SOCIAL MEDIA, SENTIMENT AND PUBLIC OPINIONS: EVIDENCE FROM #BREXIT AND #USELECTION

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Abstract: This paper studies information diffusion in social media and the role of bots in shaping public opinions. Using Twitter data on the 2016 E.U. Referendum ("Brexit") and the 2016 U.S. Presidential Election, we find that diffusion of information on Twitter is largely complete within 1-2 hours. Stronger interactions across agents with similar beliefs are consistent with the "echo chambers" view of social media. Bots have a tangible effect on the tweeting activity of humans but the degree of bots' influence depends on whether bots provide information consistent with humans' priors. Overall, our results suggest that the aggressive use of Twitter bots, coupled with the fragmentation of social media and the role of sentiment, could contribute to the vote outcomes.

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1. Introduction

The rise of Internet has changed the way people communicate and acquire information. Recent years have witnessed a decline in the traditional news media consumption (Stempel et al., 2000) while the number of online news users soared (Gottfried and Shearer, 2016; Bialik and Matsa, 2017). Among different types of Internet-based media, social networks have become an increasingly important information source for many people. Through social media, individuals can have instant and open access to news and narratives and can build networks to interact and share opinions. Key questions are how this communication revolution has influenced information flows across individuals and how one can influence these flows.

We attempt to answer this question by examining dissemination of information in social media and using recent developments in the U.K. (2016 E.U. Referendum, also known as Brexit) and the U.S. (2016 Presidential Election) as two natural experiments. These two events were extremely high-profile so that people paid as much attention to these as one may reasonably expect. In addition, these experiments are "clean" in the sense that platforms in these plebiscites were diametrically opposed, which allows us to separate providers of information as well as consumers of information.

In this exercise, we identify sources of information that might have been used to shape public opinions. Specifically, we study two types of social media agents: real ("human") users and social bots, computer algorithms used to produce automated content. Bots can create new bits of information and a sense of consensus in the society that is favorable for a given candidate/outcome. We use these bots as a source of variation in people's information sets and see how this information influences "humans", how it is spread across "humans", and how the sentiment (tonality) of bots' messages affects "humans".

Our analysis use data from Twitter, one of the most popular microblogging platforms with a large number of users. For example, as of 2016, the number of U.K. Twitter users is estimated at 15.8 million while the number of U.S. Twitter users is about 67 million (Benoit, 2017). Given this popularity, Twitter generates an enormous quantity of legally available data for research.[1]

[1] In contrast to Cambridge Analytica/Facebook case, our data were collected directly from Twitter and the collection process does not breach any terms and conditions of Twitter development tools. Specifically, data employed in this study were collected using Twitter Streaming Application Programming Interface (API). Twitter streaming API is a developer tool that allows collecting a semi-random sample of real-time tweets with pre-defined attributes (e.g., keywords, usernames, or hashtags). See for details https://developer.twitter.com/en/docs/tweets/filter-realtime/guides/powertrack_rules_and_filtering (Accessed on 24 August 2018).

These data include records of users, tweets, and metadata that allow us to track tweeting activities of different types of Twitter agents (bots and humans). Additionally, compared to other social network sites, Twitter connections are more about connecting with people for information sharing purposes rather than personal interactions (Gruzd et al., 2011). Hence, one would expect to see information flows as well as different information clusters during important political events on Twitter. Furthermore, Twitter is used by people with extreme views whose voices are often invisible in the mainstream media. Thus, data from Twitter could give us a broader picture about public opinions during the E.U. Referendum in the U.K. and the 2016 U.S. Presidential Election beyond what we can observe from the traditional media.

We find that tweets about the Brexit and the 2016 U.S. Presidential Election are disseminated and absorbed among Twitter users within 50-70 minutes. This suggests that information rigidity could be very low for critically important issues with wide coverage or that news cycles in social media are short-lived. We also observe the differential impact of tweeting activities by user type. For example, “remain” supporters in the Brexit Referendum respond stronger and faster to messages created by other “remain” supporters when compared with the reaction to messages from “leave” supporters. Furthermore, human tweeting activity could be influenced by bots. The degree of influence depends on whether a bot provides information consistent with the priors of a human. For instance, a bot supporting the “leave” campaign has a stronger impact on a “leave” supporter than a “remain” supporter. Similarly, Trump supporters are more likely to react to messages spread by pro-Trump bots. Further examination shows that the sentiment of tweets plays an important role in how information is disseminated: a message with positive (negative) sentiment generates another message with the same sentiment. These results provide evidence consistent with the “echo chambers” effect in social media; that is, people tend to select themselves into groups of like-minded people so that their beliefs are reinforced while information from outsiders might be ignored. Therefore, social media platforms like Twitter could enhance ideological segmentation and make information more fragmented rather than more uniform across people. Finally, we provide a quantitative assessment of how bots’ traffic contributed to the actual vote outcomes. Our results suggest that, given narrow margins of victories in each vote, bots’ effect was likely marginal but possibly large enough to affect the outcomes.

This study is related to several strands of research. The first strand has assessed the influence of news media on the economic and political outcomes. For example, Tetlock (2007), Engelberg and

Parsons (2011), and Chen et al. (2014) show that media coverage of a company's stock is significantly related to future stock prices and trading volume. Media exposure could also have impacts on political outcomes or voter behavior. Gerber et al. (2009) find that the subscription to either Washington Post or Washington Times increases the support for Democratic candidates. Similarly, DellaVigna and Kaplan (2007) suggest that the introduction of Fox News channel improves the vote shares of Republican candidates as well as increases voter turnout. In contrast, the introduction of television which has less political coverage leads to a decline in political knowledge and thus turnout rates (Gentzkow, 2006). We contribute to this literature by shifting our attention to information flows in online media as well as documenting its correlation with political preferences and outcomes.

With the development of the Internet, there is an emerging yet limited number of studies that examine the real-life impacts of information in social media. Steinert-Threlkeld et al. (2015) show a positive correlation between the coordination of messages about Arab Spring on Twitter and the number of protests on the following day. Similarly, using a sample of historical tweets related to Egypt's Arab Spring, Acemoglu et al. (2018) find a significant association between Twitter activities indicated by the number of Tahrir hashtags in tweets by opposition leaders and the number of protesters in Tahrir Square. Regarding the impacts of social media news on economic outcomes, Enikolopov et al. (2018) document that publication of blog posts on corruption of Russian-state owned firms can negatively affect stock prices of the exposed firms. We contribute to this emerging literature by quantifying bots' influence on humans' political preferences in social media platforms which in turn could possibly have impacts on real-life decisions.

Our study also contributes to the literature which examines the motivations of news and information consumption. Some papers suggest the ideological segregation that people tend to select themselves into groups of like-minded people so their beliefs are reinforced (see, e.g., Mullainathan and Shleifer, 2005; Halberstam and Knight, 2016). For instance, using Twitter data on the 2012 the House candidates and their followers (voters), Halberstam and Knight (2016) measure the degree to which Twitter users engage with other users with similar ideology and find a high degree of homophily (e.g., conservative voters tend to follow each other). Furthermore, the majority of retweets of tweets by Democratic candidates are created by liberal voters and a similar pattern is also observed for tweets by Republican candidates. The result provides evidence for the preference for transmitting like-mind information and reflects an exposure mechanism. More specifically, individuals are more likely to expose themselves to news and information consistent with their political views (Adamic and Glance, 2005; Garrett, 2009a; Gruzd and Roy, 2014; Hong and Kim, 2016). However, Gentzkow and Shapiro (2011) suggest that although ideological segregation does exist in both online and offline news consumption, the level of polarization is low. In other words, exposure to information reinforcing individuals' pre-existing views does not shield them from following information that they disagree with (Hargittai et al., 2008; Garrett, 2009b; DellaVigna et al., 2014). There is also evidence that polarization is greater for political issues than non-political issues (Barberá et al., 2015). Our contribution to this strand of research is in documenting interaction across different groups of Twitter users at high frequencies.

The fourth strand of research investigates the role of sentiment in the transmission of information (e.g., Heath, 1996; Chen and Lurie, 2013). In political discourse on Twitter, it is observed that tweets containing a high degree of emotionality reach wider readership and are more likely to be disseminated (Kim and Yoo, 2012; Dang-Xuan et al., 2013; Stieglitz and Dang-Xuan, 2013). There is also evidence for the negativity bias in information consumption that people react faster to the information having emotionally negative tone (e.g., Baumeister et al., 2001). In a similar vein, Meffert et al. (2006) find the existence of negativity bias in voters' information selection, processing, and recall during a political campaign. However, it is not always the case. During the 2012 U.S. General Election, voters were more exposed to the content mentioning their favorite candidates with positive sentiment (Halberstam and Knight, 2016). In a contribution to this line of research, we show how sentiment intensity of messages posted by bots influences reactions of "human" users.

Finally, this paper contributes to the literature on the presence of bots in social media. It has been shown that social bots become increasingly sophisticated and can mimic human behavior, making bots detection more difficult (Ferrara et al., 2016; Haustein et al., 2016). A recent study by Howard et al. (2018) provides a detailed discussion on the existence and creation of political bots as well as cases when bots are used to manipulate public opinions and/or interfere political discourse. For instance, during elections, political bots can create and pitch information for voters who are seeking for political information while elected officials use bots to increase their popularity. Further, several studies (e.g., Bastos and Mercea, 2017; Bessi and Ferrara, 2016; Howard et al., 2016; Howard and Kollanyi, 2016) have attempted to document the role of Twitter bots in the discussions about the Brexit Referendum and the 2016 U.S. Presidential Election. Generally, the findings show that Twitter bots effectively spread information during these two events. These studies focus on describing the automated accounts' tweeting activities as well as examining the interactions between bots and humans by mapping their networks. In contrast, we contribute to this literature by studying the behavior of bots and employing econometric techniques to investigate bots' influence on humans.

The rest of this paper is organized as follows. In the next section, we describe the dataset and how we collected data. Section 3 presents our empirical strategy and results. Section 4 concludes and provides implications.

2. Data

This section describes how data were collected and filtered and presents a summary of the dataset. First, we distinguish the tweeting activities of bots and humans to examine later how these two types of agents interact. Next, we perform the sentiment analysis and classify the tone of a tweet into positive, neutral, or negative. Finally, we explore the power of tweeting intensity to predict outcomes of the E.U. Referendum and the 2016 U.S. Presidential Election.

2.1. Data collection and cleaning

The data for analysis were collected using Twitter Streaming APIs. API can be viewed as a tool for collecting data directly from Twitter in real-time. A user sets selection criteria (filters) such as keywords or location and Twitter sends a sample of selected tweets as they happen. Each retrieved tweet contains the plain text of the tweet as well as information about users like user ID (user name) and other fields such as date, source, location, friend counts, follower counts, URL, etc.

According to Twitter's documentation and information provided by Twitter staff in the Twitter Developer forum, the Streaming APIs return at most 1% of the all public tweets (Firehose) at any given point of time.[2] This means that if the filter (e.g., keywords) matches less than 1% of *all* traffic on Twitter at a time, then the returned tweets are *all* public tweets that contain the keywords. However, if an event is extremely popular, the total number of public tweets containing

[2] For more information and discussion about Twitter Streaming API rate limit, see, for instance, https://twittercommunity.com/t/how-much-is-1/95878; https://twittercommunity.com/t/streaming-api-rate-limit/15082/4; https://twittercommunity.com/t/streaming-api-limit/93991; https://twittercommunity.com/t/current-streaming-api-sampling-rate/74864 (Accessed on 24 August 2018).

event-related keywords might excess the 1% cap. In this case, a random sample of the filter-matched tweets (capped at 1% of Twitter traffic) is returned.

To put this cap in the context of our data, consider the following fictitious example. Let's assume that on 23 June 2016, the volume of all public tweets created per minute was 350,000 (this is the average per-minute traffic on Twitter), making the per-minute cap 3,500 tweets per minute. At 04:00, suppose that the total number of tweets with "Brexit" keyword was 2,000. In this case, based on the filters set in Streaming API, we would get the full set of 2,000 tweets posted at 4:00 on 23/06/2016 since the volume was far lower than the 1% cap. Now suppose that at 05:01 on the same day, the volume of tweets with "Brexit" keyword reached 10,000. Since this was above the 1% cap, a random sample drawn from 10,000 tweets would be returned and the size of the sample streamed at 5:01 on 23/06/2016 would be 3,500 tweets. While Brexit and 2016 U.S. Presidential Elections were popular events, the volume of tweets related to these events was still too small to hit the cap in a way that can measurably distort our results: the daily volume of Brexit and U.S. Election tweets was in hundreds of thousands while the daily volume of all traffic on Twitter is in hundreds of millions.[3]

González-Bailón et al. (2014) and Morstatter et al. (2013) report that the quality of samples increases with more comprehensive coverage (e.g., longer harvested periods to get larger sample size or well-specified filtering parameters). Consistent with this recommendation, we make API requests to collect tweets that contain the following keywords and leave the connections open to collect as many tweets as possible.[4] The Brexit-related tweets were tracked if they contain the keyword "Brexit". The 2016 U.S. Election-related tweets were collected if they contained the following keywords: "Election2016", "BlackLivesMatter", "CampaignZero", "ClintonEmails", "ImWithHer", "NeverClinton", "FeelTheBern", "CruzCrew", "MakeAmericanGreatAgain", "Trump", "Clinton".

The screening/cleaning process is as follows. First, we process each tweet to extract the relevant content and store in a new tweet content variable. Specifically, we exclude special characters

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[3] Through an access to Twitter Firehose, Lopez et al. (2017) are able to extract a sample of more than 30 million Brexit-related tweets covering the period from January 6 2016 to the Referendum day, equivalent to the daily volume of approximately 175,000 tweets. This study also suggests that in the context of research that use Brexit-related tweets, Streaming API would provide similar outcomes to Firehose.

[4] We continue collecting data until now. However, data used in the analysis is restricted to the tweets posted during 24 May - 23 July 2016 period for the Brexit sample and 8 October 2016 - 8 December 2016 period for the 2016 U.S. Presidential Election sample.

such as link tokens (starting with "http://", "https://", "www.") or user identifier tokens (starting with "@") from the tweet content. Second, we do not include tweets that contained only links or URLs in our analysis.[5] Third, we separate tweets with English as the language description from those with other languages. Finally, we adopt the approach proposed by Howard and Kollanyi (2016) and Howard et al. (2016)[6] and define campaign endorsement for each tweet based on the hashtags/keywords specified in Appendix Table A1. After screening, our sample contains about 2.7 million tweets for the E.U. Referendum and 7.2 million tweets for the 2016 U.S. Presidential Election.

To illustrate our screening procedure, consider the following tweet posted on 26/05/2016: "RT @Nigel_Farage: I don't believe these official figures and I'm sure the real numbers are much higher. We must Leave EU and control our border https://t.co/3pr." While processing this tweet, we remove "https://t.co/3pr" and the user identifier token "@". We classify this tweet as pro-leave. Now consider another tweet posted on 10/06/2016: "This is an awesome TED talk from a couple years ago about thinking globally. Very relevant in light of #Brexit vote. https://t.co/BZeZ3fMFyA." We also remove the hashtag token and the URL link in tweet processing. Although this tweet includes references to Brexit, we do not include it in our analysis because it does not contain endorsement of any side of the debate.

In the next step, we identify original tweets (i.e., the tweets were created rather than copied) and their retweets. First, we screen each tweet's content in the original dataset and create a new indicator variable which equals 1 if the tweet starts with "RT @" (which means a retweet in the Twitter language; that is, a repost of an original tweet) and 0 otherwise. Next, we extract the content after "@" and before the main text to create a new variable that contains the user name of the Twitter account from which the tweet was retweeted. After these steps, we could identify (1) the original tweets and (2) their retweets (if any). An example of this process is provided in Appendix Table A2.

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[5] This criterion effectively removes Twitter accounts of many standard media (e.g., BBC, Times) because these media typically post only links (URLs) to articles on their Twitter pages.

[6] In these studies, the authors analyse all Brexit-related and U.S. Election-related tweets and use some specific hashtags to define supporting sides. Our approach is different in two ways. First, we do not analyse the tweets that contain only a URL even if the URL includes the hashtags/keywords. Second, we do not include some of the hashtags/keywords used by Howard and Kollanyi (2016) and Howard et al. (2016) such as #Brexit, #Trump, or #Clinton to classify tweets as being in favour or against a side or a campaign because these hashtags have been often used to support both sides of the argument.

2.2. Identification of bots

Since Twitter bots are run by software, it is extremely difficult to establish who bot-makers are really and how their content is created. Indeed, bots' tweets are automatedly generated and the content of the tweets could be pre-determined or could be links to popular sites, news sites, or sites focused on current events (Wojcik, 2018). Furthermore, Twitter bots become increasingly sophisticated at mimicking humans (Ferrara et al., 2016; Haustein et al., 2016). However, previous research (e.g., Chu et al., 2010; Sivanesh et al., 2013; Cook et al., 2014) documents several patterns that help distinguish bots and human users. First, a human agent tends to be more active in tweeting during the regular workdays and during the daytime while the daily and hourly tweeting activity of a bot agent is even. Second, bots often tweet the same content many times while humans do not. Given the aggressive use of social bots during the political events like election, previous studies also suggest some event-specific criteria to detect bots. For example, bot accounts are more likely to be created just on or about the event announcement date. Further, bot agents could have the inactivity before and after the event but create mass tweets or retweets on event-specific days and times.

Building on these earlier results, we use the following procedure to classify Twitter accounts into humans and bots. Consider a given Twitter account on a given day. We flag this account/day as a potential bot if *any* of the following conditions is satisfied.

First, Haustein et al. (2016) document that the average number of daily tweets for a bot is about 5 (standard deviation ≈5) while the daily average for humans is about 2 (standard deviation ≈2). Given these differences in the volume of tweeting, our first criterion is an unusually large number of tweets in a day created by an account. For both samples, we choose the threshold of 10 which is about 4 standard deviations above normal human activity.

Second, since the period from 00:00 to 06:00 is often considered as the inactive time for humans, any actively tweeting activities during this time period could be viewed as "abnormal tweeting time". We flag an account as a potential bot if the account creates at least 5 tweets during the abnormal tweeting time on a given. Abnormal time is defined based on British Summer Time for the U.K. or Eastern Time for the U.S.

Third, previous studies in computer science (e.g., Lee et al., 2010; Chu et al., 2012) suggest that one of bots' characteristics is to repeatedly post identical messages. Thus, we flag an account as a potential bot if the number of tweets with the same content per day is 3 or more for both samples.

Fourth, Twitter bots may be created and used for particular events. Hence, the next criterion examines newly created accounts. We define an account as "newly created" if the account is created on or after 20 February 2016 for the Brexit sample when the Referendum was announced and 15 July 2016 for the 2016 U.S. Election sample when by-then Republican presumptive nominee Donald Trump announced his vice-presidential running mate. These accounts are flagged as potential bots if they have an unusually high average daily tweet volume relative to what one might have expected for a Twitter account of that age. The chosen threshold is 10.

If an account is flagged as a bot for majority of days (that is, more than 50 percent of days) during its lifetime in the sample, then the account is defined as a bot; otherwise the user is defined as a human. We experimented with variations of these criteria (e.g., a user is defined as a bot if tweeting activities are observed for at least three days and on more than 50 percent of days tweeting activities match all four criteria; raising or lowering the threshold point for each criterion) and we found similar results in our regression analysis. To check the validity of our procedure to identify bots, we compare our bot definition with bot detection based on an online classification tool called Botometer (formerly BotOrNot).[7] We find that these two approaches return similar results for 90% of accounts in our sample.

Table 1 presents summary statistics for bot and human accounts in the Brexit and U.S. Election samples. The number of bot accounts is small (0.14% of total accounts observed in the Brexit sample and 0.2% for the U.S. Election sample) but bot accounts generate a lot of traffic (9% of all tweets in the Brexit sample and 8% of all tweets in the U.S. Election sample). The average age of bot accounts is generally younger than that of human accounts. This pattern is consistent with the fact that many bots are often created for a particular event. However, there are also some bots (e.g. "marketing" bots) that have been existing for a long period of time, which are likely to be used for marketing/spamming purposes or even inactive in no-event periods.

2.3. Dynamics of Twitter posts

Figure 1 illustrates the evolution in the daily and hourly volumes of Brexit-related tweets for humans (Panels B and D) and bots (Panels A and C). There is a significant increase in the number

[7] This tool is developed by researchers from Indiana University and Northeastern University. Botometer tool cannot classify the accounts that have been suspended or deactivated. See Davis et al. (2016) for more details.

of tweets created by humans on the 23rd and 24th June 2016. While bots also show more intensity around these dates, the increase is much more modest. Interestingly, the daily volume of pro-leave tweets was always higher than the daily volume of pro-remain tweets. This gap was greatest during the time around the E.U. Referendum day: between 00:00 and 06:00 on the 24th June, the difference in the hourly pro-leave tweets and pro-remain tweets reached its peak of about 10,000 tweets. There is a clear pattern in humans' hourly tweeting volume: humans' accounts are more active between 6 am and 6 pm and they show considerably smaller intensity in other hours.[8] In contrast, we do not observe any clear pattern in the hour-by-hour tweeting activity of bots.

The time series of 2016 U.S. Election-related tweets are shown in Figure 2. Most of the time, the number of pro-Trump tweets exceeded the daily volume of pro-Clinton tweets. A large increase in pro-Clinton tweets only appeared during the time running up to the Election Day. Specifically, approximately 5 days before and on the Election Day, the number of pro-Clinton tweets soared with the peak of more than 8,000 tweets per hour and was higher than the number of pro-Trump tweets. Comparing the differences in the number of tweets created by the two sides before and after the voting day, we observe a significant reduction in the hour-by-hour gap between two periods. Note that the intensity of tweeting activity declined sharply after the Election Day while in the U.K. the decline was more spread out in time during the post-Referendum period.

2.4. Sentiment of the tweets

Baumeister et al. (2001), Kim and Yoo (2012), Stieglitz and Dang-Xuan (2013), and others show that the intensity of information flows can depend on sentiment (tonality) of messages. To measure the intensity of sentiment, we use TextBlob, a publicly available text-processing tool written in Python, to get a polarity score for each tweet (see Loria, 2018 for TextBlob details). TextBlob can perform various tasks such as part-of-speech tagging, noun-phrase extraction, sentiment analysis, spelling correction, text translation and many more.

The sentiment analysis using PatternAnalyzer in TextBlob is done in the following steps. First, the text is divided into constituent words. Second, stop words such as function words (the, that, which, etc.) are filtered out. Third, part-of-speech tagging is performed. In this step, the remaining words after

[8] Appendix Figure B1 shows how intensity of tweeting activity by humans and bots changes by hour of the day and by day of the week.

the second step are classified into categories i.e. noun, verb, adjectives, adverb, etc. Finally, words are passed into Sentiment Classifier to determine the popularity/subjectivity scores for each word and for the whole sentence. TextBlob's Sentiment Classifier scores sentiment mostly based on English adjectives and modifiers then averages sentiment of a single word and the text. To make it clear, let's consider this sentence: "It is interesting and funny" which has two adjectives ("funny" and "interesting"). The word "funny" has 4 entries in TextBlob's pre-classified lexicon with popularity scores of 0.5, 0, 0.5, and 0, making the word's average popularity score 0.25. The word "interesting" has only 1 entry in the lexicon with the popularity score of 0.5. Thus, the popularity score of the sentence is 0.375 ($=\frac{0.25+0.5}{2}$). The similar process is applied in analyzing sentiment of this sentence "It is interesting and very funny" with the only difference is that "very" is a modifier of which only its intensity score (1.3) is taken into account. In this case, the phrase "very funny" has the popularity score of 0.325 ($= 0.25 \times 1.3$). Hence, the popularity score of the whole sentence is 0.4125 ($=\frac{0.325+0.5}{2}$).[9]

The abovementioned process returns the polarity score between -1 and 1. A score in [-1,0) represents negative sentiment, a score in (0,1] represents positive sentiment, and a score of 0 refers to neutral sentiment. For example, TextBlob scores "RT @Nigel_Farage: I don't believe these official figures and I'm sure the real numbers are much higher. We must Leave EU and control our border https://t.co/3pr.", a tweet we consider above, as having a positive sentiment (the score is 0.32). On the other hand, TextBlob assigns a score of -0.5 (a negative sentiment) to the tweet "If we allow the 18 Albanians who arrived on our shores illegally to stay then UK faces a migrant crisis this summer". "Brexit may break Britain's Tory party" is an example of a neutral tweet.[10]

Overall, the volume of emotionally-colored tweets was relatively moderate: neutral messages are the most prevalent (the average share is 50% and 61% for the Brexit and U.S. Election samples, respectively). Messages with positive sentiment have the second place (the average share is 33% and 25% for the Brexit and U.S. Election samples, respectively). Negative messages are the least frequent (the average share is 17% and 15% for the Brexit and U.S. Election samples, respectively). The distribution of scores is reported in Appendix Figure B2.

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[9] For more discussions about sentiment analysis using TextBlob, see e.g., https://planspace.org/20150607-textblob_sentiment/; https://www.greycampus.com/blog/data-science/sentiment-analysis-on-twitter-tweets-using-python. (Accessed on 24 August 2018).
[10] More examples of how TextBlob works in our samples are presented in Appendix Table A3.

Figure 3 shows the daily volume of tweets by sentiment and type of user for the Brexit sample and the 2016 U.S. Presidential Election sample. The daily volumes by sentiment tend to comove strongly. This pattern is observed for both humans and bots. We also find similar results when we focus on the hourly volume of tweets around the voting dates and when we split the sample by the sides of the campaign (see Appendix Figures B3-B5). This co-movement suggests that the distribution of sentiment was approximately constant during both campaigns.

2.5. Predictive power of public opinions on Twitter

Previous studies show that Twitter activity may have predictive power for electoral outcomes (e.g., Bermingham and Smeaton, 2011; Tumasjan et al., 2011; Burnap et al., 2016). To explore whether this is the case in our sample, we compare Twitter support and the actual shares of votes received by the sides of the campaigns at the regional level.

To construct the former, we use the location of Twitter users to measure how intensively a given geographical location (a state for the U.S. and a region for the U.K.) supports a given side. Takhteyev et al. (2012) documents that 75 percent of Twitter accounts in their large sample report geographical locations of their owners. We find that a very similar share of users reports their location in our sample. While owners may choose locations different from where they actually reside, available evidence (e.g., Takhteyev et al., 2012; Haustein and Costas, 2014) suggests that, while imperfect, this information is useful for determining geography of Twitter users.

Once the location of users is established, we compute the share of pro-leave "human" tweets in total "human" tweets on the day before Referendum for the Brexit sample and the share of pro-Trump "human" tweets in total "human" tweets on the day before the vote date for the 2016 U.S. Presidential Election sample. Figure 4 shows that these shares are highly correlated with the shares of votes received by the corresponding platform.[11] To be clear, these correlations are not causal, and they do not measure persuasion rates in the spirit of DellaVigna and Kaplan (2007). Instead, these results only suggest that the volume of Twitter activity may be a useful predictor of electoral outcomes in our samples.[12]

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[11] Because voters could write in candidates in the U.S., the actual votes by the U.S. states are calculated using this formula: Actual vote = Votes for Trump/(Votes for Trump + Votes for Clinton).

[12] We find similar results when we weight tweets with sentiment.

3. Interactions between bots and humans

This section examines how information flows across different types of users. The main focus of our analysis is how bots can influence Twitter activity of humans. We use two approaches to measure direction and intensity of the flows. First, we study how frequently a user type retweets (i.e., re-posts) messages of the other user types. Second, we employ time-series tools to investigate how bots' messages (original and retweets) generate humans' messages (original and retweets).

3.1. Retweeting

Similar to other social media, Twitter allows users to repost existing messages. Typically, reposting (retweeting) a message means that a user wants to spread the message in his or her social circle. Messages with many retweets are often labeled as popular/trending and, as a result, have higher ranking/priority in internet searches. In other words, a message with many retweets is often treated as important. Because retweeting a message generates a link from a user who originated the message to a user who reposted it, we can observe the direction of the information flow. Thus, retweeting provides us with measures of intensity and direction for interaction between different types of users.

To understand our approach, consider the following fictitious example. Suppose an original (i.e., not a copy) tweet supporting the leave campaign appears at 1pm. We compute how many retweets between 1pm and 1:10pm this tweet generated by human accounts and by bot accounts. Then we count the number of (new) retweets by humans and bots that were generated for the original tweet between 1:10pm and 1:20pm. This procedure is continued at ten-minute intervals for 2 hours after the original tweet appeared. The resulting path provides us with an impulse response function for the original tweet. We repeat this procedure for all original tweets and compute the average impulse response function.

Figure 5 reports these average impulse response functions by type of users who generated original tweets and by type of users who retweeted original messages.[13] Panels A and B of the figure show that, relative to traffic generated by humans, traffic generated by bots is small. Indeed, the intensity of bots' retweeting is an order of magnitude smaller than retweeting activity of humans.

[13] In the Brexit sample, the average number of retweets per original tweet is 0.5 and the standard deviation is around 4. In the U.S. Election sample, these figures are 0.3 and 12, respectively. Because most tweets generate few or no retweets, we restrict the sample to relatively popular original tweets (the ones get more than 5 retweets) to have meaningful variation over time.

Humans and bots are most active in retweeting in the first 10 minutes right after the time when original tweets are generated. The number of new retweets reduces over time and reaches a stable level within two hours.

To establish which account type is more likely to respond to a tweet of a given account type, we restrict the sample to include only original messages generated by humans (Panels C and D) or to include only original messages generated by bots (Panels E and F).[14] Note that humans' traffic reacts much more strongly to tweets generated by other humans than to tweets generated by bots (e.g., compare the magnitude of the responses in Panels C and E for the Brexit sample and Panels D and F for the U.S. sample). In contrast, the volume of bots' traffic is equally weak in retweeting messages of humans and messages of other bots. For instance, during the first 10 minutes since humans post original tweets about Brexit, the number of retweets made by humans is significantly higher than that made by bots (35 retweets vs. 2 retweets for every 10 original tweets, respectively).

These patterns lead us to three tentative conclusions. First, information flows are most intensive between humans, while information flows across bots are weak. Second, information flows from bots to humans are tangible while information flows from humans to bots are very weak. Third, reactions tend to be relatively short-lived in the sense that the vast majority of the reaction is completed within two hours.

These results are consistent with the view that humans had little (if any) effect on bots while bots had a perhaps limited, but tangible effect on humans. These results also suggest that bots are not likely to be successful in persistently moving tweeting activity of humans. The short duration of the response is consistent with the fast news cycles in social media (e.g., Kwak et al., 2010; Yoo et al., 2016) and/or low information rigidity (Coibion and Gorodnichenko, 2012).

3.2. Time series analysis

While the analysis in the previous section is informative, it is focused on reposts of original messages. Obviously, interaction between different types of users may also happen via generation of new messages. In this subsection, we use standard tools of time-series analysis to construct

[14] Similar patterns are also observed when we separate tweets by sentiment.

impulse responses of all messages (that is, retweets and new posts) by a type of users to a message generated by a given type of users.

This exercise relies on two key ingredients. First, we build on our earlier findings for retweets and assume that humans can respond contemporaneously to bots while bots do not respond contemporaneously to humans. Second, to ensure that this identifying assumption holds, we use data at 10-minute intervals. Apart from strengthening our identification, this short duration of time intervals allows us to control for low-frequency variation in the volume of tweeting activity (e.g., days closer to the vote date have higher volume than more distant days).

A. Econometric specification

To estimate impulse responses flexibly, we use local projections method developed by Jordà (2005). To see how this method works, suppose that we are interested in estimating reactions of humans supporting campaign X to bots advocating campaign X and to bots advocating campaign Y. The method amounts to estimating $h = 0, \dots, H$ regressions of the following type:

$$\begin{aligned} \ln Human_{t+h,d}^{(X)} = & \sum_{k=0}^{K} \alpha_{X,k}^{(h)} \ln Bot_{t-k,d'}^{(X)} + \sum_{k=0}^{K} \beta_{X,k}^{(h)} \ln Bot_{t-k,d'}^{(Y)} \\ & + \sum_{k=1}^{K} \gamma_{X,k}^{(h)} \ln Human_{t-k,d'}^{(X)} + \sum_{k=1}^{K} \phi_{X,k}^{(h)} \ln Human_{t-k,d'}^{(Y)} \\ & + \psi_{X,d}^{(h)} + Seasonal_{X,td}^{(h)} + error_{X,td}^{(h)} \end{aligned} \quad (1)$$

where t and h index ten-minute intervals, d indexes the day of a campaign, $Human_{t+h,d}^{(X)}$ is the volume of new tweets generated by humans supporting campaign X during the $t + h$ ten-minute interval on day d, $Bot_{t-k,d'}^{(C)}$ is the volume of new tweets by bots supporting campaign $C = \{X, Y\}$ during the $t - k$ ten-minute interval on day d' where $d' = d$ if the $t - k$ interval is on the same day with t and $d' = d - 1$ if the $t - k$ interval is on the day proceeding t. Because there are considerable variations in tweeting activity across days of the week, we include $Seasonal_{td}^{(h)}$, a set of "seasonal" dummy variables. Specifically, for each 1-hour interval during a 24-hour day period we have a dummy variable; note that each weekday (Monday, Tuesday, etc.) is allowed to have a potentially different 24-hour profile of intra-day activity. Finally, $\psi_d^{(h)}$ is a dummy variable equal to one if the day of campaign is equal to $d = \{-30, -29, \dots 0, \dots, 29, 30\}$.

Note that in this specification, the lag polynomial of humans supporting campaign Y ($\ln Human^{(Y)}_{t-k,d'}$) starts with $k = 1$ while the lag polynomials for bots start at $k = 0$. This timing means that we allow bots to have a contemporaneous effect on humans and bots do not respond to humans. Consistent with earlier studies using the Jordà approach, we use Newey-West standard errors to account for serial correlation of the error term for $h \geq 1$. We use $K = 24$ for the reported results but our findings are largely unchanged for alternative values of K.

We compute the impulse response to bots supporting campaign X as $\left\{\hat{\alpha}^{(h)}_{X,0}\right\}^{H}_{h=0}$ and the impulse response to bots supporting campaign Y as $\left\{\hat{\beta}^{(h)}_{X,0}\right\}^{H}_{h=0}$. Note that we use logs in specification (1) to transform the volume of tweeting activity (this helps to make the distribution of tweet volume better behaved) so that α_0 and β_0 are elasticities. To convert these elasticities into "multipliers" (that is, a tweet from bot X generates N tweets by humans supporting X), we multiply α by the ratio $\overline{Human^{(X)}}/\overline{Bot^{(X)}} \approx \overline{(Human^{(X)}/Bot^{(X)})}$, that is, the time-series average of the $Human^{(X)}_{d}/Bot^{(X)}_{d}$ ratio. Correspondingly, the multiplier from bot Y to human X is the product of β and $\overline{(Human^{(X)}/Bot^{(Y)})}$.

One can think of the Jordà method as constructing a moving average representation of a series: the lag polynomial terms control for initial conditions while $\left\{\hat{\alpha}^{(h)}_{X,0}\right\}^{H}_{h=0}$ and $\left\{\hat{\beta}^{(h)}_{X,0}\right\}^{H}_{h=0}$ describe the behavior of the system in response to a structural, serially uncorrelated shock. Indeed, if we abstract from variation in initial conditions at time t, we effectively regress a variable of interest at time $t + h$ on a shock in a given regime at time t and thus we obtain an average response of the variable of interest h periods after the shock, which is precisely the definition of an impulse response.

As discussed in Auerbach and Gorodnichenko (2012), this approach has several advantages over vector autoregressions (VARs). First, it obviates the need to estimate the equations for dependent variables other than the variable of interest and thus we can significantly economize on the number of estimated parameters. Second, it does not constrain the shape of the impulse responses. Third, one can easily test joint hypotheses about paths of estimated impulse response. Finally, specification (1) may be straightforwardly extended in various dimensions to allow for a larger set of controls or for more flexible (potentially non-linear) responses. For example, we are interested in comparing the strength of a reaction to human posts supporting campaign Y to the strength of a reaction to bot posts supporting campaign Y. To obtain this comparison, we can estimate

$$\begin{aligned}\ln Human_{t+h,d}^{(X)} = &\sum_{k=0}^{K} \alpha_{X,k}^{(h)} \ln Bot_{t-k,d'}^{(X)} + \sum_{k=0}^{K} \beta_{X,k}^{(h)} \ln Bot_{t-k,d'}^{(Y)} \\ &+ \sum_{k=1}^{K} \gamma_{X,k}^{(h)} \ln Human_{t-k,d'}^{(X)} + \sum_{k=0}^{K} \phi_{X,k}^{(h)} \ln Human_{t-k,d'}^{(Y)} \\ &+\psi_{X,d}^{(h)} + Seasonal_{X,td}^{(h)} + error_{X,td}^{(h)} \qquad (1')\end{aligned}$$

where now the lag polynomial for $\ln Human_{t-k,d'}^{(Y)}$ starts at $k = 0$ rather than $k = 1$ and one can use $\left\{\hat{\phi}_{X,0}^{(h)}\right\}_{h=0}^{H}$ as the impulse response of humans supporting X to humans supporting Y and corresponding measure multipliers are the product of ϕ and $\overline{(Human^{(X)}/Human^{(Y)})}$. Note that this specification is equivalent to ordering $Human^{(Y)}$ before $Human^{(X)}$ in a VAR.

B. Baseline results

Figure 6 reports estimated impulse responses for the Brexit sample. Panel A of the figure shows the reaction of humans supporting the leave campaign to messages generated by bots supporting the leave campaign and by bots supporting the remain campaign. The response to “remain” bots is generally small with a weak reaction on impact and a modest, positive multiplier in subsequent periods. In contrast, the contemporaneous reaction of “leave” humans to “leave” bots is strong: the multiplier is close to 2, that is, a new bot post generates two new human posts. However, this elevated tweeting activity of humans is short-lived: after approximately 2-4 hours of the bot post we observe little difference in the response of “leave” humans to “leave” bots and to “remain” bots. These patterns are similar to the behavior of humans in retweeting posts thus providing additional evidence of fast news cycles and/or low information rigidity.

Panel B of the figure plots the responses of “remain” humans to “leave” bots and “remain” bots. Similar to what we observe in Panel A, the reaction of “remain” humans to bots advocating the other side of the campaign is rather mute (the multiplier is close to zero), while the reaction to bots from the same side of the campaign is stronger (the multiplier is about 0.7 which is smaller in absolute terms than the contemporaneous multiplier for “leave” humans in response to “leave” bots). Likewise, the effect of “remain” bots on “remain” humans is rather transitory. The asymmetric response of humans to posts consistent/inconsistent with their views suggests that social media can create "echo chambers" fostering amplification of messages within a group of similarly-minded people and inhibiting communication of people with different views.

The patterns are similar for the 2016 U.S. Presidential Election (Figure 7). Human supporters of the Trump (Clinton) campaign are more reactive to messages posted by bots supporting the Trump (Clinton) campaign than to messages posted by bots supporting the Clinton (Trump) campaign. In a similar spirit, the reactions are not persistent and most of the response happens within a few hours after a message appears.

C. Sentiment

As discussed above, the intensity of human responses may vary with the strength of the sentiment in messages posted by bots. To study this possible heterogeneity in responses, we modify specification (1) as follows:

$$\begin{aligned}\ln Human_{t+h,d}^{(\tau,X)} &= \sum_{s\in\{positive,neutral,negative\}} \sum_{k=0}^{K} \alpha_{X,s\to\tau,k}^{(h)} \ln Bot_{t-k,d'}^{(s,X)} \\ &+ \sum_{s\in\{positive,neutral,negative\}} \sum_{k=0}^{K} \beta_{X,s\to\tau,k}^{(h)} \ln Bot_{t-k,d'}^{(s,Y)} \\ &+ \sum_{s\in\{positive,neutral,negative\}} \sum_{k=1}^{K} \gamma_{X,s\to\tau,k}^{(h)} \ln Human_{t-k,d'}^{(s,X)} \\ &+ \sum_{s\in\{positive,neutral,negative\}} \sum_{k=1}^{K} \phi_{X,s\to\tau,k}^{(h)} \ln Human_{t-k,d'}^{(s,Y)} \\ &+\psi_{X,\tau,d}^{(h)} + Seasonal_{X,\tau,td}^{(h)} + error_{X,\tau,td}^{(h)} \qquad (2)\end{aligned}$$

where τ and s index sentiment (tonality) from positive to neutral to negative. One can now interpret slopes as the strength of the response that may vary by tonality of messages posted by humans and bots. For example, $\alpha_{X,s\to\tau,k}^{(h)}$ measures the elasticity of the h-horizon response of humans supporting campaign X with sentiment τ to bot posts supporting campaign X with sentiment s. Then we use appropriate ratios of the regressand to a regressor to convert the estimated elasticities into multipliers. Figure 8 and Figure 9 plot the estimated impulse responses (measured as multipliers) for the U.K. and U.S. samples respectively. By and large, we observe results similar to the baseline results: humans supporting a given side of a campaign tend to react stronger to posts generated by bots supporting the same side and the sentiment of human responses mimics the sentiment of bot posts.

D. Humans vs. bots

Our analysis so far has presented evidence consistent with the view that the Twitter activity of bots can affect the Twitter activity of humans who share beliefs advocated by bots. However, a bot appears to have a weak effect on humans who have beliefs opposite to what is advocated by the bot. Would humans be more effective in reaching across the aisle?

To answer this question, we use specification (1') to compare response multipliers for humans who support a given campaign side to posts by humans and bots from the other camp. Panel A of Figure 10 shows response multipliers of "leave" humans in the Brexit sample to tweets posted by "remain" humans and "remain" bots. We observe that, if anything, bots appear to have larger multipliers than humans. Likewise, "remain" humans appear to have larger multipliers in response to "leave" bots than to "leave" humans (Panel B). The results are similar for the U.S. sample (Figure 11): bots appear to be as effective (if not more effective) as humans in moving humans with opposite views.

These results suggest that while human touch and personal connections may be important, in the world of social media bots and other "strangers" can play an equally important role in bringing together or distancing people with different beliefs. Given that bot traffic is considerably cheaper than traffic generated by humans (Forelle et al., 2015), one may anticipate ever greater use of bots in political campaigns as well as various attempts of humans to shield themselves from bots.

E. Historical contribution of bots

Our analysis suggests that bots may have tangible influence on the tweeting activity of humans. To quantify the contribution of bots' traffic to the volume of human tweets, we use the method developed by Coibion et al. (2017) to construct historical decomposition of the time series for human tweet volumes. In particular, we are interested in constructing counterfactual time series of human tweets that would have been observed in the absence of bot traffic.

To implement the Coibion et al. method, we make two departures from specification (1). First, we use innovations to bots' volume of tweets rather than the level of bots' tweets on the right-hand side of specification (1).[15] This step is necessary to have the dynamics of human tweet

[15] The shocks to bots are constructed as follows. We use specification (1) with bot traffic as the dependent variable and all lag polynomials starting with $k = 1$. We estimate this specification separately for bots supporting campaign X

activity as a moving average process in terms of "bot" shocks so that we can construct a counterfactual dynamic of human tweet activity when we turn off "bot" shocks. We continue using lags of human tweets in levels (rather than in shocks). As a result, we have a combination of moving average (MA) terms (that is, current and lagged values of bot shocks) and autoregressive (AR) terms (that is, lags of human traffic supporting campaign X and lags of human traffic supporting campaign Y). To ensure that we have enough persistence in this vector ARMA representation of the stochastic process for human tweets, we increase the number of lags K from 24 to 99. We find that impulse responses based on this modification are virtually identical to the impulse responses based on specification (1). Thus, for all practical purposes, this modification does not alter our previous conclusions.

Second, we do not include dummies ψ_d for each day of a campaign. While these dummy variables are helpful to control for trends in the data, they also demean bots' traffic so that the contribution of bots to the *daily* volume of human tweet activity is zero by construction. Fortunately, we find that removing ψ_d makes little difference for the estimated impulse response and, therefore, our previous conclusions continue to apply.

Note that the dynamics of human tweets are now modelled as a system of two equations with two endogenous variables (e.g., "leave" human tweets and "remain" human tweets) driven by bot shocks (e.g., "leave" bot shocks and "remain" bot shocks) and by shocks to human tweet activity (e.g., $error^{(0)}_{"leave",td}$ and $error^{(0)}_{"reman",td}$). By plugging these shocks into the estimated vector ARMA process, we recover actual time series of human tweet activity. By setting bot shocks to zero, we construct counterfactual dynamics for human tweet activity when bots are not present. To make time series easier to interpret, we aggregate the generated volumes from 10-minute frequency to daily frequency.

Panel A of Figure 12 plots times series of actual and counterfactual ("no bot") daily volume for pro-"leave" human tweets in the Brexit sample. The difference between the lines is the bots' contribution. The dynamics of the series suggest that bots had a considerable contribution to the volume of human tweeting with the largest contribution around the vote date. Panel B of the figure documents a similar pattern for pro-"remain" human tweets. Importantly, the two surges generated

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and for bots supporting campaign Y. The residual of each regression is interpreted as the shock to bots supporting the corresponding campaign.

by bots roughly offset each other: the share of pro-"leave" human tweets in all tweets is similar for actual tweeting volume and counterfactual tweeting volume (Panel C). Specifically, the actually observed share of pro-"leave" human tweets on the day before the vote day is 62.76 percent, while the counterfactual share is 60.69 percent. This is a small absolute difference but one should bear in mind that the Brexit outcome was decided by a small margin (the share of "leave" votes was at 51.9 percent). Our analysis in Section 2.5 indicates that a percentage point increase in the share of pro-"leave" tweets in total tweets is associated with a 0.85 percentage point increase in the share of actual pro-"leave" votes. While this relation is not causal, we can use it for prediction. With this interpretation in mind, we find that the difference between actual and counterfactual traffic could translate into 1.76 percentage points of actual pro-"leave" vote share. Hence, while bots nearly offset each other, the difference could have been sufficiently large to influence the outcome given how close the actual vote was.

Panels D-F replicate the analysis for the 2016 U.S. Presidential Election sample. Similar to the Brexit sample, bots appear to have a considerable contribution to the human tweet traffic. In a similar spirit, the pro-Trump and pro-Clinton human traffic generated by bots nearly offsets each other: actual and counterfactual shares of pro-Trump human tweet volume in total tweet volume are 48.09 and 54.13 percent respectively on the day before the vote date (note that pro-Clinton traffic surged days before the vote date while pro-Trump traffic was more stable so that, in aour calculations, bots "helped" the Clinton campaign). But again, even this small difference could have played an important role in the outcome of these close-call elections. Specifically, our analysis in Section 2.5 suggests that a percentage point increase in the share of pro-Trump tweets in total tweets is associated with a 0.60 percentage point increase in the share of actual pro-Trump votes. Therefore, the observed difference between actual and counterfactual pro-Trump tweet shares suggests that 3.62 percentage points of the actual vote could be rationalized with the influence of bots.

4. Concluding remarks

Social media are a powerful tool for spreading news and information. However, social media might also propagate misinformation and fake news, especially during high-impact events. It is necessary to understand how information is diffused and acquired in social networks as it might affect individuals' decision-making in real life. Furthermore, the rise of bots (automated agents) in social media potentially creates greater risks of manipulation as humans cannot detect bots and thus could be driven and possibly deceived by bots.

This study explores the diffusion of information on Twitter during two high-impact political events in the U.K. (2016 E.U. Referendum, "Brexit") and the U.S. (2016 Presidential Election). Specifically, we empirically examine how information flows during these two events and how individuals' actions might be influenced by different types of agents. We have two key results. First, information about the Brexit Referendum and the U.S. Election is disseminated quickly on Twitter. During these two highly covered campaigns, reaction to new messages is largely complete within 1-2 hours which is consistent with fast news cycles and/or low information rigidity in social media.

Second, we find that individuals are more active in interacting with similar-minded Twitter users. That is, e.g. pro-leave users react faster and stronger to the messages created by other pro-"leave" users. We document that the extent to which bots can affect humans' tweeting activities depends on whether bots' information is consistent with humans' preferences. For example, a message by a pro-leave bot generates a response of pro-leave humans and approximately no response of pro-remain humans. Furthermore, bots' messages with a given sentiment largely generate human messages with the same sentiment. These results lend support to the "echo chambers" view that Twitter and other social media create networks for individuals sharing similar political beliefs so that they tend to interact with others from the same communities and thus their beliefs are reinforced. By contrast, information from outsiders is more likely to be ignored. Consequently, ideological polarization in social media like Twitter is likely amplified rather than attenuated, which makes reaching consensus on important public issues more difficult.

Since Twitter and other platforms of social media may create a sense of public consensus or support, social media could indeed affect public opinions in new ways. Specifically, social bots could spread and amplify (mis)information thus influencing what humans think about a given issue and likely reinforcing humans' beliefs. Not surprisingly, bots were used during the two campaigns we study to energize voters. While we cannot establish the causal effects of bots on the outcomes of the Brexit and the 2016 U.S. Presidential Election, predictive properties of Twitter traffic suggest that bots could marginally contribute to rationalizing the outcomes.

These two campaigns and subsequent debates about the role of bots in shaping the campaigns raise a number of questions about whether policymakers should consider mechanisms to prevent abuse of bots in the future. Obviously, regulating information flows is an extremely delicate business in a democratic society characterized by diverse views and tolerance for this diversity. However, cherishing diversity does not mean that one should allow dumping lies and manipulations to the extent that the public cannot make a well-informed decision. Where one should draw the line (e.g., disclose ultimate owners of accounts, improve media literacy, or introduce "code of practice" for social networks) is a central question for the society.

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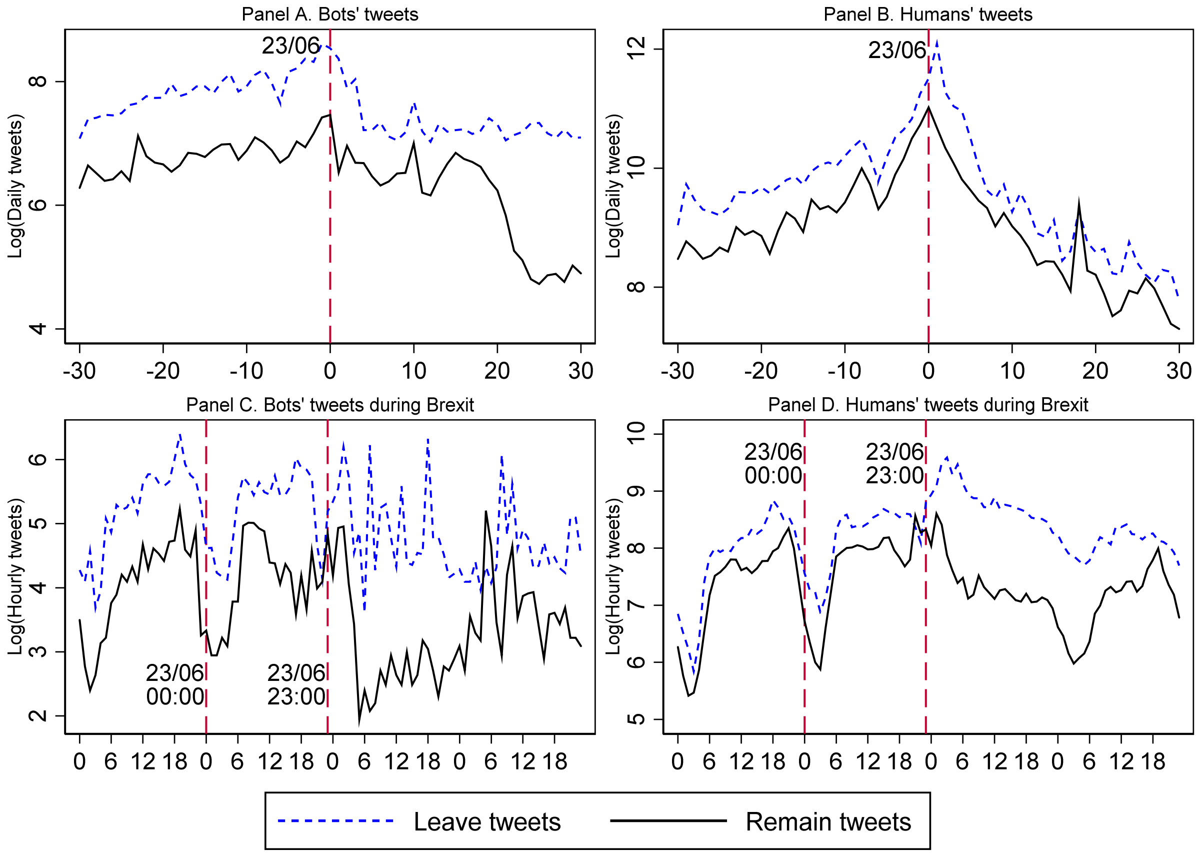
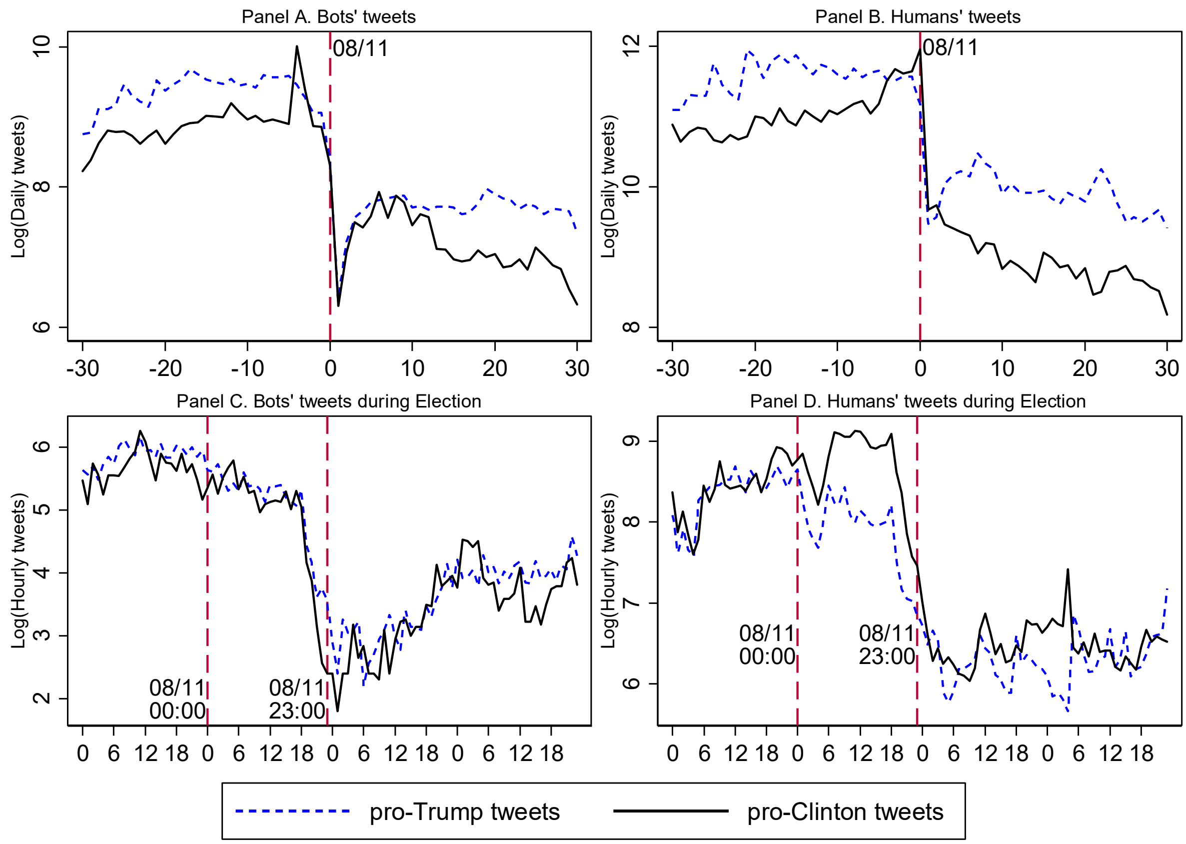
Figure 1. Dynamics of tweets generated by humans and bots: U.K. Brexit



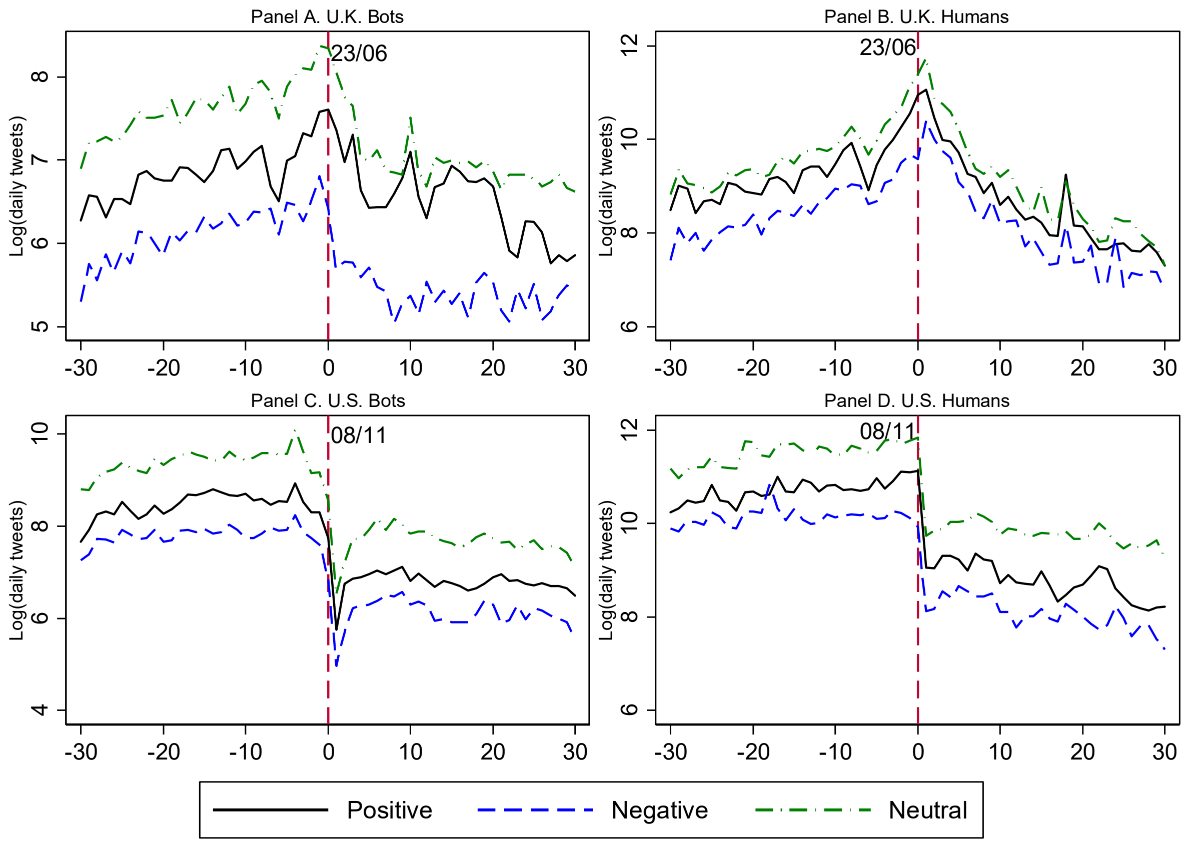
Notes: This figure shows the dynamics of tweets created by bots (Panels A and C) and humans (Panels B and D) for the Brexit sample. Time (horizontal axis) in Panels A and B shows 30 days before and after the Referendum day while time (horizontal axis) in Panels C and D presents hours of days around the event. The dashed blue line and the solid black line show the volumes of pro-leave and pro-remain tweets, respectively.

Figure 2. Dynamics of tweets generated by humans and bots: 2016 U.S. Presidential Election



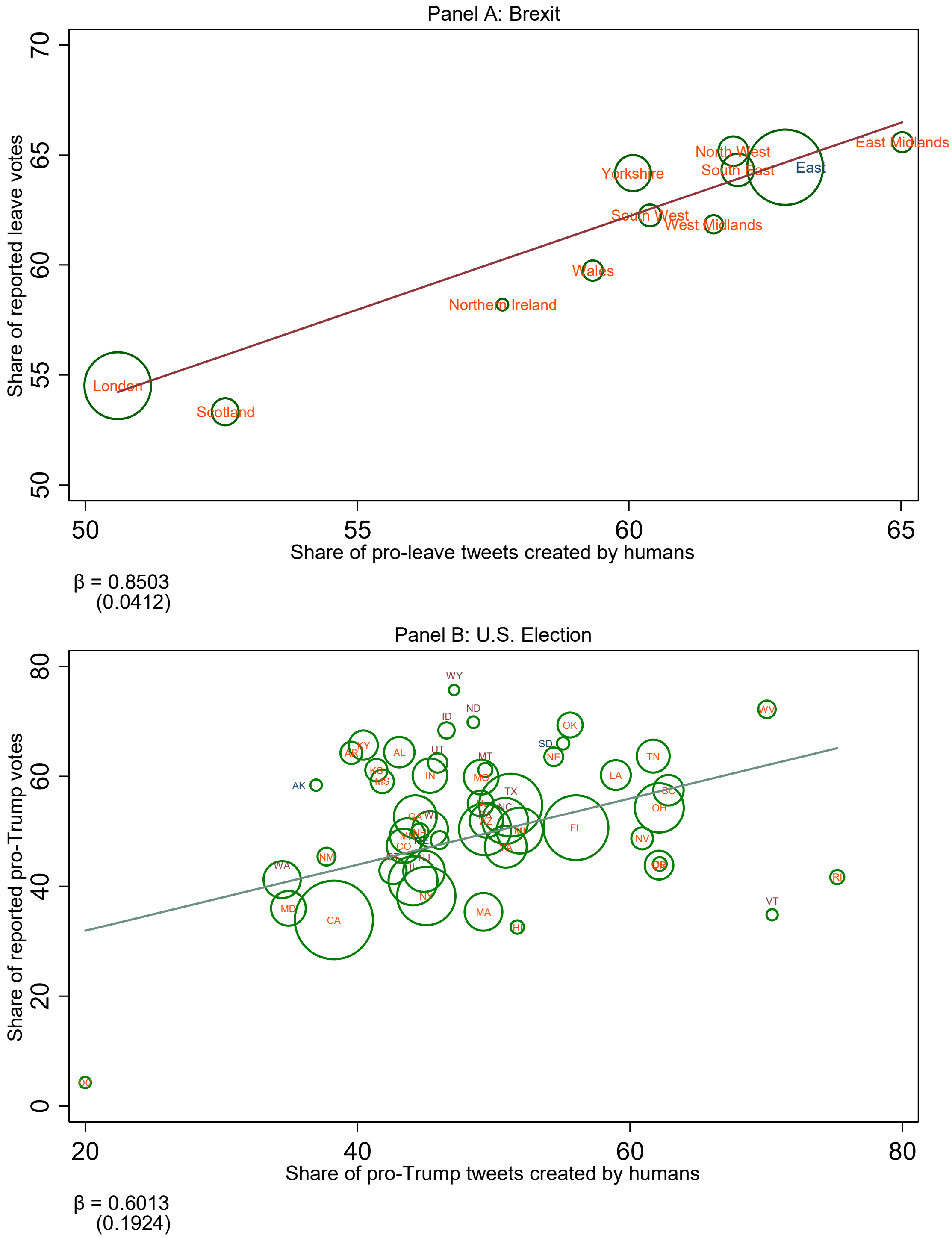
Notes: This figure shows the dynamics of tweets created by bots (Panels A and C) and humans (Panels B and D) for the U.S. Election sample. Time (horizontal axis) in Panels A and B shows 30 days before and after the Election Day while time (horizontal axis) in Panels C and D presents hours of days around the event. The dashed blue line and the solid black line show the volumes of pro-Trump and pro-Clinton tweets, respectively.

Figure 3. Sentiment



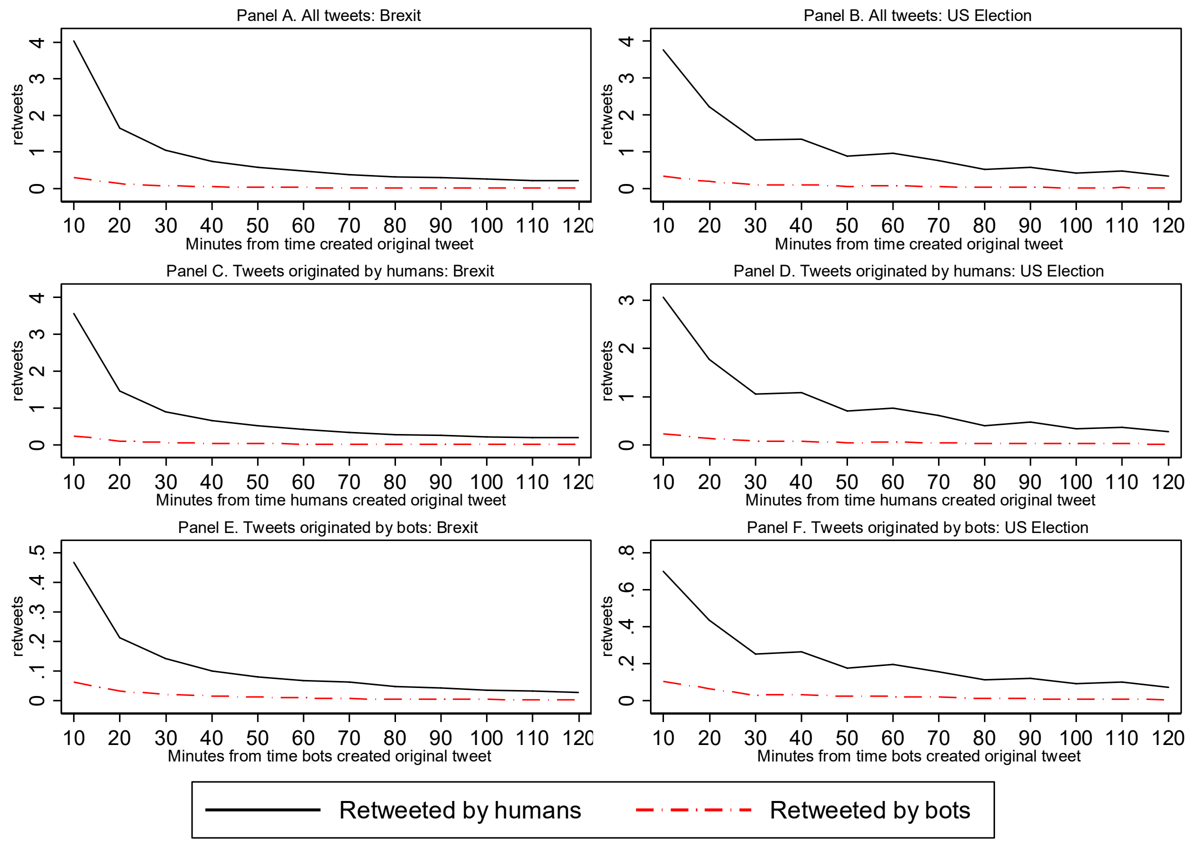
Notes: This figure shows the dynamics of tweets with different sentiment created by bots and humans for the samples of Brexit (Panels A and B) and U.S. Election (Panels C and D). Time (horizontal axis) shows 30 days before and after the event day. The dashed blue line, the solid black line, and the dashed-dotted green line show the volumes of tweets with negative, positive, and neutral sentiment, respectively.

Figure 4. Twitter activity and vote outcomes by geography



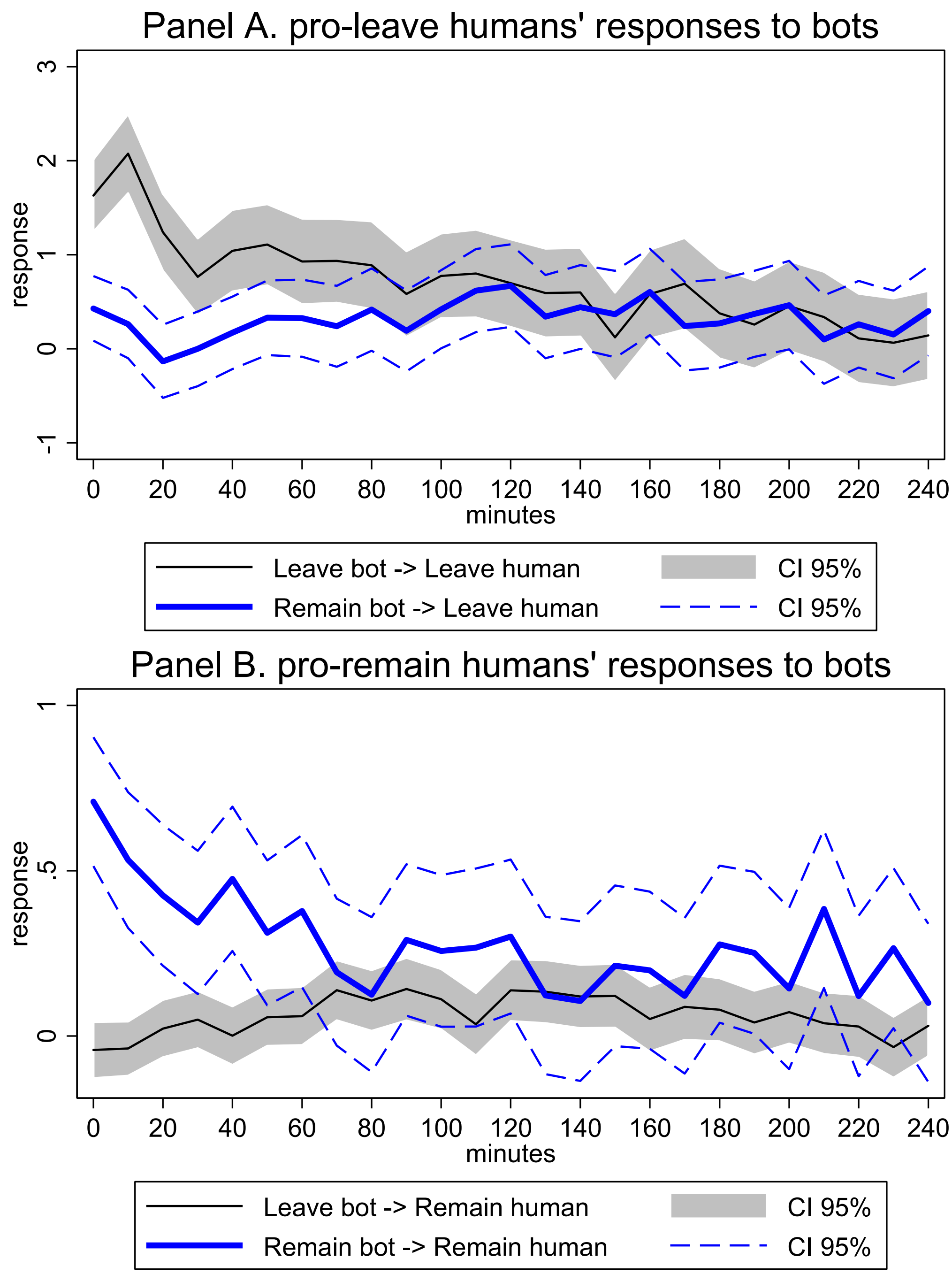
Notes: This figure shows the correlation between the shares of humans' pro-leave tweets and the actual vote shares by regions for the Brexit sample (Panel A) and the correlation between the shares of humans' pro-Trump tweets and the actual vote shares for the 2016 U.S. Presidential Election sample (Panel B). β below each panel shows the estimated slope and standard error (in parentheses).

Figure 5. Retweeting activity by humans and bots



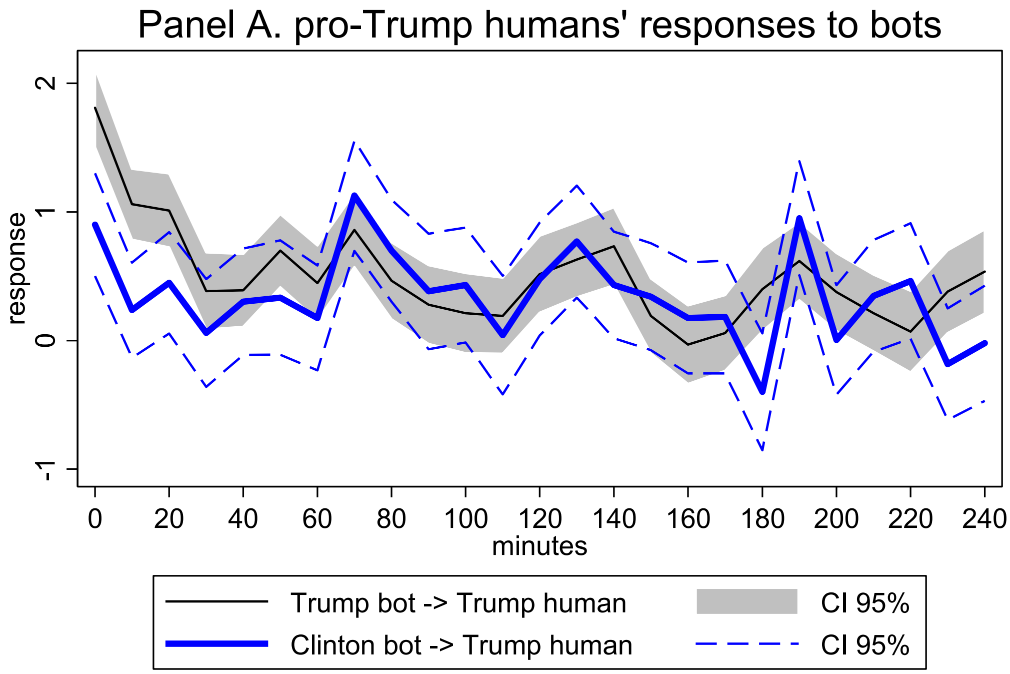
Notes: This figure shows the average number of retweets made after 10-120 minutes since the original tweets were created for the Brexit sample (Panels A, C, E) and the 2016 U.S. Presidential Election sample (Panels B, D, F). Panels A and B show the average retweets of all tweets. Panels C and D show the average retweets of the tweets originated by humans. Panels E and F show the average retweets of the tweets originated by bots. The solid black line refers to the retweeting activities of humans while the dashed red line refers to the retweeting activities of bots. Time (horizontal axis) is in 10-minute intervals.

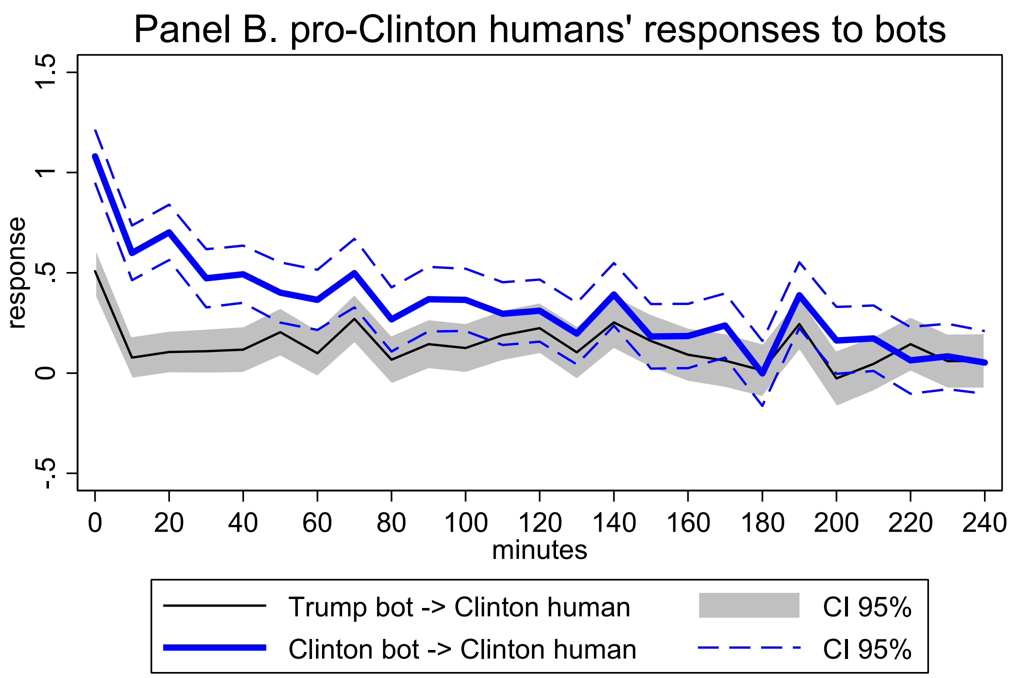
Figure 6. U.K. (baseline)



Notes: This figure reports estimate impulse responses of humans to tweets created by bots for the Brexit sample. Panels A and B show the reactions of humans supporting the leave campaign and the remain campaign, respectively. Time (horizontal axis) is in 10-minute intervals. The thin black line refers to the reactions to pro-leave bots while the thick blue line refers to the reactions to pro-remain bots. The grey shaded area and the dashed blue lines indicate 1.96 standard deviation confidence intervals for responses to pro-leave bots and pro-remain bots, respectively.

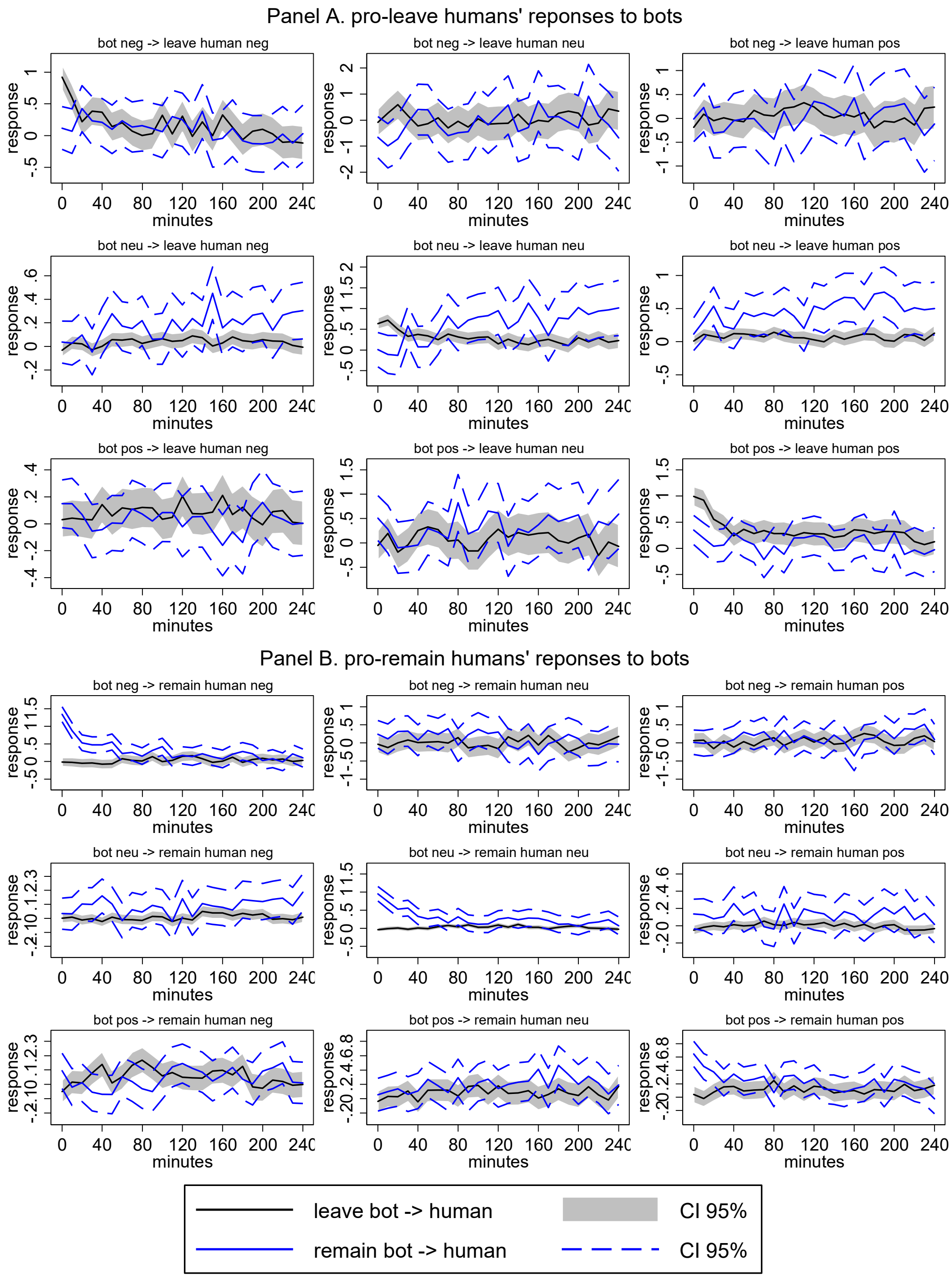
Figure 7. U.S. (baseline)





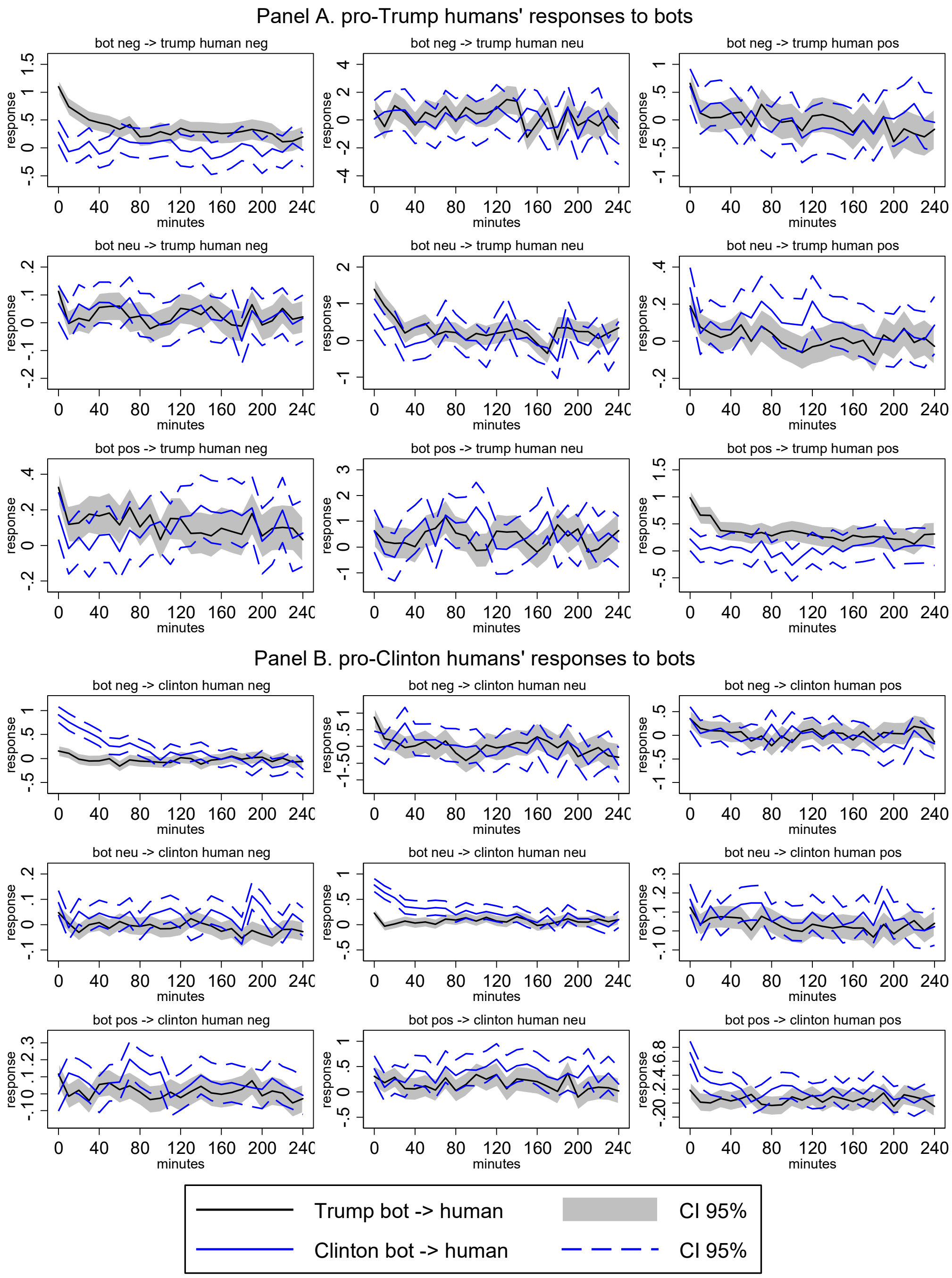
Notes: This figure reports estimate impulse responses of humans to tweets created by bots for the 2016 U.S. Presidential Election sample. Panels A and B show the reactions of humans supporting Trump and Clinton, respectively. Time (horizontal axis) is in 10-minute intervals. The thin black line refers to the reactions to pro-Trump bots while the thick blue line refers to the reactions to pro-Clinton bots. The grey shaded area and the dashed blue lines indicate 1.96 standard deviation confidence intervals for responses to pro-Trump bots and pro-Clinton bots, respectively.

Figure 8. U.K. (by sentiment)



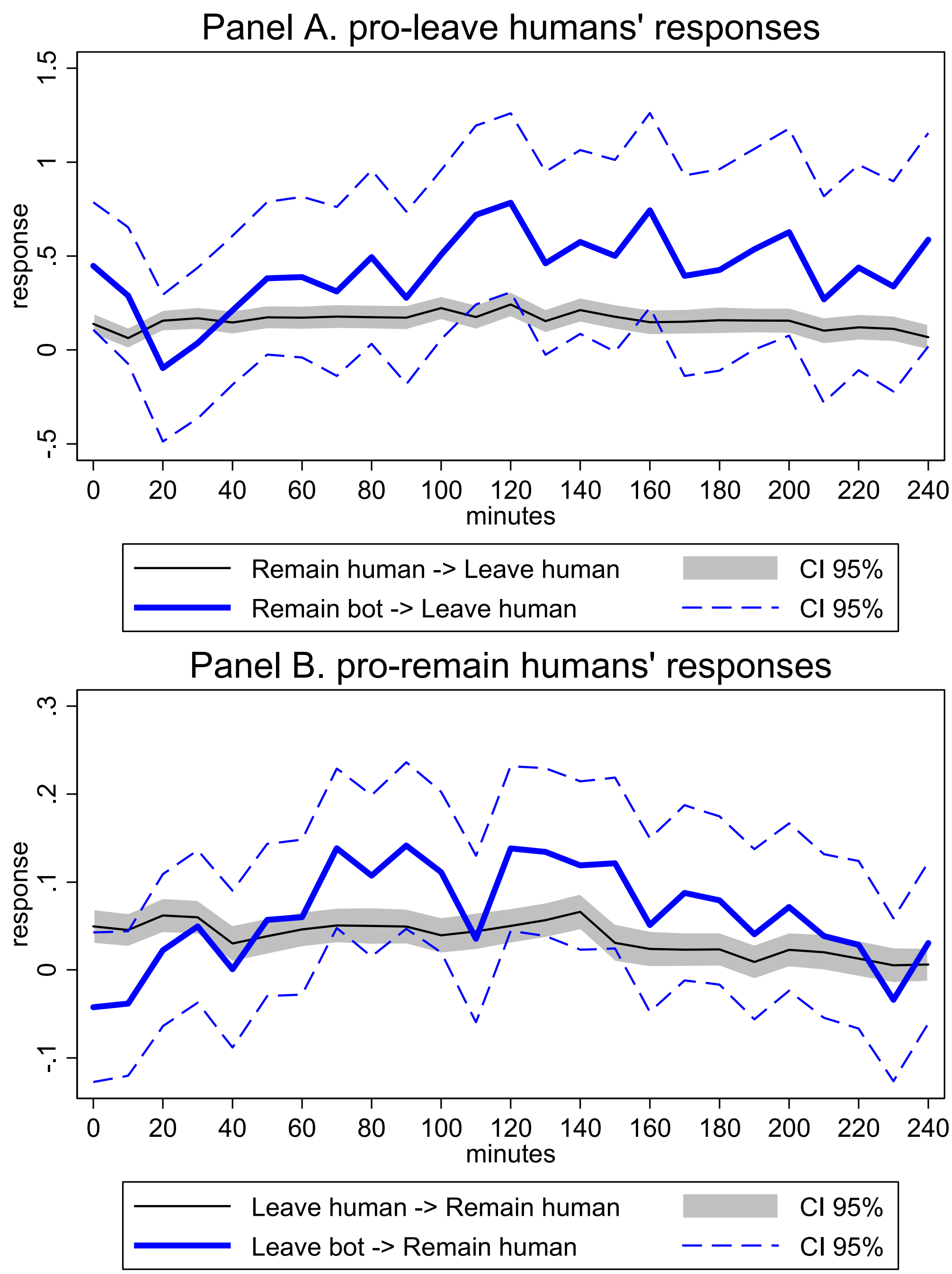
Notes: This figure reports the estimated impulse responses (measured as multipliers) of humans to bots' tweets with different sentiment for the Brexit sample. Panels A and B show reactions of humans supporting the leave campaign and the remain campaign, respectively. Time (horizontal axis) is in 10-minute intervals. The solid black line refers to the reactions to pro-leave bots while the solid blue line refers to the reactions to pro-remain bots. The grey shaded area and the dashed blue lines indicate 1.96 standard deviation confidence intervals for responses to pro-leave bots and pro-remain bots, respectively. *neg*, *neu*, and *pos* stand for negative, neutral, and positive sentiment respectively.

Figure 9. U.S. (by sentiment)



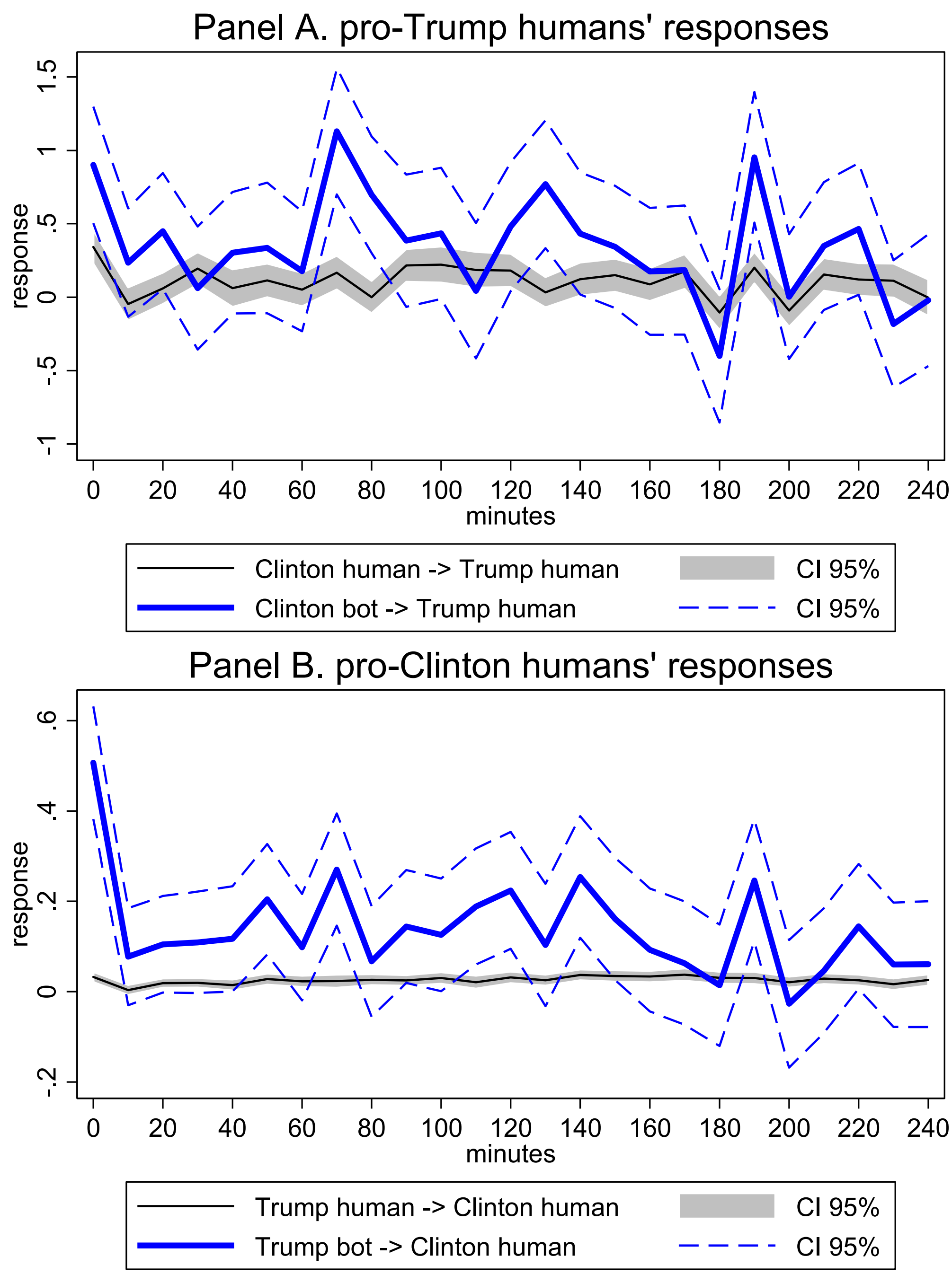
Notes: This figure reports the estimated impulse responses (measured as multipliers) of humans to bots' tweets with different sentiment for the 2016 U.S. Presidential Election sample. Panels A and B show reactions of humans supporting Trump and Clinton, respectively. Time (horizontal axis) is in 10-minute intervals. The solid black line refers to the reactions to pro-Trump bots while the solid blue line refers to the reactions to pro-Clinton bots. The grey shaded area and the dashed blue lines indicate 1.96 standard deviation confidence intervals for responses to pro-Trump bots and pro-Clinton bots, respectively. *neg*, *neu*, and *pos* stand for negative, neutral, and positive sentiment respectively.

Figure 10. U.K.: humans vs bots in effectiveness to generate tweets of the other side



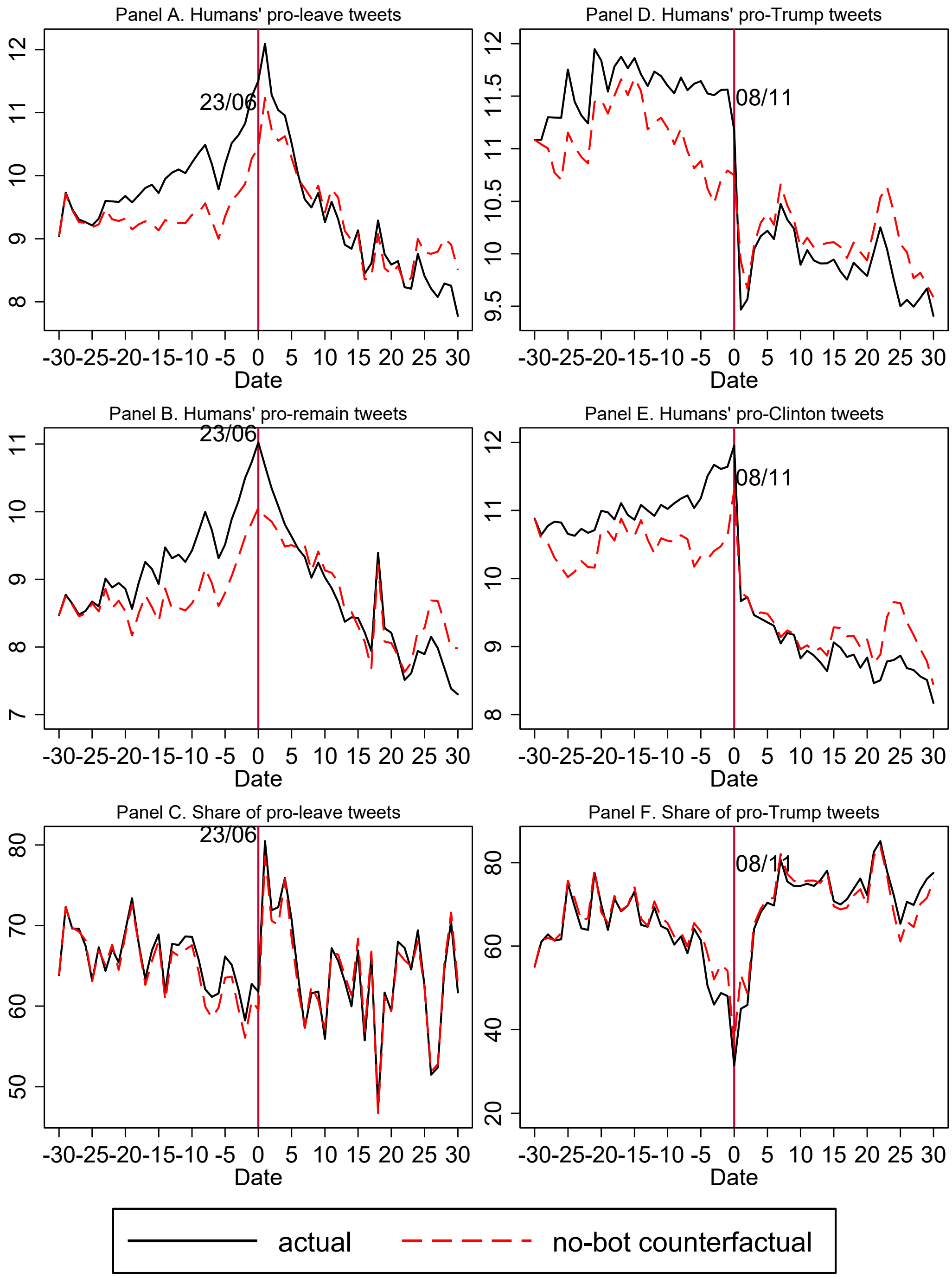
Notes: This figure reports the estimated impulse responses (measured as multipliers) of humans to tweets supporting the opposite campaign for the Brexit sample. Panels A and B show reactions of humans supporting the leave campaign and the remain campaign, respectively. Time (horizontal axis) is in 10-minute intervals. The thin black line refers to the reactions of humans to humans while the thick blue line refers to the reactions of humans to bots. The grey shaded area and the dashed blue lines indicate 1.96 standard deviation confidence intervals for responses to tweets created by humans and bots, respectively.

Figure 11. U.S.: humans vs bots in effectiveness to generate tweets of the other side



Notes: This figure reports the estimated impulse responses (measured as multipliers) of humans to tweets supporting the opposite campaign for the 2016 U.S. Presidential Election sample. Panels A and B show reactions of humans supporting Trump and Clinton, respectively. Time (horizontal axis) is in 10-minute intervals. The thin black line refers to the reactions of humans to humans while the thick blue line refers to the reactions of humans to bots. The grey shaded area and the dashed blue lines indicate 1.96 standard deviation confidence intervals for responses to tweets created by humans and bots, respectively.

Figure 12. Historical contribution



Notes: This figure reports the historical contribution of bots' traffic to humans' tweet volumes. Panels A, B, and C show bots' contribution to the volumes of pro-leave, pro-remain tweets and the share of pro-leave tweets, respectively. Panels D, E, and F show bots' contribution to the volumes of pro-Trump, pro-Clinton tweets, and the share of pro-Trump tweets, respectively. Time (horizontal axis) is in days. The solid black line refers to the observed human tweet activity while the dashed red line refers to human tweet activity when bots are not present.

Table 1. Descriptive statistics by bot and human accounts

	Brexit		U.S. Election	
	Bots	Humans	Bots	Humans
	(1)	(2)	(3)	(4)
No. of accounts	850	586,879	1,754	871,432
Age	1,206	1,580	944	1,467
Followers	4,646	3,130	1,071	2,316
Statuses	34,581	14,903	18,784	12,627
Daily volume of original tweets	15.5	1.0	10.4	1.6
Daily volume of retweets	15.2	0.6	11.4	0.5

Notes: This table presents summary statistics for bot and human accounts in the Brexit and U.S. Election sample. *Age* is the average account age (in days) as of the end of each sample (23 July 2016 for the Brexit sample and 08 December 2016 for the U.S. Election sample). *Followers* and *Statuses* are the average number of followers and statuses, respectively. *Daily volume of original tweets* indicates the average number of the daily original tweets created by an account. *Daily volume of retweets* indicates the average number of the daily retweets created by an account.

APPENDIX

Appendix A.

Table A1. Hashtags/keywords used to define tweets

Pro-leave tweets	leave, voteleave, leaveeu, takecontrol, betteroffout, voteout, beleave, brexitthemovie, euistheproblem, brexitbustour, strongerout
Pro-remain tweets	strongerin, remain, voteremain, votein, bremain, votestay, intogether, labourinforbritain, greenerin
Pro-Trump tweets	americanfirst, imwithyou, lawandorder, makeamericagreatagain, neverClinton, draintheswamp, teamtrump, crookedClinton, trumpwon, lockherup, trumptrain, fortrump, clintonfoundation, trump2016, sendhertojail, Clintonforprison, votetrump
Pro-Clinton tweets	imwithher, lovetrumpshate, nevertrump, clintonkaine, ohhillyes, strongertogether, dirtydonald, Clintonwon, votedems, trumpeduptrickledown, whyiwantClinton, proClinton, Clintonsarmy, tntweeters, uniteblue, womenstoptrumpparty, dumptrump, donaldtrumpthemovie, trumpsajoke, trumpsacrifices, makedonalddrumpfagain, forClinton, lasttimetrumppaidtax, boycotttrump, Clintonsupporter

Notes: This table shows the hashtags/keywords used to define supporting side during the 2016 E.U. Referendum and the 2016 U.S. Presidential Election.

Table A2. Process of defining original tweets and their retweets

	Step 1: Create retweet indicator	Step 2: Information about the user from whom the tweet was retweeted	
Text	RT	RT_from	Tweet type
RT @jameswilson: RT @abcnews: After this brexit campaign europe cannot remain the same	1	jameswilson	Retweet
After this brexit campaign europe cannot remain the same	0		Original tweet
RT @abcnews: After this brexit campaign europe cannot remain the same	1	abcnews	Retweet

Notes: In this table, we show an example of how we define retweets in our data.

Table A3. Examples of tweets with polarity scores from TextBlob

Text	Polarity score
Is there a prize for being the most ironic idiot on the planet?	-0.033
I don’t believe those official figures and I’m sure the real numbers are much higher. We must Leave EU and control our border	0.317
Brexit frees the Tories to destroy workers’ right	-0.25
If we allow the 18 Albanians who arrived on our shores illegally to stay then UK faces a migrant crisis this summer	-0.5
I’m voting leave because nobody owns allegiance to an unelected elite	0
To All Trump Voters You are my brothers and sisters. Thank you for giving America more reasons for hope and joy this Thanksgiving	0.65
Donald Trump doesn’t like poor people	-0.4
NBCSandiego and also JAIL THE CLINTON MAFIA lol lyinmedia	0.35
Trump’s showing himself to be corrupt AF and he’s only getting started folks	-0.25
PresidentElect Trump Releases Thanksgiving Message Focused on Unity VIDEO gatewaypundit	0

Notes: In this table, we show some examples of polarity score obtained from TextBlob.

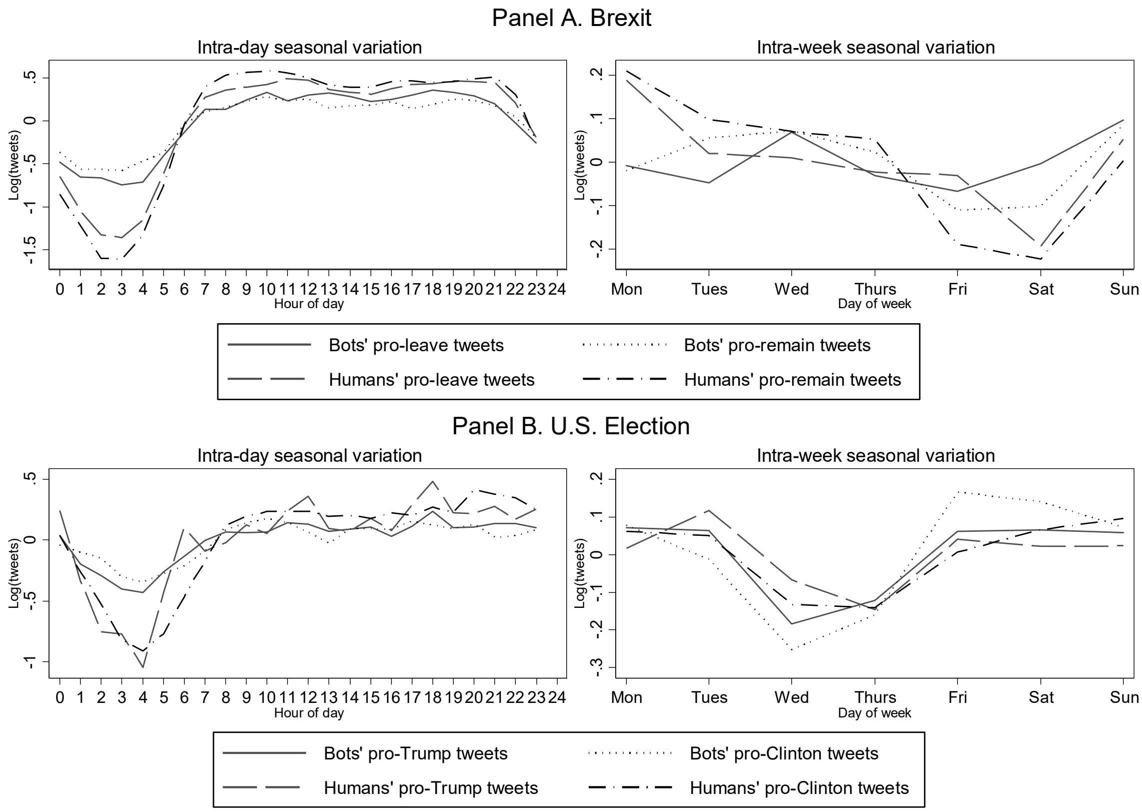
Table A4. Key statistics for estimation samples

	Brexit sample (24 May to 23 July 2016)	U.S. Election sample (09 Oct to 08 Dec 2016)
Campaign endorsement		
No. of pro-leave tweets	1,536,115	
No. of pro-remain tweets	739,536	
No. of pro-Trump tweets		4,353,896
No. of pro-Clinton tweets		2,571,208
Tweet sentiment		
No. of positive tweets	728,619	1,800,557
No. of negative tweets	361,847	985,045
No. of neutral tweets	1,185,185	4,139,502
Tweet classification		
No. of original tweets	845,926	1,911,423
No. of retweets	1,429,725	5,013,681
No. of bots' tweets	178,601	705,262

Notes: This table presents summary statistics for some key variables in our analysis.

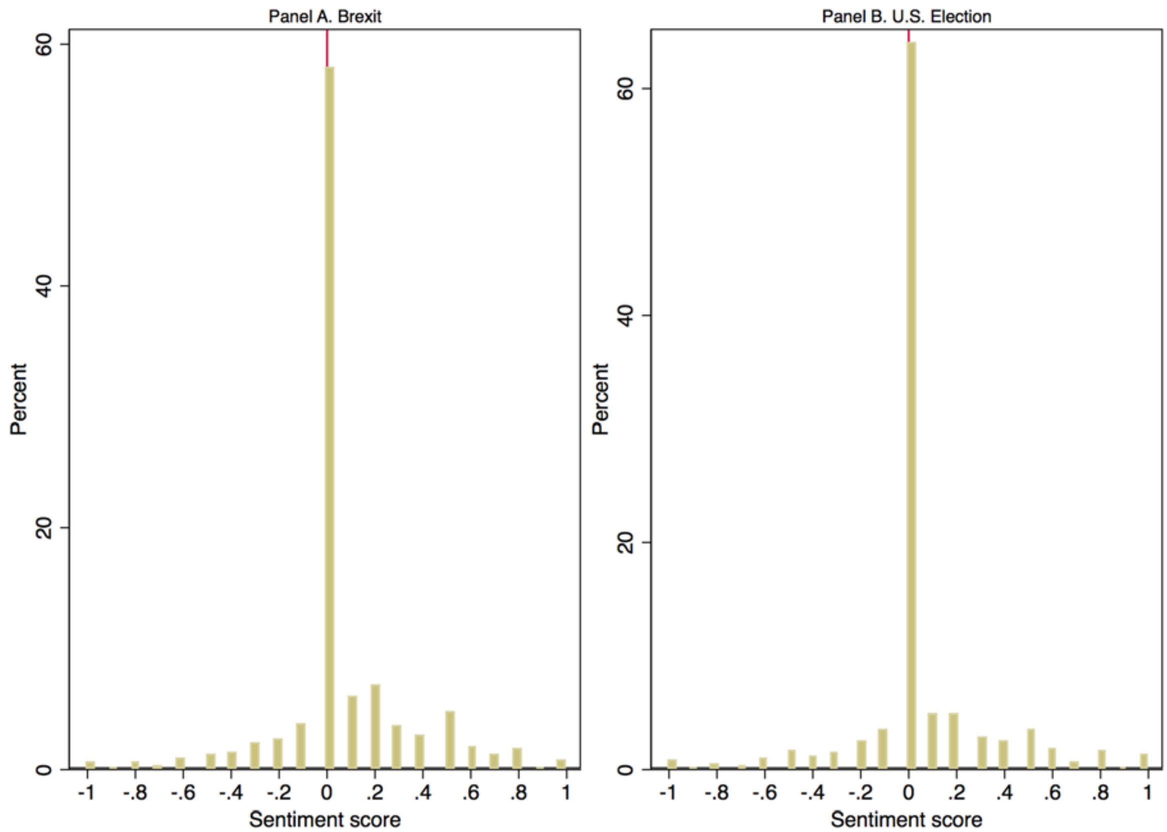
Appendix B. Figures

Figure B1. Seasonality



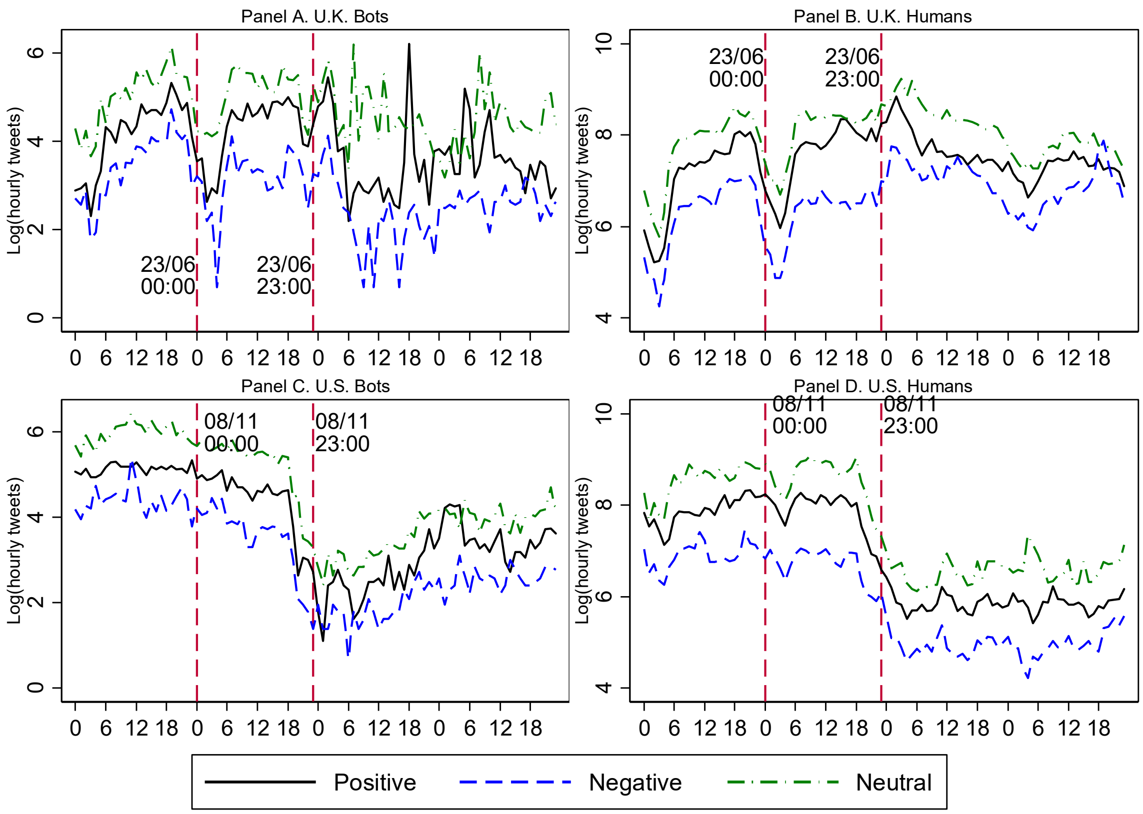
Notes: This figure shows the changes in the intensity of humans' and bots' tweeting activity by hour of the day and by day of the week.

Figure B2. Distribution of tweet sentiment



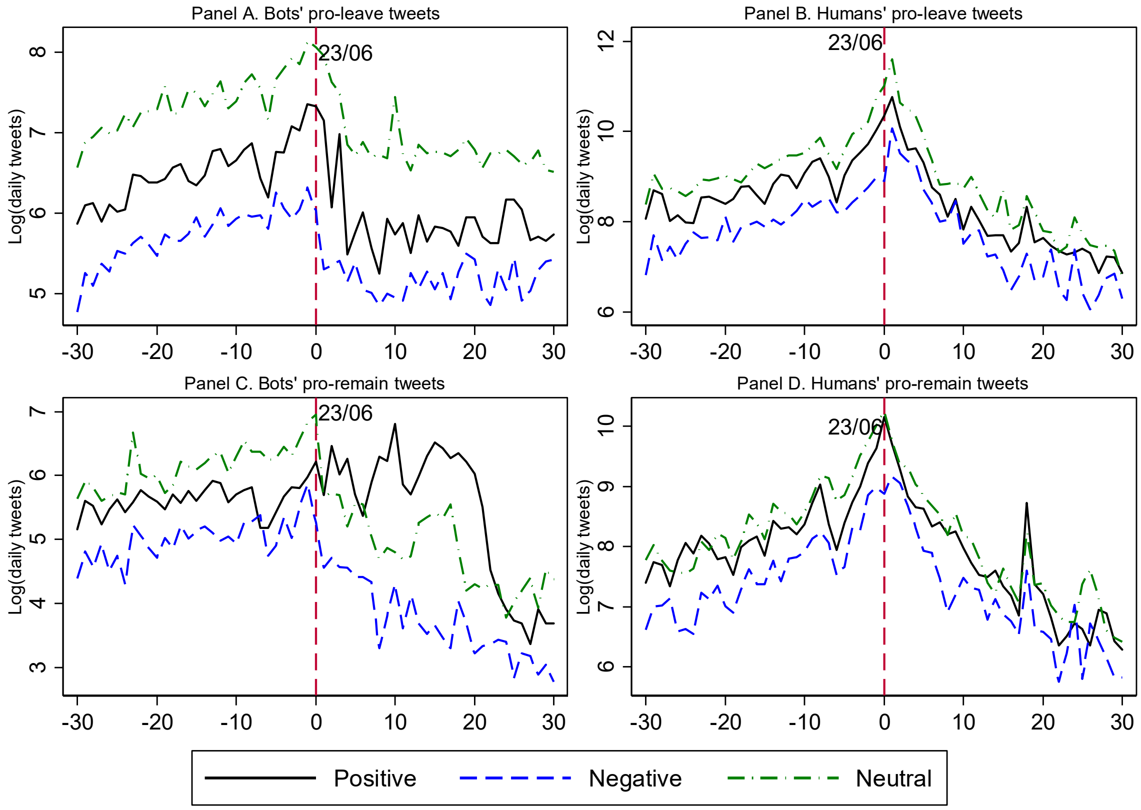
Notes: This figure shows the distribution of tweet sentiment.

Figure B3.



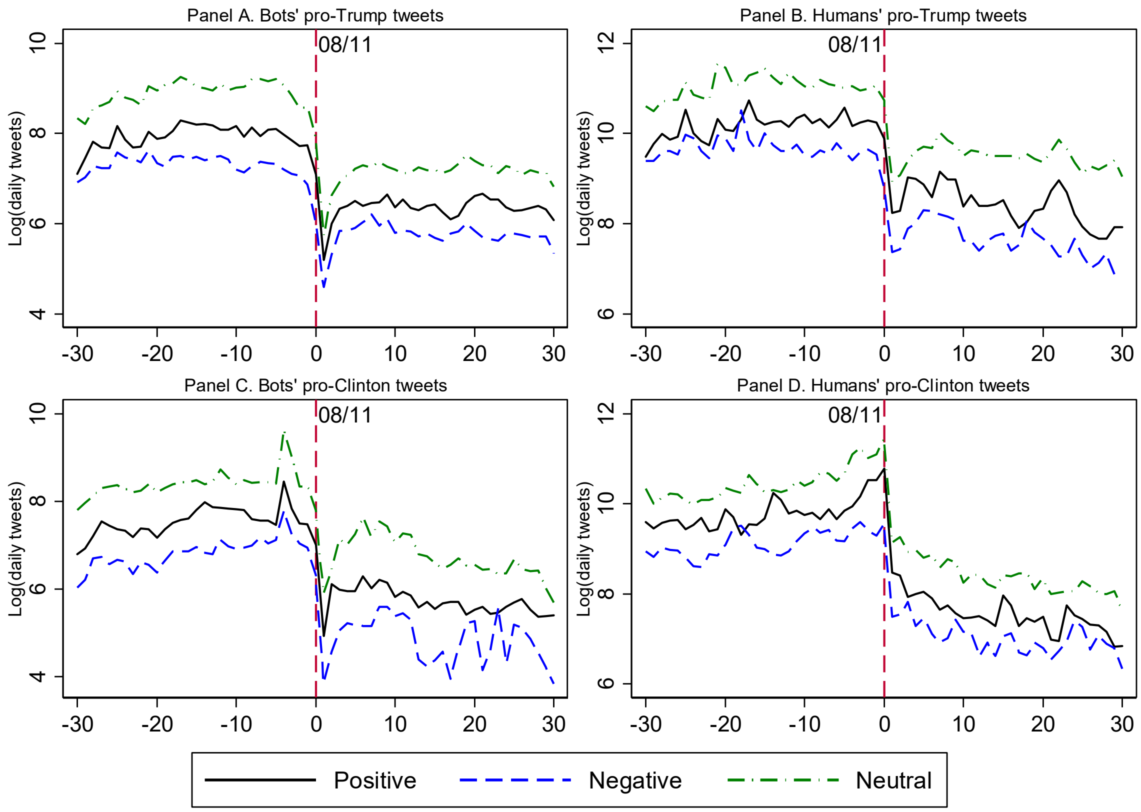
Notes: This figure shows the hourly volume of tweets around the voting days with sentiment created in humans and bots in the Brexit sample (Panels A and B) and the U.S. Election sample (Panels C and D). The dashed blue line, the solid black line, and the dashed-dotted green line show the volumes of tweets with negative, positive, and neutral sentiment, respectively.

Figure B4.



Notes: This figure shows the daily volume of tweets with sentiment created in humans and bots for pro-leave tweets (Panels A and B) and pro-remain tweets (Panels C and D). The dashed blue line, the solid black line, and the dashed-dotted green line show the volumes of tweets with negative, positive, and neutral sentiment, respectively.

Figure B5.



Notes: This figure shows the daily volume of tweets with sentiment created in humans and bots for pro-Trump tweets (Panels A and B) and pro-Clinton tweets (Panels C and D). The dashed blue line, the solid black line, and the dashed-dotted green line show the volumes of tweets with negative, positive, and neutral sentiment, respectively.