column (2) shows that, compared to independents, partisan users, are less emotional when they comment non-consonant scandals on Megathreads, relative to the difference between partisan and independents when commenting a general news, and the

ity of a text, as positive or negative. Even cognitive and rational statements can contain positive or negative content.

[36]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, which reassures that measurement error is within reasonable bounds (see Appendix Section C.6 for the details of the classification).

[37]In particular, for each comment c, the sentiment score is computed as $\frac{1-cos(c,p)}{1-cos(c,n)}$, where $cos(c,p)$ and $cos(c,n)$ represent the cosine distance between a vector representing comment c and a positive (p) and negative (n) sentiment centroid respectively. We represent comments using word embeddings trained on our `r/politics` corpus. The positive (p) and negative (n) centroids are computed as a weighted average of the positive and negative seed-words identified by Demszky et al. (2019) and the 10 most similar embeddings for each seed in our vector space. Differently from Gennaro and Ash (2021), we do not restrict the number of seeds used.

[38]In the Reuters sample the estimated coefficients of interest are not statistically signifcant.

Table 8: Emotionality and Sentiment of Comments to Scandals on Megathreads

	Dependent variable: Content of Comment i to Post p $(\times 100)$					
	Emotionality		Sentiment (RoBERTa)		Sentiment (Gennaro-Ash Score)	
	(1)	(2)	(3)	(4)	(5)	(6)
Consonant Scandal$_{i,p}$ (β_1^S)	-1.2743^{***}	-0.0321	-5.1164^{***}	1.8944^{*}	2.0569^{***}	0.2008
	(0.2932)	(0.1595)	(0.8934)	(1.0432)	(0.6546)	(0.3158)
Non-consonant Scandal$_{i,p}$ (β_2^S)	-1.7500^{***}	-0.5740^{***}	-7.8137^{***}	-2.6515^{***}	0.8465	-0.4524
	(0.3466)	(0.1313)	(0.8327)	(0.9138)	(0.6895)	(0.3480)
FE and Controls	No	Yes	No	Yes	No	Yes
p-value $(\beta_1^S - \beta_2^S)$	0.0057	0.0001	0.0278	0.0002	0.0017	0.0309
Dep. Var. Mean	94.7621	94.7621	29.4361	29.4361	102.9419	102.9419
Observations	436,825	436,825	439,175	439,175	432,403	432,403
R2	0.0026	0.1844	0.0009	0.0988	0.0008	0.1387

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Sample restricted to Megathreads. Dependent variable is the emotion vs. reason ratio in columns (1) and (2); sentiment score in columns (3) to (6), as tagged by RoBERTa in columns (3) and (4); and using the Gennaro-Ash score in columns (5) and (6). All dependent variables are multiplied by 100. The sample is restricted to comments of authors classified as either Trump Supporters, Clinton Supporters or Independent. FE refer to post and author fixed effects. Controls refer to whether p reports a poll, interacted with the affiliation of i; the share of right- and left-wing sources shared in p (separately), interacted with the affiliation of i; the activity of user i in a five-day window around p.

estimated difference $\beta_1 - \beta_2$ between comments on consonant and non-consonant scandals is positive and significant. Note however that the magnitudes of the effect, although statistically significant, is not large. The estimated coefficient of 0.57 in column (2) on non-consonant news implies that the affection/cognition ratio of partisan comments on a non-consonant scandal is roughly a tenth of a standard deviation lower, 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, this does not happen, because they don't need to find excuses or explanations. 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), as well as with findings in neuroscience (Westen et al., 2006).

Sentiment Next, consider our preferred measure of sentiment, in column (4) of Table 8. Compared to independents, partisan users are significantly more likely to express a positive sentiment in their comments to consonant scandals than on general news, and to express negative sentiment if the scandal is non-consonant. The estimated difference $\beta_1 - \beta_2$ between comments on consonant and non-consonant scandals is positive and significant. Thus, partisan users are more positive when commenting consonant rather than non-consonant scandals, compared to how independents comment on the same news, and viceversa if the news is non-consonant. Compared to comments on general news, partisan comments are 1.9 p.p. more likely to display a positive sentiment on a consonant scandal (6% at the mean), and 2.65 p.p. less likely on a non-consonant one (9% at the mean), compared to the same difference for independents. To alleviate concerns of measurement error, column (6) shows that the estimated difference $\beta_1 - \beta_2$ remains positive and significant when sentiment is measured by an alternative indicator of sentiment developed by Gennaro and Ash (2021).

6 Conclusion

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

First, on days of major scandals on their supported candidate, partisan users disengage from political discussion altogether and substitute into non-political news, compared to independents—while the opposite is true when the scandal falls on the opponent.

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. In the Reuters sample partisans are about 30% more or less likely to comment depending on whether the news is consonant or not, and effects are even larger in the Megathreads sample which attracts a larger active audience. 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 number of net likes received by partisan comments on consonant news is much larger than those received on non-consonant news, as one would expect if news engagement reflects a social motive.

Fourth, 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. 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 can shed light on why individuals with different partisan affiliations hold starkly different beliefs on controversial issues.

Our analysis also suggests that social media amplify the relevance of these psychological drivers of news engagement. The new web platforms provide enhanced opportunities to exchange views with others, allowing users to self-select into more or less congenial debates. If individuals are motivated by the expectation of positive feedback on their views, as suggested by our survival analysis of commenting on Megathreads, this will give rise to echo chambers, where individuals with similar political views engage with the same kind of news. Even if these echo chambers do not directly influence beliefs, they create social incentives to pay more attention to consonant vs non-consonant news, amplifying the effects of motivated cognition on belief formation.

References

Acemoglu, Daron, Asuman Ozdaglar, and James Siderius (2023). "A Model of Online Misinformation". In: *The Review of Economic Studies*, rdad111.

Alesina, Alberto, Armando Miano, and Stefanie Stantcheva (2023). "Immigration and Redistribution". In: *The Review of Economic Studies* 90 (1), pp. 1–39.

Alesina, Alberto, Stefanie Stantcheva, and Edoardo Teso (2018). "Intergenerational Mobility and Preferences for Redistribution". In: *American Economic Review* 108 (2), pp. 521–554.

Allcott, Hunt, Levi Boxell, Jacob Conway, Matthew Gentzkow, Michael Thaler, and David Yang (2020a). "Polarization and Public Health: Partisan Differences in Social Distancing during the Coronavirus Pandemic". In: *Journal of Public Economics* 191, p. 104254.

Allcott, Hunt, Luca Braghieri, Sarah Eichmeyer, and Matthew Gentzkow (2020b). "The Welfare Effects of Social Media". In: *American Economic Review* 110 (3), pp. 629–676.

Amir, Rabah (2005). "Supermodularity and Complementarity in Economics: An Elementary Survey". In: *Southern Economic Journal* 71 (3), pp. 636–660.

Aridor, Guy, Rafael Jiménez-Durán, Ro'ee Levy, and Lena Song (2024). "The Economics of Social Media". In: *Journal of Economic Literature*.

Bail, Christopher A., Lisa P. Argyle, Taylor W. Brown, John P. Bumpus, Haohan Chen, M. B. Fallin Hunzaker, Jaemin Lee, Marcus Mann, Friedolin Merhout, and Alexander Volfovsky (2018). "Exposure to Opposing Views on Social Media Can Increase Political Polarization". In: *Proceedings of the National Academy of Sciences* 115 (37), pp. 9216–9221.

Bakshy, Eytan, Solomon Messing, and Lada A. Adamic (2015). "Exposure to Ideologically Diverse News and Opinion on Facebook". In: *Science* 348 (6239), pp. 1130–1132.

Ballard, Jamie (2024). *What Americans Think of the Charges against Donald Trump in Four Cases | YouGov*.

Bartoš, Vojtěch, Michal Bauer, Julie Chytilová, and Filip Matějka (2016). "Attention Discrimination: Theory and Field Experiments with Monitoring Information Acquisition". In: *American Economic Review* 106 (6), pp. 1437–1475.

Bénabou, Roland and Jean Tirole (2011). "Identity, Morals, and Taboos: Beliefs as Assets *". In: *The Quarterly Journal of Economics* 126 (2), pp. 805–855.

— (2016). "Mindful Economics: The Production, Consumption, and Value of Beliefs". In: *Journal of Economic Perspectives* 30 (3), pp. 141–164.

D'Amico, Leonardo (2018). *Verba Volant, Consequences May Stay: Do Loud Rallies Move Minds? Evidence from the 2016 U.S. Electoral Campaign*. M.Sc. Thesis, Bocconi University 2017/2018 BI09 0026359.

D'Amico, Leonardo and Guido Tabellini (2022). "Online Political Debates". In: Cesifo Working Papers, p. 96.

Demszky, Dorottya, Nikhil Garg, Rob Voigt, James Zou, Jesse Shapiro, Matthew Gentzkow, and Dan Jurafsky (2019). "Analyzing Polarization in Social Media: Method and Application to Tweets on 21 Mass Shootings". In: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. Ed. by Jill Burstein, Christy Doran, and Thamar Solorio. Minneapolis, Minnesota: Association for Computational Linguistics, pp. 2970–3005.

Di Tella, Rafael, Sebastian Galiani, and Ernesto Schargrodsky (2007). "The Formation of Beliefs: Evidence from the Allocation of Land Titles to Squatters". In: *Quarterly Journal of Economics* 122 (1), pp. 209–241.

Flynn, D. J., Brendan Nyhan, and Jason Reifler (2017). "The Nature and Origins of Misperceptions: Understanding False and Unsupported Beliefs About Politics". In: *Political Psychology* 38 (S1), pp. 127–150.

Garz, Marcel, Jil Sörensen, and Daniel F. Stone (2020). "Partisan Selective Engagement: Evidence from Facebook". In: *Journal of Economic Behavior & Organization* 177, pp. 91–108.

Gennaro, Gloria and Elliott Ash (2021). *Emotion and Reason in Political Language*. Working Paper.

Gentzkow, Matthew and Jesse M. Shapiro (2006). "Media Bias and Reputation". In: *Journal of Political Economy* 114 (2), pp. 280–316.

— (2010). "What Drives Media Slant? Evidence From U.S. Daily Newspapers". In: *Econometrica* 78 (1), pp. 35–71.

— (2011). "Ideological Segregation Online and Offline". In: *The Quarterly Journal of Economics* 126 (4), pp. 1799–1839.

Golub, Benjamin and Evan Sadler (2016). "Learning in Social Networks". In: *The Oxford Handbook of the Economics of Networks*. Ed. by Yann Bramoullé, Andrea Galeotti, and Brian W. Rogers. Oxford University Press, p. 0.

Hampton, Keith, Lee Rainie, Weixu Lu, Maria Dwyer, Inyoung Shin, and Kristen Purcell (2014). *Social Media and the 'Spiral of Silence'*.

Hartmann, Jochen, Mark Heitmann, Christian Siebert, and Christina Schamp (2023). "More than a Feeling: Accuracy and Application of Sentiment Analysis". In: *International Journal of Research in Marketing* 40 (1), pp. 75–87.

Jones, Jeffrey (2019). *More Democrats Want Trump Removed Than Wanted Nixon Out*.

Kahan, Dan M. (2015). “Climate-Science Communication and the Measurement Problem”. In: *Political Psychology* 36 (S1), pp. 1–43.

Karlsson, Niklas, George Loewenstein, and Duane Seppi (2009). “The Ostrich Effect: Selective Attention to Information”. In: *Journal of Risk and Uncertainty* 38 (2), pp. 95–115.

Kim, Jin and Eunji Kim (2021). “Temporal Selective Exposure: How Partisans Choose When to Follow Politics”. In: *Political Behavior* 43, pp. 1–21.

Levy, Gilat and Ronny Razin (2019). “Echo Chambers and Their Effects on Economic and Political Outcomes”. In: *Annual Review of Economics* 11 (1), pp. 303–328.

Lilley, Matthew and Brian Wheaton (2024). “Are Preconceptions Postconceptions? Evidence on Motivated Political Reasoning”. Working Paper.

Liu, Yinhan, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov (2019). “RoBERTa: A Robustly Optimized BERT Pretraining Approach”. In: *CoRR* abs/1907.11692.

Maćkowiak, Bartosz, Filip Matějka, and Mirko Wiederholt (2023). “Rational Inattention: A Review”. In: *Journal of Economic Literature* 61 (1), pp. 226–273.

Matějka, Filip and Guido Tabellini (2020). “Electoral Competition with Rationally Inattentive Voters”. In: *Journal of the European Economic Association* (jvaa042).

Matthes, Jörg, Johannes Knoll, and Christian von Sikorski (2017). “The “Spiral of Silence” Revisited: A Meta-Analysis on the Relationship Between Perceptions of Opinion Support and Political Opinion Expression”. In: *Communication Research* 45, p. 009365021774542.

Moehring, Alex (2022). “News Feeds and User Engagement: Evidence from the Reddit News Tab”. In: *SSRN Electronic Journal*.

Nadarajah, Saralees and Samuel Kotz (2008). “Exact Distribution of the Max/Min of Two Gaussian Random Variables”. In: *IEEE Transactions on Very Large Scale Integration (VLSI) Systems* 16 (2), pp. 210–212.

Pew Research Center (2016). *Nearly Eight-in-Ten Reddit Users Get News on the Site*.

— (2019). *Share of U.S. Adults Using Social Media*.

Srinivasan, Karthik (2023). “Paying Attention”.

Sunstein, Cass R. (2017). *#Republic: Divided Democracy in the Age of Social Media*. Princeton ; Oxford: Princeton University Press.

Thaler, Michael (2024). “The Fake News Effect: Experimentally Identifying Motivated Reasoning Using Trust in News”. In: *American Economic Journal: Microeconomics* 16 (2), pp. 1–38.

Tyler, Matthew, Justin Grimmer, and Shanto Iyengar (2022). “Partisan Enclaves and Information Bazaars: Mapping Selective Exposure to Online News”. In: *The Journal of Politics* 84 (2), pp. 1057–1073.

Vives, Xavier (2005). “Complementarities and Games: New Developments”. In: *Journal of Economic Literature* 43 (2), pp. 437–479.

Westen, Drew, Pavel S. Blagov, Keith Harenski, Clint Kilts, and Stephan Hamann (2006). “Neural Bases of Motivated Reasoning: An FMRI Study of Emotional Constraints on Partisan Political Judgment in the 2004 U.S. Presidential Election”. In: *Journal of Cognitive Neuroscience* 18 (11), pp. 1947–1958.

Yun, Gi Woong and Sung-Yeon Park (2011). “Selective Posting: Willingness to Post a Message Online”. In: *Journal of Computer-Mediated Communication* 16 (2), pp. 201–227.

Appendix

A Theoretical Appendix

A.1 Optimal allocation of attention

By (2), from the perspective of individual i, his/her posterior means are normally distributed, with mean and variance given by:

$$\begin{aligned} E^i(\hat{Q}^i_{kc}) &= \chi^i_{kc}[(1-\xi^i_{kc})\mu^i_{kc} + \xi^i_{kc}E^i(s^i_{kc})] + \Lambda^i_{kc} = \chi^i_{kc}\mu^i_{kc} + \Lambda^i_{kc} = \sum_h \chi^i_{hc}\mu^i_{hc} \\ Var^i(\hat{Q}^i_{kc}) &= (\chi^i_{kc})^2(\xi^i_{kc})^2 Var^i(s^i_{kc}) + \Psi^i_{kc} = \xi^i_{kc}(\chi^i_{kc})^2(\sigma^i_{kc})^2 + \Psi^i_{kc} \end{aligned} \tag{9}$$

where $E^i(s^i_{kc})$ and $Var^i(s^i_{kc})$ are computed based on voter i prior distribution of q_{kc} and the true distribution of the noise term ε^i_{kc}, and where $\Psi^i_{kc} = \sum_{h\neq k}(\chi^i_{hc})^2(\sigma^i_{hc})^2$. These expressions define the *ex-ante* mean and variance of conditional expectations of candidate quality, before attention is chosen and signal s_{kc} is observed, from the perspective of voter i given his/her prior beliefs. 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). If no signal on candidate c is observed, then posterior means coincide with prior means.[39]

To compute equilibrium attention, we exploit the properties of the distribution of the random variable $\Delta^i_{kc} = \hat{Q}^i_{kc} - Q^i_{c'}$, for $c' \neq c$, which measures the expected difference in candidates quality for voter i, conditional on observing signal s^i_{kc}. Ex-ante (i.e. before observing the signal), Δ^i_{kc} is also normally distributed, with mean

$$x^i_c = \sum_h (\chi^i_{hc}\mu^i_{hc} - \chi^i_{hc'}\mu^i_{hc'}) \tag{10}$$

[39]Note that the variance of posterior means, $Var^i(\hat{Q}^i_c)$, should not be confused with the variance of posterior beliefs on q^i_{kc} (i.e the posterior variance), which instead is: $\rho^i_{kc} = \xi^i_{kc}(\eta^i_{kc})^2$. Note also that the subjective distribution of posterior means differs from the true distribution of posterior means if individual priors are not rational (i.e., if prior beliefs over the random variable q_{kc} differ from true distribution of q_{kc}).

and variance

$$(\theta^i_{kc})^2 = \xi^i_{kc}(\chi^i_{kc})^2(\sigma^i_{kc})^2 + \Gamma^i_{kc} \tag{11}$$

where $\Gamma^i_{kc} = \sum_{h\neq k}(\chi^i_{hc})^2(\sigma^i_{hc})^2 + \sum_h(\chi^i_{hc'})^2(\sigma^i_{hc'})^2$. Higher attention increases the (ex-ante) variance of Δ^i_{kc}, because voters' expectations reflect more closely the signals received.

Throughout we assume that:

$$|x^i_c| < \theta^i_{kc} \tag{A1}$$

$$\phi(\frac{x^i_c}{\bar{\theta}^i_{kc}})\frac{(\sigma^i_{kc})^2(\chi^i_{kc})^2}{2\bar{\theta}^i_{kc}} > \frac{\lambda^i_{kc}}{1-\bar{\xi}} \tag{A2}$$

for all ξ^i_{kc} and for all kc and all i, where $(\bar{\theta}^i_{kc})^2 = \bar{\xi}(\chi^i_{kc})^2(\sigma^i_{kc})^2 + \Gamma^i_{kc}$ and $\phi(.)$ is the density of the standard normal distribution. As shown below, (A1) implies that the sufficient second order conditions for an optimum are satisfied, and (A2) implies the optimum is not at the corner corresponding to the lower bound of the choice set $[\bar{\xi}, 1]$.

The first order conditions for an interior optimum of (4) with respect to ξ^i_{kc} are:

$$\frac{\partial\Omega^i_{kc}(\xi^i_{kc})}{\partial\xi^i_{kc}} - \frac{\partial M^i_{kc}(\xi^i_{kc})}{\partial\xi^i_{kc}} + \frac{\partial\beta V_{\xi^i_{kc}}(\xi^i_{kc}, \xi^{-i}_{kc}; \varepsilon^i_{kc})}{\partial\xi^i_{kc}} = 0 \tag{12}$$

We have:[40]

$$\frac{\partial\Omega^i_{kc}(\xi^i_{kc})}{\partial\xi^i_{kc}} = \left\{\phi(\frac{x^i_c}{\theta^i_{kc}})[1-(\frac{x^i_c}{\theta^i})^2] - \phi'(\frac{x^i_c}{\theta^i_{kc}})\frac{x^i_c}{\theta^i_{kc}}\right\}\frac{\partial\theta^i_{kc}}{\partial\xi^i_{kc}} \tag{13}$$

$$\frac{\partial\beta V_{\xi^i_{kc}}(\xi^i_{kc}, \xi^{-i}_{kc}; \varepsilon^i_{kc})}{\partial\xi^i_{kc}} = P'(\xi^i_{kc})\beta A(\xi^{-i}_{kc}; \varepsilon^i_{kc}) \tag{14}$$

[40] In deriving (12), we used the fact that, since $\hat{Q}^i_T, \hat{Q}^i_C$ are jointly normal :

$$EMax[\hat{Q}^i_T, \hat{Q}^i_C] = \chi^i_T\mu^i_T\Phi(\frac{\chi^i_T\mu^i_T - \chi^i_C\mu^i_C}{\theta^i}) + \chi^i_C\mu^i_C\Phi(\frac{\chi^i_C\mu^i_C - \chi^i_T\mu^i_T}{\theta^i}) + \theta^i\phi(\frac{\chi^i_T\mu^i_T - \chi^i_C\mu^i_C}{\theta^i})$$

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

where $A(\xi_{kc}^{-i};\varepsilon_{kc}^{i}) = F[W(\xi_{kc}^{-i};\varepsilon_{kc}^{i})]W(\xi_{kc}^{-i};\varepsilon_{kc}^{i}) > 0$. Note that $\phi'(x) = -\phi(x)x$, and

$$\begin{aligned}
\frac{\partial \theta_{kc}^{i}}{\partial \xi_{kc}^{i}} &= \frac{1}{2\theta_{kc}^{i}}(\chi_{kc}^{i})^2(\sigma_{kc}^{i})^2 \\
\frac{\partial M_{kc}^{i}(\xi_{kc}^{i})}{\partial \xi_{kc}^{i}} &= \lambda_{kc}^{i}/(1-\xi_{kc}^{i})
\end{aligned}$$

Inserting these expressions in (12) and simplifying yields:

$$\phi(\frac{x_c^i}{\theta_{kc}^i})\frac{(\sigma_{kc}^i)^2(\chi_{kc}^i)^2}{2\theta_{kc}^i} - \frac{\lambda_{kc}^i}{1-\xi_{kc}^i} + \beta P'(\xi_{kc}^i)A(\xi_{kc}^{-i};\varepsilon_{kc}^i) = 0 \tag{15}$$

Hence, the second order conditions for an optimum is:

$$\left\{\frac{(\sigma_c^i)^2(\chi_{kc}^i)^2}{2(\theta_{kc}^i)^2}\phi(\frac{x_c^i}{\theta_{kc}^i})(-1+(\frac{x_c^i}{\theta_{kc}^i})^2)\right\}\frac{\partial\theta_{kc}^i}{\partial\xi_{kc}^i} - \frac{\lambda_{kc}^i}{1-\xi_{kc}^i}\beta P''(\xi_{kc}^i)A(\xi_{kc}^{-i};\varepsilon_{kc}^i) < 0$$

or:

$$\left\{\frac{(\sigma_c^i)^4(\chi_{kc}^i)^4}{4(\theta_{kc}^i)^3}\phi(\frac{x_c^i}{\theta_{kc}^i})(-1+(\frac{x_c^i}{\theta_{kc}^i})^2)\right\} - \frac{\lambda_{kc}^i}{1-\xi_{kc}^i}P''(\xi_{kc}^i)\beta A(\xi_{kc}^{-i};\varepsilon_{kc}^i) < 0$$

which is certainly satisfied if (A1) holds.

A.2 Equilibrium Attention

To study the equilibrium, rewrite (15) more succinctly as:

$$G(\xi_{kc}^i;\delta) + \beta A(\xi_{kc}^{-i};\varepsilon_{kc}^i) = 0 \tag{16}$$

where $\delta = (\lambda_{kc}^i, \sigma_{kc}^i, \chi_{kc}^i, \varepsilon_{kc}^i)$ is a vector of parameters of interest and

$$G(\xi_{kc}^i,\delta) = \frac{1}{P'(\xi_{kc}^i)}\left\{\phi(\frac{x_c^i}{\theta_{kc}^i})\frac{(\sigma_{kc}^i)^2(\chi_{kc}^i)^2}{2\theta_{kc}^i} - \frac{\lambda_{kc}^i}{1-\xi_{kc}^i}\right\}$$

Equation (16) defines implictly the best response function: $\xi_{kc}^i = H(\xi_{kc}^{-i})$, which of course depends on all parameters of the model. The equilibrium is a fixed point of $H(.)$, such that

$\xi^{i*}_{kc} = H(\xi^{i*}_{kc})$. Hence, the equilibrium is implicitly defined by:

$$G(\xi^{i*}_{kc};\delta) + \beta A(\xi^{i*}_{kc};\varepsilon^{i}_{kc}) = 0 \tag{17}$$

Next, we prove the following:

Lemma 1 *If $\beta > 0$ is sufficiently small, then the equilibrium is unique.*

Proof. We show that $H(.)$ is a contraction, so that it admits a unique fixed point. By the assumption in footonote 6, $\xi^{i}_{kc} \in [\bar{\bar{\xi}},1]$. The function $G : [\bar{\bar{\xi}},1] \to R$ is continuously differentiable and, by the second order condition and by concavity of $P(.)$, $\partial G(\xi^{i*}_{kc};\delta)/\partial\xi^{i*}_{kc} < 0$ in $[\bar{\bar{\xi}},1]$. Thus, $G(.)$ admits an inverse function $G^{-1} : \mathbb{R} \to [\bar{\bar{\xi}},1]$ that is continuous, differentiable, and bounded. Dropping ε^{i}_{kc} for brevity, the composite function $H : [\bar{\bar{\xi}},1] \to [\bar{\bar{\xi}},1]$ is:

$$H\left(\xi^{-i}_{kc}\right) = G^{-1}\left(-\beta A\left(\xi^{-i}_{kc}\right);\delta\right)$$

and it is also bounded and differentiable. By the mean value theorem, for any points $y, y' \in [\bar{\bar{\xi}},1]$, there exist a point m between y and y' such that:

$$H(y) - H(y') = H'(m)(y - y')$$

Taking absolute values, one has, for all y, y', that there exists a m such that:

$$\begin{aligned} \left|H(y) - H(y')\right| &= \left|H'(m)\right| \left|(y - y')\right| \\ &= \beta \left| A'(m) \frac{\partial G^{-1}\left(-\beta A\left(m\right);\delta\right)}{\partial m} \right| \left|(y - y')\right| \end{aligned}$$

Since, for all y, y', $|H(y) - H(y')|$ is bounded, one has that for $y \neq y'$, there exists a finite scalar

$$M = \sup_{y,y'} \left| A'(m) \frac{\partial G^{-1}\left(-\beta A\left(m\right);\delta\right)}{\partial m} \right| > 0 \tag{18}$$

such that:

$$\frac{|H(y) - H(y')|}{|(y - y')|} \leq \beta M$$

Thus:

$$\left|H(y) - H(y')\right| \leq \beta M \left|(y - y')\right|$$

If $\beta < 1/M$, $H(.)$ is a contraction and admits a unique fixed point. ■

Let δ_n be the nth component of δ, and M be defined by (18). We then establish:

Lemma 2 *If $1/M > \beta > 0$ satisfies the condition stated above and $G(\xi_{kc}^{i*};\delta)$ is monotone in δ_n for all ξ_{kc}^{i}, then sign $\left\{\partial\xi_{kc}^{i*}/\partial\delta_n\right\} = sign \left\{\partial G(\xi_{kc}^{i*};\delta)/\partial\delta_n\right\}$, $\partial\xi_{kc}^{i*}/\partial\varepsilon_{kc}^{i} > 0$ and $|\partial^2\xi_{kc}^{i*}/\partial\delta_n\partial\varepsilon_{kc}^{i}|$, $|\partial^2\xi_{kc}^{i*}/\partial\delta_n\partial\beta| > 0$.*

Proof. Consider (17), that we rewrite here for convenience:

$$G(\xi_{kc}^{i};\delta) + \beta A(\xi_{kc}^{-i};\varepsilon_{kc}^{i}) = 0$$

By the implicit function theorem applied to (17):

$$\frac{\partial\xi_{kc}^{i*}}{\partial\delta_n} = -\frac{\partial G(\xi_{kc}^{i*};\delta)/\partial\delta_n}{\partial G(\xi_{kc}^{i*};\delta)/\partial\xi_{kc}^{i*} + \beta\partial A(\xi_{kc}^{i*};\varepsilon_{kc}^{i})/\partial\xi_{kc}^{i*}} \tag{19}$$

$$\frac{\partial\xi_{kc}^{i*}}{\partial\varepsilon_{kc}^{i}} = -\frac{\partial A(\xi_{kc}^{i*};\varepsilon_{kc}^{i})/\partial\varepsilon_{kc}^{i}}{\partial G(\xi_{kc}^{i*};\delta)/\partial\xi_{kc}^{i*} + \beta\partial A(\xi_{kc}^{i*};\varepsilon_{kc}^{i})/\partial\xi_{kc}^{i*}}$$

By the second order conditions and by concavity of $P(.)$, $\partial G(\xi_{kc}^{i*};\delta)/\partial\xi_{kc}^{i*} < 0$, while

$$\frac{\partial A(\xi_{kc}^{i*};\varepsilon_{kc}^{i})}{\partial\xi_{kc}^{i*}} = \left\{\varphi W(\xi_{kc}^{i*};\varepsilon_{kc}^{i}) + F[W(\xi_{kc}^{-i};\varepsilon_{kc}^{i})]\right\}\frac{\partial W(\xi_{kc}^{i*};\varepsilon_{kcn}^{i})}{\partial\xi_{kc}^{i*}} > 0$$

Consider the condition stated above , namely $\beta < 1/M$ with

$$\begin{aligned} M &= \sup_{x\in(\bar{\xi},1)}\left|A'(x)\frac{\partial G^{-1}(-\beta A(x);\delta)}{\partial x}\right| \\ &= -\sup_{x\in(\bar{\xi},1)}\frac{\partial A(x;\varepsilon_{kc}^{i})/\partial x}{\partial G(x;\delta)/\partial x} \end{aligned}$$

Under this condition,

$$\beta < -\frac{\partial G(\xi_{kc}^{i*};\delta)/\partial\xi_{kc}^{i*}}{\partial A(\xi_{kc}^{i*};\varepsilon_{kc}^{i})/\partial\xi_{kc}^{i*}}$$

implying $\partial G(\xi_{kc}^{i*};\delta)/\partial\xi_{kc}^{i*} + \beta\partial A(\xi_{kc}^{i*};\varepsilon_{kc}^{i})/\partial\xi_{kc}^{i*} < 0$. Then clearly $sign\left\{\partial\xi_{kc}^{i*}/\partial\delta_n\right\} =$

$sign\left\{\partial G(\xi^{i*}_{kc};\delta)/\partial\delta_n\right\}$ and $sign\left\{\partial\xi^{i*}_{kc}/\partial\varepsilon^i_{kcn}\right\} = sign\left\{\partial A(\xi^{i*}_{kc};\varepsilon^i_{kcn})/\partial\varepsilon^i_{kcn}\right\} > 0$ since

$$\frac{\partial A(\xi^{i*}_{kc};\varepsilon^i_{kcn})}{\partial\varepsilon^i_{kcn}} = \left\{\varphi W(\xi^{i*}_{kc};\varepsilon^i_{kc}) + F[W(\xi^{-i}_{kc};\varepsilon^i_{kc})]\right\}\frac{\partial W(\xi^{i*}_{kc};\varepsilon^i_{kcn})}{\partial\varepsilon^i_{kcn}} > 0$$

by our assumption that $\frac{\partial W(\xi^{i*}_{kc};\varepsilon^i_{kcn})}{\partial\varepsilon^i_{kcn}} > 0$ and where φ is the density of the uniform distribution $F(.)$.

Note also that, as long as $\beta < 1/M$, the denominator of (19) decreases in absolute value as β gets larger since $\partial A(\xi^{i*}_{kc};\varepsilon^i_{kc})/\partial\xi^{i*}_{kc} > 0$, implying $|\partial^2\xi^{i*}_{kc}/\partial\delta_n\partial\beta| > 0$.

Finally, note that

$$\begin{aligned}\frac{\partial^2 A(\xi^{i*}_{kc};\varepsilon^i_{kcn})}{\partial\xi^{i*}_{kc}\partial\varepsilon^i_{kcn}} &= \left\{\varphi W(\xi^{i*}_{kc};\varepsilon^i_{kc}) + F[W(\xi^{-i}_{kc};\varepsilon^i_{kc})]\right\}\frac{\partial^2 W(;\varepsilon^i_{kcn})}{\partial\xi^{i*}_{kc}\partial\varepsilon^i_{kcn}} + \\ &\quad + 2\varphi\frac{\partial W(\xi^{i*}_{kc};\varepsilon^i_{kcn})}{\partial\varepsilon^i_{kcn}}\frac{\partial W(\xi^{i*}_{kc};\varepsilon^i_{kcn})}{\partial\xi^{i*}_{kc}} > 0\end{aligned}$$

where the last inequality follows from our assumptions that $\frac{\partial^2 W(;\varepsilon^i_{kcn})}{\partial\xi^{i*}_{kc}\partial\varepsilon^i_{kcn}}, \frac{\partial W(\xi^{i*}_{kc};\varepsilon^i_{kcn})}{\partial\varepsilon^i_{kcn}}, \frac{\partial W(\xi^{i*}_{kc};\varepsilon^i_{kcn})}{\partial\xi^{i*}_{kc}} > 0$. Thus, as ε^i_{kcn} rises, and as long as $\beta < 1/M$, the denominator of (19) becomes smaller, implying $|\partial^2\xi^{i*}_{kc}/\partial\delta_n\partial\varepsilon^i_{kc}| > 0$. ■

To complete the proof of Proposition 1, we take the partial derivatives of the function $G(.)$ with respects to the parameters in δ. Using (11) we have:

$$\begin{aligned}\frac{\partial G(.)}{\partial\lambda^i_{kc}} &= -\frac{1}{1-\xi^i_{kc}}\frac{1}{P'(\xi^i_{kc})} < 0 \\ \frac{\partial G(.)}{\partial(\sigma^i_{kc})^2} &= \frac{\phi(\frac{x^i_c}{\theta^i_{kc}})(\chi^i_{kc})^2}{2\theta^i_{kc}}\left\{1 + \frac{(\sigma^i_{kc})^2(\chi^i_{kc})^2}{2(\theta^i_{kc})^2}\xi^i_{kc}[-1 + (\frac{x^i_c}{\theta^i_{kc}})^2]\right\}\frac{1}{P'(\xi^i_{kc})} > 0\end{aligned}$$

where the sign of the last expression follows from $(\sigma^i_{kc})^2(\chi^i_{kc})^2\xi^i_{kc} < 2(\theta^i_{kc})^2$ by (11).

Next, consider $\frac{\partial G(.)}{\partial\chi^i_{kc}}$ and suppose that $\sum_h \chi^i_{hc}\mu^i_{hc} < \sum_h \chi^i_{hc'}\mu^{i\prime}_{hc}$, and hence that $x^i_c < 0$ by (10). Note that:

$$\frac{\partial \theta^i_{kc}}{\partial \chi^i_{kc}} = \frac{\xi^i_{kc}\chi^i_{kc}(\sigma^i_{kc})^2}{\theta^i_{kc}}$$

$$\frac{\partial (x^i_c/\theta^i_{kc})}{\partial \chi^i_{kc}} = \frac{\mu^i_{kc}}{\theta^i_{kc}} - \frac{x^i_c}{\theta^i_{kc}}\xi^i_{kc}\frac{\chi^i_{kc}(\sigma^i_{kc})^2}{(\theta^i_{kc})^2}$$

so that:

$$\begin{aligned}\frac{\partial G(.)}{\partial \chi^i_{kc}} &= \left\{\phi(\frac{x^i_c}{\theta^i_{kc}})\frac{(\sigma^i_{kc})^2\chi^i_{kc}}{\theta^i_{kc}}(1-\frac{x^i_c}{\theta^i_{kc}}\frac{\chi^i_{kc}\mu^i_{kc}}{2\theta^i_{kc}}) + \phi(\frac{x^i_c}{\theta^i_{kc}})\frac{(\sigma^i_{kc})^4(\chi^i_{kc})^3}{2(\theta^i_{kc})^3}\xi^i_{kc}[-1+(\frac{x^i_c}{\theta^i_{kc}})^2]\right\}\frac{1}{P'(\xi^i_{kc})} = \\ &= \phi(\frac{x^i_c}{\theta^i_{kc}})\frac{(\sigma^i_{kc})^2\chi^i_{kc}}{\theta^i_{kc}}[1-\frac{x^i_c}{\theta^i_{kc}}\frac{\chi^i_{kc}\mu^i_{kc}}{2\theta^i_{kc}} + \frac{(\sigma^i_{kc})^2(\chi^i_{kc})^2}{2(\theta^i_{kc})^2}\xi^i_{kc}(-1+(\frac{x^i_c}{\theta^i_{kc}})^2)]\frac{1}{P'(\xi^i_{kc})} > 0\end{aligned}$$

where the sign follows from $x^i_c < 0$ and from the fact that $\frac{(\sigma^i_{kc})^2(\chi^i_{kc})^2}{2(\theta^i_{kc})^2}\xi^i_{kc} < 1$.

This completes the proof of Proposition 1. QED

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[41] 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

[41] https://web.archive.org/web/20160601000340/https://www.reddit.com/

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 Engagement with Posts

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.

B.3 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).

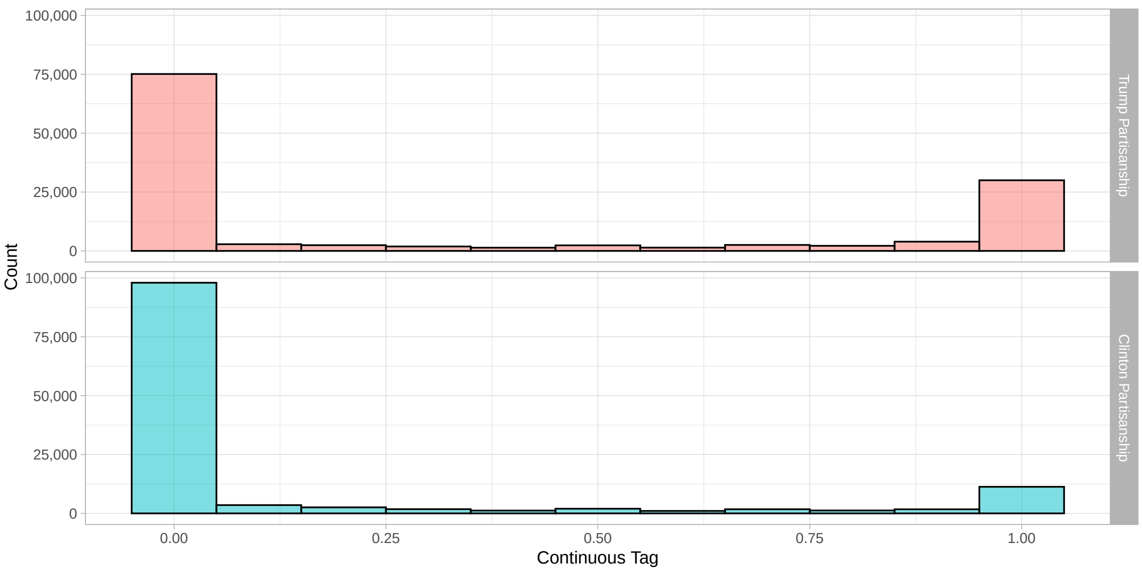
To define a list of political fora, we start from the 1,417 biggest fora by total number of comments (during our sample period) written by users who have posted or commented at least once on `r/politics`. Together, these 1,417 fora host 90% of their comments on the platform in our period. Within these 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 3.1. 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.2 reports all the political fora, along with their classification.

B.4 More on `r/politics` and Our Sample

The total number of `r/politics` 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.

As described in the main text, `r/politics` is moderated by a team that ensures a civil debate. In particular, 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 B.1: Distribution of Trump and Clinton Partisanship



Notes: The top and bottom panels report the distribution across users of the Trump and Clinton partisanship indexes, respectively, as defined in Section (3.1.1).

Table B.1: 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

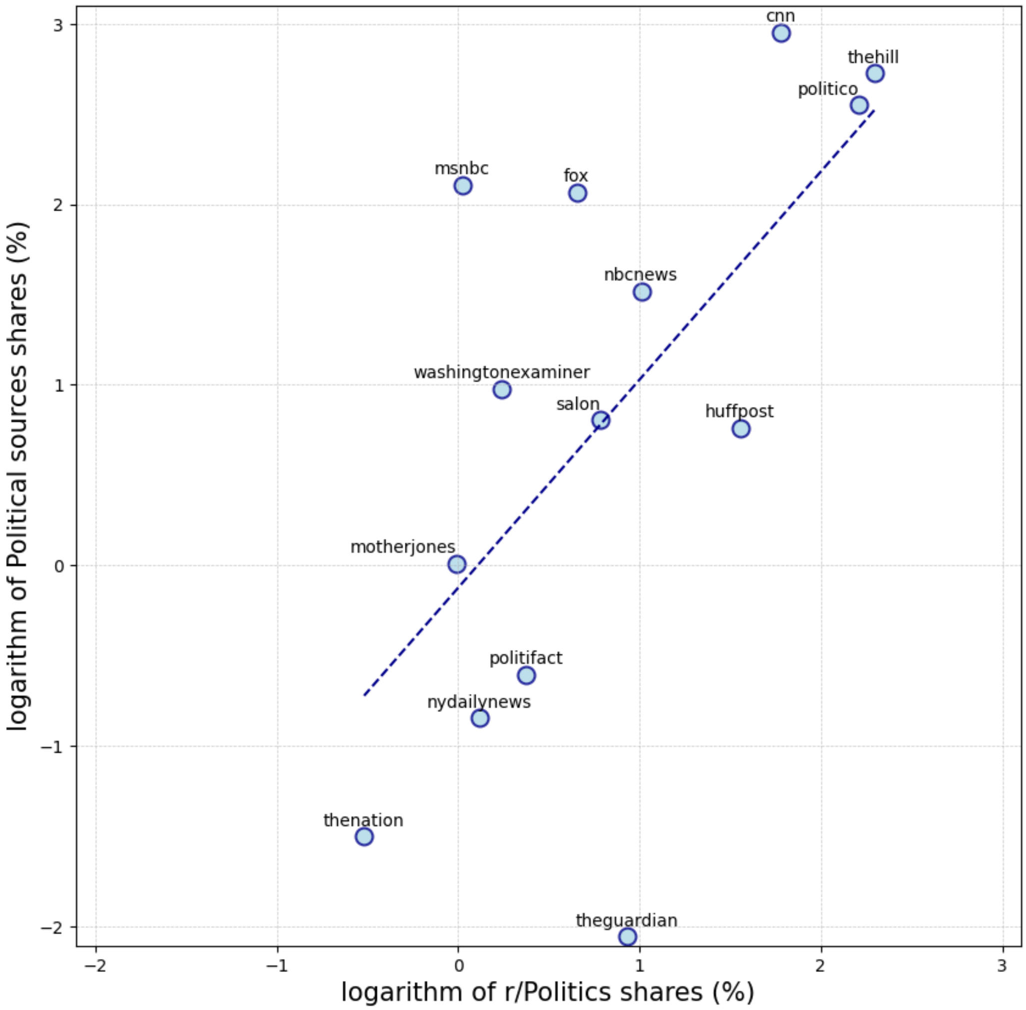
Notes: % of U.S. adults who say they ever use the following online platforms or messaging apps. (Pew Research Center, 2019)

Table B.2: 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"

Figure B.2: Top News Media Websites in Comscore (by Visits) and in Reddit (by Comments)



Note: Variables are in logarithmic form. The horizontal axis reports the log of the share of comments on each source as a fraction of the total comments made on the top 50 sources by number of comments in `r/politics` during our sample period. The vertical axis reports the log of the share of visits to each source as a fraction of the total visits made to the top 50 websites by number of visitors in Comscore between May 2017 and May 2021 (earlier dates are not available), restricting to news sources that are classified as exclusively political by Comscore. The sample restricts to the top 50 sources of `r/politics` that are also in the top 50 of Comscore. These 14 sources account for 78% of visits of the top 50 Comscore sources.

C Empirical Appendix

Table C.1: Number of Active Authors and Affiliation on r/politics

Panel A: Discrete Classification

	Samples		
	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

Panel B: Continuous Classification

	r/politics	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 6 comments on non partisan fora or on partisan fora: here, furthermore, we restrict the sample to authors with at least one comment on `r/politics`.

Table C.2: Average and median comments per user, by affiliation

User	`r/politics`		Reuters		Megathreads	
	mean	median	mean	median	mean	median
All users	28.97	3	3.43	2	9.05	2
Clinton Supporters	99.37	16	4.18	2	17.90	4
Independents	81.47	17	3.88	2	14.80	4
Non-classified	14.81	2	2.87	1	5.66	2
Trump Supporters	42.81	7	3.68	2	10.95	3

Table C.3: 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

Note: The Table reports the total number of scandals and bad polls posted in the Reuters and Megathreads samples, by candidate and affiliation of the user that is posting the scandal (in the rows).

Table C.4: Scandals covered by Megathreads

Post ID	MT Title	Scandal Series	Clinton Scandal	Trump Scandal	Publication	Num Comments	% TS	% CS
t3_4rd7ly	Comey: FBI recommends no indictment re: Clinton emails	Comey, Clinton e-mails (5/7/16)	1	0	05jul2016 15:26:44	9,508	9.61	4.61
t3_4u5ztv	DNC Email Leak Megathread	DNC, Clinton e-mails (23/7/16)	1	0	23jul2016 01:01:08	10,133	16.74	3.74
t3_4uewdj	Debbie Wasserman Schultz Resignation Megathread	DNC, Clinton e-mails (23/7/16)	1	0	24jul2016 20:32:40	12,179	11.37	3.29
t3_4uive8	DNC Email Leak Megathread	DNC, Clinton e-mails (23/7/16)	1	0	25jul2016 14:30:54	1,313	12.72	3.05
t3_4yj7po	Trump campaign chairman Paul Manafort resigns megathread	Paul Manafort resigns (19/8/16)	0	1	19aug2016 14:27:30	1,899	10.85	15.06
t3_50utmo	FBI Releases Documents in Hillary Clinton E-Mail Investigation Megathread	FBI Releases Documents, Clinton e-mails (2/9/16)	1	0	02sep2016 18:50:12	9,664	22.55	5.41
t3_52sps2	Megathread - Clinton Campaign releases additional medical records	Clinton medical records (14/9/16)	1	0	14sep2016 21:01:42	3,295	19.39	10.59
t3_55oth1	Megathread - Trump Foundation ordered to stop fundraising in NY	Trump stop fundraising in NY (3/10/16)	0	1	03oct2016 17:32:17	3,496	6.04	13.42
t3_56dqes	Megathread: Donald Trump leaked comments from 2005 re:women	Trump comments on women (7/10/16)	0	1	07oct2016 21:19:38	15,333	8.57	9.35
t3_56fgfr	Megathread 2: Donald Trump Leaked Video and Campaign Statement; GOP Statements	Trump comments on women (7/10/16)	0	1	08oct2016 04:23:31	5,935	5.54	11.95
t3_56igk9	Megathread 3: Donald Trump Leaked Video & Statement; GOP/RNC Reactions incl. defunding of Victory Project, cancelled events, and unendorsements	Trump comments on women (7/10/16)	0	1	08oct2016 19:08:11	8,324	2.86	12.63
t3_59vuny	Megathread: FBI reopens investigation into Clinton emails	FBI reopens investigation, Clinton e-mails (28/10/16)	1	0	28oct2016 17:51:40	24,278	17.50	7.07
t3_59y2ct	Megathread II: FBI / Clinton Emails	FBI reopens investigation, Clinton e-mails (28/10/16)	1	0	29oct2016 00:53:47	8,461	15.84	9.13

C.1 Definition of Bad Polls

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 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 Tables C.11 and C.12 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.

Table C.5: **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.

C.2 Classification of News Sources' Ideological Bias

To control for the share of left-wing and right-wing sources cited in each Megathread, we use the Political Bias Index constructed by the website `mediabiasfactcheck.com`. The index assigns to several media sources a score on a 7-point scale, from "Extreme Left" to "Extreme Right". The score is based on four evaluations, namely whether: (i) the source uses biased wording or headlines; (ii) it reports 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/` for more details.

C.3 Supplementary Material for Event Studies

C.3.1 ChatGPT Tagging of Bad News

We used a fine-tuned version of ChatGPT to tag posts coming from `r/politics` and partisan fora as Trump scandals, Clinton scandal, or neither. This was done using gpt-3.5-turbo as the base model.

1. **Task Definition and Training Data:** To fine-tune ChatGPT for a specific task, we first need to define the task and gather a dataset that we can train the AI on. We used as a training set the Reuters articles we tagged manually, split in train/valuation/test with a standard 70/20/10 split. 95 Clinton scandals and 71 Trump scandals, while the validation dataset consisted of 335 no scandals, 28 Clinton scandal, and 23 Trump scandals. We used the following prompt:

   "You are a helpful research assistant. I am going to present you with some post titles taken from Reddit. I want you to tell me whether you think the post refers to a scandal that involves Trump, a scandal that involves Hillary Clinton, or neither. Some of the names or text may contain typos. Fix these in the output if needed."

   This prompt was chosen as the one providing us with the best results in the pre-fine-tuning trials.

2. **Training Process:** The model has been trained for 3 epochs on 470,955 tokens on the OpenAI servers. Following best practices, the hyperparameters' values were the

default ones optimized by the `openai.fine_tuning.jobs.create` function of the `openai` library.

3. **Evaluation:** To evaluate model performance, we test it on *i)* the 181 Reuters articles that were not included in the training data, 200 Reddit posts taken at random from our initial database of posts, and other 119 posts around the Hollywood scandal from fora that were not pro-Trump. This last step was done to ensure that we have some Trump scandals in our manual evaluation dataset. Table C.6 to Table C.8 report the confusion matrices for each of these three sets.

Table C.6: Reuters confusion matrix

gpt Manual tagging	trump	clinton	neither
trump	5	0	2
clinton	0	13	6
neither	1	0	154

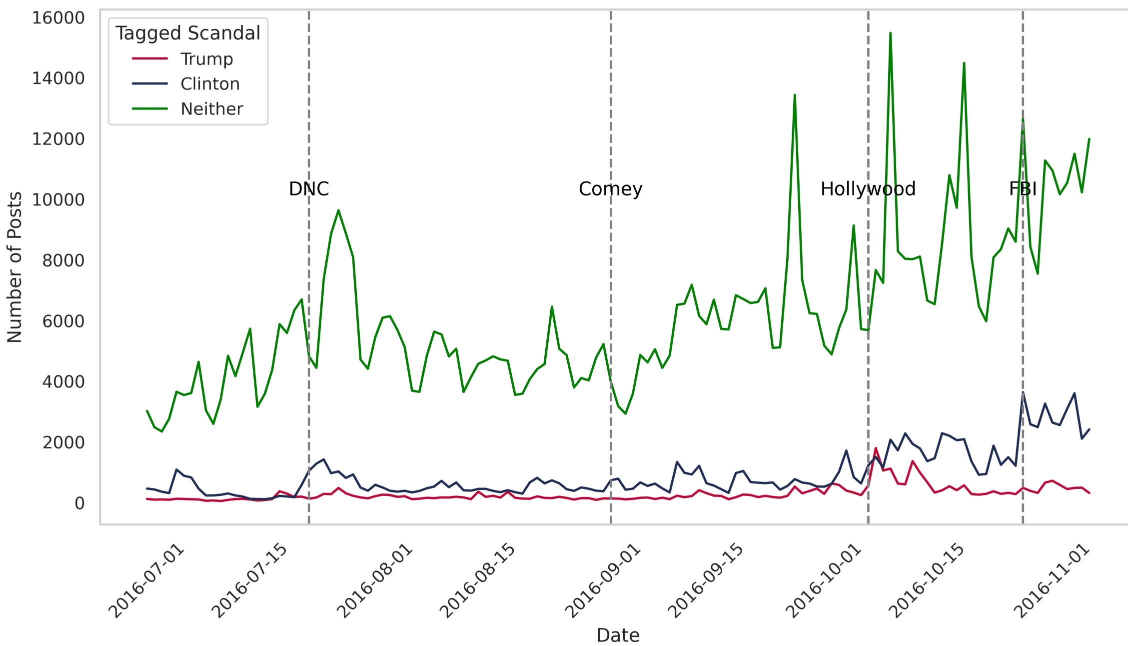
Table C.7: Random 200 confusion matrix

gpt_finetuned Manual tagging	trump	clinton	neither
trump	1	0	0
clinton	0	35	2
neither	1	10	151

Table C.8: Random 119 confusion matrix: only around Hollywood scandal and no Trump fora

gpt_finetuned Manual tagging	trump	clinton	neither
trump	4	0	2
clinton	0	0	0
neither	3	2	108

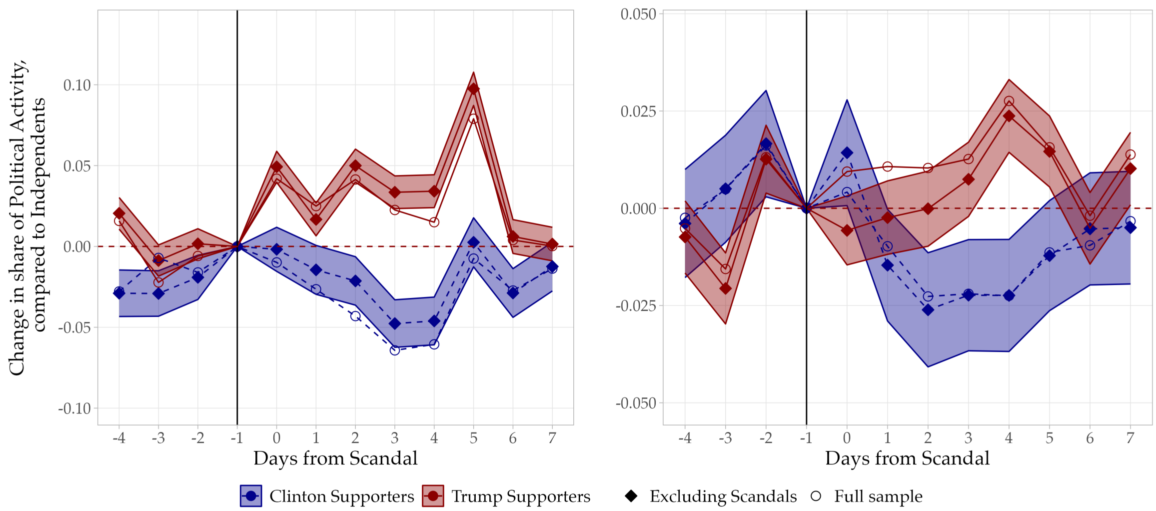
Figure C.1: Number of Posts per Day, by GPT-Tagging



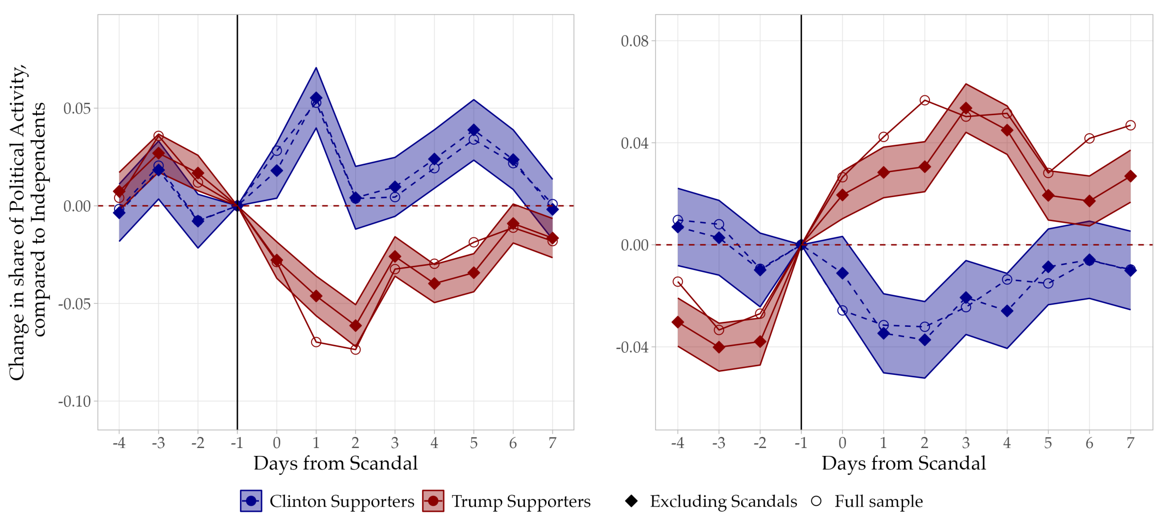
C.3.2 Event Studies Across Scandals and Non-scandals Posts, Using the GPT Tagging

Figure C.2: Engagement with Political News Around Scandal Dates, Restricted to Posts not Covering Scandals

(a) DNC Email leak (Clinton scandal) **(b) FBI Email leak (Clinton)**



(c) Hollywood Access Scandal (Trump) **(d) Comey Scandal (Clinton)**



Notes: The figure presents the average change, with respect to day $t = -1$, of the ratio of comments on political fora over total comments on the entire Reddit platform, for Trump supporters (solid red line, with diamonds) and Clinton supporters (dashed blue line, with diamonds), expressed as a difference with the same measure for independent users. The sample drops comments to posts that explicitly discuss scandals. The bands denote 95% confidence intervals (standard errors are clustered by user). Day $t = 0$ is the date when a scandal on either candidate became public, with the four panels covering the four scandals described in the notes of Figure 2. All regressions control for individual fixed effects. The extra lines marked by hollow circles report the coefficient estimates without dropping posts that strictly discuss scandals, shown in Figure 2.

C.4 Engagement with News, Supplementary Tables

Table C.9: Summary Statistics on Engagement with News

	Reuters		Megathreads	
Panel A: Balanced User-Post (i, p) level Dataset	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
	Reuters		**Megathreads**	
Panel B: Unbalanced User-Post (i, p) level Dataset	Mean	St. Dev.	Mean	St. Dev.
Number of Comments	202.804	290.505	450.078	951.661
	Reuters		**Megathreads**	
Panel C: Comment (i, p, c) level Dataset	Mean	St. Dev.	Mean	St. Dev.
Average Comment Score	5.429	35.043	5.995	55.713
Comment Score Dummy	0.794	0.405	0.864	0.342

Notes: Variables on number of comments and dummy for commenting are all multiplied by 100.

Table C.10: Activity Analysis of News on Reuters, Reporting Coefficients on Candidates' Mentions

	Dependent variable: Comments of User i on Post p ($\times 100$)							
	Num. of Comments (Intensive Margin)				Num. of Comments > 0 (dummy, 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)
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

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. 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. Dependent variable is multiplied by 100. Sample restricted to comments of authors classified as either Trump Supporters, Clinton Supporters or Independent. Estimates in columns (2) to (4) and (6) to (8) include additional controls not reported in table: the partisan affiliation (if any) of the author of p or whether it is not classified, interacted with the partisan affiliation (if any) of i; whether p reports a poll, interacted with the affiliation of i; the length of the article shared in p, interacted with the affiliation of i; the activity of user i in a five-day window around p. Estimates in columns (2), (3), (6), (7) include controls for the affiliation of i. Estimates in columns (2) and (6) include controls for whether the post is a Trump/Clinton scandal/bad poll.

Table C.11: Activity Analysis of News on Reuters, 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)
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

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. 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. Dependent variable is multiplied by 100. Sample restricted to comments of authors classified as either Trump Supporters, Clinton Supporters or Independent. Estimates in columns (2) to (4) and (6) to (8) include additional controls not reported in table: the partisan affiliation (if any) of the author of p or whether it is not classified, interacted with the partisan affiliation (if any) of i; whether p reports a poll, interacted with the affiliation of i; the length of the article shared in p, interacted with the affiliation of i; the activity of user i in a five-day window around p. Estimates in columns (2), (3), (6), (7) include controls for the affiliation of i. Estimates in columns (2) and (6) include controls for whether the post is a Trump/Clinton scandal/bad poll.

Table C.12: 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 3.

Table C.13: Activity Analysis, Robustness

	Dependent variable: Comments of User i on Post p					
	Num. of Comments (Intensive Margin)			Num. of Comments > 0 (dummy, 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)	(0.1507)	(0.0988)	(0.0272)	(0.1491)	(0.0925)
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)	(0.1550)	(0.1007)	(0.0339)	(0.1360)	(0.0994)
$\beta_1^P - \beta_2^P$, only Bad Polls	0.2220**	0.5160*	0.4451**	0.1097**	0.5779*	0.4122**
	(0.1013)	(0.2848)	(0.2064)	(0.0447)	(0.3111)	(0.1901)
Dep. Var Mean	0.2700	0.0030	0.0030	0.1330	0.0010	0.0010
R2	0.0122	0.3094	0.3208	0.0236	0.1778	0.1884
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)	(0.1509)	(0.1236)	(0.5800)	(0.1428)	(0.0876)
Dep. Var Mean	12.7770	0.1470	0.1280	3.0250	0.0330	0.0300
R2	0.0784	0.4409	0.4228	0.0871	0.1763	0.1649
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 3 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. Megathreads refer only to scandals because negative polls cannot be defined in that sample. Sample restricted to comments of authors classified as either Trump Supportes, Clinton Supporters or Independent.

Table C.14: Score Analysis, Robustness

	Dependent variable: Score of Comment c of User i on Post p			
	Comment Score	Comment Score >0		
	OLS	OLS	Logit	
	Continuous Tag (1)	Continuous Tag (2)	Discrete Tag (3)	Continuous Tag (4)
Panel A1: Reuters				
$\beta_1 - \beta_2$, all Bad News	4.0322***	0.1955***	2.3205***	1.8145***
	(1.1609)	(0.0335)	(0.3616)	(0.2808)
Dep. Var Mean	5.3259	0.7918	0.7938	0.7918
Observations	55,323	55,323	20,478	29,769
R2	0.2790	0.4465	−0.0173	−0.0250
Panel B: Megathreads				
$\beta_1^S - \beta_2^S$, only Scandals	5.8888***	0.1477***	2.2198***	1.6400***
	(1.4364)	(0.0275)	(0.2510)	(0.1889)
Dep. Var Mean	5.9655	0.8618	0.8644	0.8618
Observations	670,421	670,421	352,691	532,454
R2	0.1639	0.2257	0.1014	0.0868

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 3 are always included. Dependent variable is multiplied by 100 for linear models (columns (1) and (2)). For Reuters, "all Bad News" refers to specifications where Consonant and Non-consonant is defined using both scandals and bad polls. Megathreads refer only to scandals because negative polls cannot be defined in that sample. Sample restricted to comments of authors classified as either Trump Supportes, Clinton Supporters or Independent.

Table C.15: Activity Analysis, Restricted to Very Active Users

	Dependent variable: Comments of User i on Post p ($\times 100$)							
	Num. of Comments (Intensive Margin)				Num. of Comments > 0 (dummy, Extensive Margin)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reuters								
Consonant News$_{i,p}$ (β_1)	1.1953**	0.1485	0.1436	0.1389	0.3646***	0.1214*	0.1207*	0.1195*
	(0.5810)	(0.4744)	(0.4769)	(0.4768)	(0.1081)	(0.0684)	(0.0689)	(0.0691)
Non-consonant News$_{i,p}$ (β_2)	0.2831	−1.0466**	−1.0452**	−1.0258**	−0.0507	−0.2611***	−0.2608***	−0.2558***
	(0.4318)	(0.4270)	(0.4285)	(0.4270)	(0.0590)	(0.0709)	(0.0710)	(0.0708)
p-value $(\beta_1 - \beta_2)$	0.0295	0.0385	0.0405	0.0437	0.0000	0.0007	0.0008	0.0009
Dep. Var Mean	1.4310	1.4310	1.4310	1.4310	0.4600	0.4600	0.4600	0.4600
Observations	1,151,550	1,151,550	1,151,550	1,151,550	1,151,550	1,151,550	1,151,550	1,151,550
R2	0.0000	0.0019	0.0229	0.0237	0.0001	0.0067	0.0247	0.0277
Panel B: Megathreads								
Consonant Scandal$_{i,p}$ (β_1^S)	21.9559*	29.8361***	29.9411***	27.4147***	6.6456***	6.1092***	6.1274***	6.0045***
	(13.0186)	(8.1715)	(8.1791)	(8.3463)	(2.0557)	(1.2362)	(1.2388)	(1.2376)
Non-consonant Scandal$_{i,p}$ (β_2^S)	−8.8048	9.0814	9.0283	10.3062	−0.1615	−0.7138	−0.7231	−0.6609
	(11.3295)	(7.7569)	(7.7583)	(7.8318)	(1.5674)	(1.1294)	(1.1298)	(1.1300)
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 $(\beta_1^S - \beta_2^S)$	0.0001	0.0006	0.0005	0.0049	0.0001	0.0000	0.0000	0.0000
Dep. Var Mean	45.4790	45.4790	45.4790	45.4790	7.2160	7.2160	7.2160	7.2160
Observations	812,375	812,375	812,375	812,375	812,375	812,375	812,375	812,375
R2	0.0001	0.0384	0.0610	0.1071	0.0013	0.0393	0.0960	0.1393

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 Supporters, Clinton Supporters or Independent who also made more than 10 comments during our sample period. Variables and controls are as defined in Table 3.

Table C.16: Activity Analysis, Restricted to Users Also Active in Non-Political Fora

	Dependent variable: Comments of User i on Post p $(\times 100)$							
	Num. of Comments (Intensive Margin)				Num. of Comments > 0 (dummy, Extensive Margin)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reuters								
Consonant News$_{i,p}$ (β_1)	0.2020*	0.0440	0.0436	0.0422	0.1108***	0.0490**	0.0485**	0.0478**
	(0.1031)	(0.0702)	(0.0698)	(0.0697)	(0.0411)	(0.0221)	(0.0220)	(0.0219)
Non-consonant News$_{i,p}$ (β_2)	0.0274	-0.1510^{**}	-0.1492^{**}	-0.1481^{**}	-0.0002	-0.0550^{**}	-0.0547^{**}	-0.0541^{**}
	(0.0859)	(0.0721)	(0.0717)	(0.0716)	(0.0327)	(0.0267)	(0.0267)	(0.0267)
p-value $(\beta_1 - \beta_2)$	0.0064	0.0187	0.0199	0.0214	0.0000	0.0014	0.0015	0.0017
Dep. Var Mean	0.3010	0.3010	0.3010	0.3010	0.1450	0.1450	0.1450	0.1450
Observations	9,074,700	9,074,700	9,074,700	9,074,700	9,074,700	9,074,700	9,074,700	9,074,700
R2	0.0000	0.0011	0.0116	0.0127	0.0000	0.0021	0.0234	0.0251
Panel B: Megathreads								
Consonant Scandal$_{i,p}$ (β_1^S)	10.2672**	11.4122***	11.4183***	11.0072***	5.0018***	3.5010***	3.5031***	3.4837***
	(5.1670)	(2.6290)	(2.6311)	(2.6574)	(1.6105)	(0.7963)	(0.7970)	(0.7965)
Non-consonant Scandal$_{i,p}$ (β_2^S)	-2.5842	0.6378	0.6334	0.9227	0.2589	-1.2222^{**}	-1.2236^{*}	-1.2100^{*}
	(4.2276)	(3.1177)	(3.1177)	(3.1500)	(0.8993)	(0.6169)	(0.6169)	(0.6182)
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 $(\beta_1^S - \beta_2^S)$	0.0008	0.0000	0.0000	0.0001	0.0002	0.0000	0.0000	0.0000
Dep. Var Mean	16.2560	16.2560	16.2560	16.2560	3.5600	3.5600	3.5600	3.5600
Observations	1,997,812	1,997,812	1,997,812	1,997,812	1,997,812	1,997,812	1,997,812	1,997,812
R2	0.0001	0.0258	0.0338	0.0877	0.0017	0.0256	0.0540	0.1005

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 Supporters, Clinton Supporters or Independent who also have an above median activity in non-political fora. Variables and controls are as defined in Table 3.

Table C.17: Likes net of Dislikes Across Consonant and Non-consonant News, Restricted to Very Active Users

	Dependent variable: Score of Comment c of User i on Post p							
	Comment Score				Comment Score >0			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reuters								
Consonant News$_{i,p}$ (β_1)	2.3394*	3.5859**	3.7956**	6.1031***	0.0465*	0.1347***	0.1259***	0.1452***
	(1.4081)	(1.3942)	(1.4904)	(2.3131)	(0.0245)	(0.0390)	(0.0414)	(0.0431)
Non-consonant News$_{i,p}$ (β_2)	−2.7068**	−2.4849	−1.8489	1.4311	−0.1248***	−0.0865***	−0.0865***	−0.0714*
	(1.2294)	(1.5410)	(1.4892)	(2.0264)	(0.0404)	(0.0326)	(0.0327)	(0.0383)
p-value ($\beta_1 - \beta_2$)	0.0106	0.0002	0.0015	0.0062	0.0003	0.0000	0.0001	0.0000
Dep. Var Mean	4.8912	4.8912	4.8912	4.8912	0.7803	0.7803	0.7803	0.7803
Observations	16,474	16,474	16,474	16,474	16,474	16,474	16,474	16,474
R2	0.0004	0.0158	0.0351	0.1070	0.0031	0.0465	0.1437	0.2921
Panel B: Megathreads								
Consonant News$_{i,p}$ (β_1^S)	9.7720***	4.9690**	5.2278**	5.5802**	−0.0412	0.1299***	0.0989**	0.1146***
	(2.8745)	(2.2305)	(2.1521)	(2.3480)	(0.0413)	(0.0377)	(0.0395)	(0.0318)
Non-consonant News$_{i,p}$ (β_2^S)	0.9872	−3.4106**	−3.1902*	−2.4379	−0.1868***	−0.0890**	−0.1136***	−0.0914***
	(2.1052)	(1.7054)	(1.7096)	(1.5826)	(0.0565)	(0.0406)	(0.0416)	(0.0277)
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 ($\beta_1^S - \beta_2^S$)	0.0540	0.0030	0.0021	0.0010	0.1149	0.0000	0.0002	0.0000
Dep. Var Mean	5.6461	5.6461	5.6461	5.6461	0.8680	0.8680	0.8680	0.8680
Observations	369,462	369,462	369,462	369,462	369,462	369,462	369,462	369,462
R2	0.0010	0.0077	0.0114	0.0630	0.0047	0.0459	0.0665	0.1661

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Variables and controls are defined in Table 3, except that we don't control for user's activity in a 5-day window around the post, and instead we control for the hierarchical level of the comment. Sample restricted to comments of authors classified as either Trump Supporters, Clinton Supporters or Independent who also made more than 10 comments during our sample period.

Table C.18: Likes net of Dislikes Across Consonant and Non-consonant News, Restricted to Users Also Active in Non-Political Fora

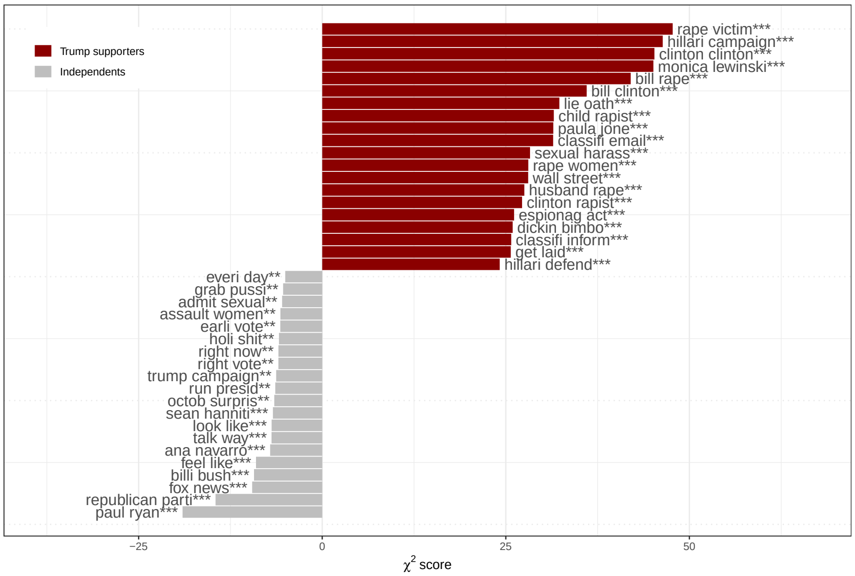
	Dependent variable: Score of Comment c of User i on Post p							
	Comment Score				Comment Score >0			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reuters								
Consonant News$_{i,p}$ (β_1)	1.6669*	2.6997***	3.1001***	5.6060***	0.0601***	0.1298***	0.1227***	0.1540***
	(0.8954)	(0.9617)	(1.0121)	(1.9406)	(0.0203)	(0.0328)	(0.0322)	(0.0399)
Non-consonant News$_{i,p}$ (β_2)	−2.7955***	−2.8034**	−2.6385**	0.4220	−0.1671***	−0.1126***	−0.1143***	−0.0864**
	(0.8925)	(1.1789)	(1.2005)	(1.8776)	(0.0357)	(0.0342)	(0.0364)	(0.0352)
p-value ($\beta_1 - \beta_2$)	0.0019	0.0002	0.0003	0.0064	0.0000	0.0000	0.0000	0.0000
Dep. Var Mean	5.5795	5.5795	5.5795	5.5795	0.8088	0.8088	0.8088	0.8088
Observations	27,285	27,285	27,285	27,285	27,285	27,285	27,285	27,285
R2	0.0004	0.0130	0.0255	0.2415	0.0066	0.0625	0.1293	0.4363
Panel B: Megathreads								
Consonant News$_{i,p}$ (β_1^S)	8.8495***	4.4592***	4.9110***	5.3395***	−0.0344	0.1260***	0.0975***	0.1083***
	(2.5137)	(1.6769)	(1.6256)	(2.0086)	(0.0342)	(0.0341)	(0.0357)	(0.0285)
Non-consonant News$_{i,p}$ (β_2^S)	0.9847	−3.6507	−3.2939	−1.6323	−0.1903***	−0.1003**	−0.1201**	−0.0805***
	(2.4738)	(2.3486)	(2.3451)	(1.5616)	(0.0614)	(0.0452)	(0.0475)	(0.0291)
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 ($\beta_1^S - \beta_2^S$)	0.0903	0.0058	0.0043	0.0021	0.0829	0.0000	0.0000	0.0000
Dep. Var Mean	6.0465	6.0465	6.0465	6.0465	0.8726	0.8726	0.8726	0.8726
Observations	324,761	324,761	324,761	324,761	324,761	324,761	324,761	324,761
R2	0.0010	0.0074	0.0109	0.1323	0.0057	0.0505	0.0700	0.2082

Notes: OLS estimates, two-way clustered standard errors at the i and p level in parenthesis. Variables and controls are defined in Table 3, except that we don't control for user's activity in a 5-day window around the post, and instead we control for the hierarchical level of the comment. Sample restricted to comments of authors classified as either Trump Supporters, Clinton Supporters or Independent who also have an above median activity in non-political fora.

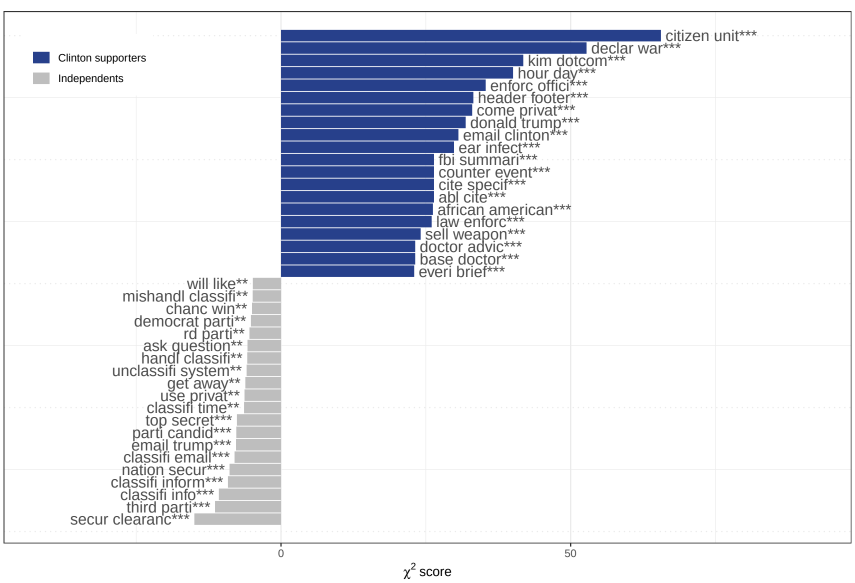
C.5 Content Analysis, Supplementary Material

Figure C.4: 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



Notes: the figures report the 20 most characteristic words, according to their χ^2 score, of comments to scandals of supporters vs independents. The top panel reports words most characteristic of Trump supporters (in red, top half) vs. independents (in gray, bottom half) when commenting scandals on Trump. The bottom panel reports words most characteristic of Clinton supporters (in blue, top half) vs. independents (in gray, bottom half), when commenting scandals on Clinton.

C.6 Sentiment Classification

Compared to our manual classification, measurement error from the classification is within reasonable bounds. Table C.19 reports the confusion matrix, which cross-tabulates our manual classification with that of the model. Table C.20 reports the accuracy, precision, and the F1-score of the model, which are 76.6%, 89.4%, and 81.2%, respectively. 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 C.19. 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.

Table C.19: 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

Notes: the Table shows a confusion matrix comparing our manual sentiment scores (in the rows) with those generated by RoBERTa (in the columns). The confusion matrix on the left reports results for the entire sample of 500 comments that we manually classified. The one on the right refers to a subset of 373 comments that were considered as decidedly negative or decidedly positive upon manual inspection, thus excluding 127 comments for which the sentiment displayed was more ambiguous.

Table C.20: 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

Notes: the Table reports several performance measures of our classifier: the precision (i.e., how many true negative over true negatives and false negatives, and similarly for positive), the recall (i.e., how many true negative over the true negatives and the false positives, and similarly for positive), the F1-score (i.e., harmonic mean between precision and recall). For each metric we show the simple average of the metric and the weighted average, using the relative size of true positives and true negatives in the sample, both for the negative and the positive label. The samples of all comments (left part of the table) and of comments with extreme scores (right part) are as described in the notes to Table C.19.