Social network, sentiment and political outcomes: Evidence from #Brexit

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Abstract

This paper studies the information diffusion in social media and its impact on political outcomes. Using Twitter data on the EU Referendum from May to August 2016, we find that public opinions on Twitter can predict the Brexit result. Our estimated share of leave tweets is about 62 percent, suggesting the vote outcome in favour of leave the EU. Adopting vector-autoregressive model, we find a considerable spillover from bots' to humans' tweeting activities. In that, leave supporters are more likely to be affected by bots compared to remain supporters. Further analyses show that bots' tweets with negative sentiment are more influential. Overall, our results suggest that the Brexit result is predictable through the social media, and public opinions about Brexit were likely to be manipulated by bots.

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1. Introduction

Since the EU Referendum date was announced, it has been a major topic for discussion inside and outside the UK. On 24 June 2016, the result of the EU Referendum was announced with the majority voting for leaving, leading to various consequences. In terms of economics, the pound plunged to the 31-year low against dollar while financial markets experienced turmoil. Following these events, the UK's credit rating has been downgraded. In terms of politics, there was a chaos with the resignation of David Cameron and the changes in the leadership races. Given all the negative short-term and long-term consequences, several critical questions have been raised. Was the Brexit result predictable? Were the public opinions about Brexit manipulated? To provide answers to these questions, this study will explore the diffusion of public opinions on Twitter before, during and after the EU Referendum.

Recent political science literature suggests a number of traditional tools for forecasting results of political events. In particular, econometric forecasts and expert opinions are viewed as two traditional and accurate tools (e.g., Pennock et al., 2001; Andersson et al., 2005; Leigh and Wolfers, 2006). However, there is no consensus about which econometric forecast is better. For example, multinomial models such as uniform swing model perform well in forecasting election results (e.g., Ford et al., 2016; Mellon and Fieldhouse, 2016). However, Lebo and Norpoth (2011) find that autoregressive models outperform uniform swing models in predicting British elections. There is also no substantial difference between predictions of expert and non-expert. This might be explained by overconfidence of experts about their forecast ability (Torngren and Montgomery, 2004). In addition to traditional techniques, social media has also been employed for forecasting political outcomes (e.g., Tumasjan et al., 2010). In particular, the combination of public opinions in social media and the sentiment of content can be a good predictor for election results. (O'Connor 2010; Sang and Bos 2012).

Social media not only helps to predict outcomes of social events but also is an important channel of information diffusion. There are three main motivations for spreading information, namely obligation, joy of sharing and helping behaviour (Kassarjian, 1981; Bloch, 1986; Mitchell and McGoldrick, 1996). Documenting information spread in social networks, several studies find that the spreading information process is affected by the influence of users (e.g., Agarwal et al., 2008). Moreover, the speed, range and scale of diffusion are associated with certain factors such as historical activity or the number of connections in social media (Yang and Counts, 2010). Since one opinion or view can be quickly disseminated in a large scale, the information dissemination could be used in decision-making. For instance, the investment of an investor could be affected by the cohorts' choices (Hong et al, 2005; Ivković and Weisbenner, 2007). Another implication of information diffusion is predicting stock returns and asset prices. For example, the dynamic of house prices in the past could predict the current price movements (Clapp et al., 1995) or the lags of big firms' stock prices could predict the current prices of small firms (Hou, 2007).

This interdisciplinary study provides a number of contributions to the existing literature. First, our paper provides evidence for the predictive power of social media in forecasting political outcomes. Second, we find a considerable spillover from bots' to humans' activities, providing insights into the interactions between users in social network. Third, there is evidence for the important role of text sentiment in information diffusion.

Our analysis employs a unique dataset containing about 28.9 million tweets with "Brexit" hashtag collected from 24 May 2016 to 17 August 2016. We observe information about users' names, tweets and their related information such as date of creating account, date of tweeting, number of followers or number of retweeting. For the purpose of this study, we only examine either pro-leave tweets or pro-remain tweets that were written in English. In general, Brexit result was largely unexpected. For example, in Financial Times post on 24 June, currency analysts at HSBC mentioned Brexit as "a seismic and largely unexpected event". In the speech in July, John McDonnell said that the Leave vote was a shock (Financial Times 2016). Despite these, we observe the domination of leave in our sample. Furthermore, a simple forecasting exercise suggests that 62 percent of voters were more likely to support the "leave" choice. In addition, the shares of leave votes broken down into geographical areas in our analysis are highly correlated with the actual results, providing evidence for the predictive power of Twitter. Further examination shows that humans are likely to retweet bots' messages and humans are more likely to react to leave messages, suggesting that humans' "leave" choice might be manipulated by bots.

To examine this probability, we employ vector-autoregressive (VAR) model. The estimates show that leave bots indeed influence the spreading information activity of humans. More specifically, the increase in the number of bots' leave tweets increases the number of tweets created by leave supporters. However, the speed of leave bots' information diffusion is faster than the one of leave supporters. In contrast, remain supporters are barely affected by bots. Moreover, bots seem to be more active in the pre-Brexit period, suggesting that bots are used mainly to create artificial trend about Brexit and compel public opinions. Incorporating sentiment analysis into VAR model, we find that people react to negative messages more rapidly compared to positive messages. This is in line with results from previous studies about adjustment to news' sentiment.

Our results can provide some implications. First, social media like Twitter can be used during high-impact events, especially political events to track public opinions and forecast results. Second, since bots play an important role in aggregating information on Twitter and indeed could compel humans' opinions, there should be a legal framework to control the use of online bots. Third, as humans are more responsive to negative news, sentiment analysis can be employed in different aspects, such as forecasting depositors' or lenders' reaction in respond to the arrival of news and announcements about banking system.

The rest of this paper is organised as follows. Section 2 reviews the literature on information diffusion. Section 3 illustrates our empirical strategy and data description. Section 4 presents empirical results and discussion. Section 5 concludes and provides implications.

2. Literature review

2.1. Prediction of event outcomes

There is a growing number of studies attempting to predict the results of different social, economic and political events. In which, one of the main literature strands is about identifying an accurate predictor or forecast channels. Some studies focus on the accuracy of prediction markets in various forms, from online betting markets to financial prediction markets. One the one hand, prediction markets have been documented as an accurate forecast tool. For instance, Pennock et al. (2001) find that betting prices accurately predict the outcomes of unresolved scientific questions as well as the results of movie and music awards like Emmy, Oscar and Grammy awards. Similarly, these markets also have predictive power in predicting political elections' results (Tetlock, 2005) and this predictive power is better than the one of opinion polls (Leigh and Wolfers, 2006). On the other hand, comparing future prices of securities on Tradesport with the actual prices from Chicago Mercantile Exchange, Wolfers and Zitzewitz (2004) show that the prediction markets poorly predict small probability outcomes. Another predictor is expert opinion. Regarding the predictive ability of sport experts, it is found that they do provide accurate predictions and predict better than chance (see, Forrest and Simmons, 2000; Andersson et al., 2005). However, expert prediction's accuracy is no better than non-expert ones (Camerer and Johnson, 1997; Andersson et al., 2005). In the case of stock market professionals, the rate of successful predictions is 40 percent only, suggesting somewhat experts are no more efficient than non-experts (Torngren and Montgomery, 2004). Furthermore, experts also seem to be overconfident since they overestimate their own judgments.

The second strand focuses on the predictability of election outcomes through social media like Twitter. For example, regarding the 2009 German Federal election, Tumasjan et al. (2010) find that the election results can be predicted by the number of party mentions. However, O'Connor et al. (2010) and Chung and Mustafaraj (2011) argue that the number of mentions might not be an accurate predictor for politic success as it fails to cover the effect of sentiment and filter spams. In the attempt to provide a more accurate predictor using sentiment analysis, O'Connor (2010) discovers the correlation between Obama's high poll ratings and the sentiment of tweets on Twitter. Additionally, by incorporating sentiment measure into volume-based measure, Bermingham and Smeaton (2011) find that the combination of volume-based measure and sentiment measure is a good forecasting measure for the outcome of the 2011 Irish General election. Similar approach is developed by Sang and Bos (2012) when they normalise the counts of party mentions by the sentiment. Again, this normalised measure forecasts accurately the result of the 2011 Dutch Senate election.

Built on this existing literature, this study aims to investigate whether or not we can predict the result of the EU Referendum based on historical data on Twitter.

Hypothesis 1: Brexit result is predictable through Twitter

2.2. Information spread

Given the importance of interpersonal communication, there is a large body of studies investigating the issues of information spread in different aspects. For example, some studies examine the motivations of spreading information. Focusing on market mavens[1] as interpersonal communicators, three motivations for market mavens to spread information have been examined. First, some mavens are motivated by an obligation to share information (e.g., Kassarjian, 1981; Walsh et al., 2004). More specifically, since market mavens are a part of the community, they have sense of duty to disseminate their knowledge about marketplace. Second, some mavens actually enjoy sharing information and assisting other people (e.g., Bloch, 1986; Sundaram et al., 1998). The joy of spreading market-place information might be induced by the need of gaining esteem from the social groups (Clark and Goldsmith, 2005). Third, information spread is driven by helping behaviour (e.g., Hoffman, 1981; Mitchell and McGoldrick, 1996; Walsh et al., 2004). That is, mavens want to help other consumers to reduce purchase risk and save costs.

Some other studies examine the impact of information dissemination on decision-making. For instance, since investment information can be spread through the word-of-mouth communication, an investor can be affected by the decisions of the cohorts (e.g., Hong et al, 2005; Ivković and

[1] Market mavens refer to consumers who have up-to-date information about products, places to shop and different markets.

Weisbenner, 2007). More specifically, Hong et al. (2005) find that a mutual fund manager is more likely to buy a particular stock if that stock is hold or purchased by other managers in the same city. Similarly, Ivković and Weisbenner (2007) suggest that a household is more likely to purchase stocks from the same industry that the neighbors invest in. Examining how a firm's investment relates to its peers' valuation, Foucault and Fresard (2014) find additional evidence for the implications of information spread in investment. That is, information about the growth opportunities and future demand is conveyed from firms' valuation then is dispersed to their peers' managers. Thus, the managers can rely on this information in making investment decisions.

Another strand is about the implications of information diffusion in predicting outcomes with a large number of studies focus on the role of information spread in predicting assets prices or stock returns. For example, documenting whether price can convey information to market participant, Clapp et al. (1995) acknowledge that lagged changes in house prices in local markets can influence the current price movements. Additionally, there is a spatial information flow since the current price changes are affected by the lagged price changes from neighbouring towns. This significant impact of spatial information diffusion on house prices is also found in later studies (e.g., Dolde and Tirtiroglu, 1997). Regarding stock return prediction, information diffusion is seen as a main cause of the lead-lag effect in stock returns. One shows that if the firm has more informed traders, indicated by the number of analysts, its stock will respond to new information faster. In the other words, stock prices of less analyst firms are more predictable (Brennan et al., 1993). Further, lagged big firms' performance can strongly predict prices of small firms' stocks; and the predictive power is stronger with the arrival of negative news (Hou, 2007). Recent study by Boguth et al. (2016) provides new evidence for the role of slow information diffusion, indicated by steadily decreasing lagged betas, in predicting stock price. They find that the short-horizon average returns are biased downward when the stocks adjust slowly to the new market information.

2.3. Information spread in social media

Studies relating to information spread in social networks can be divided into different strands. First, some research argues that information diffusion in social media is driven by the influence. Some users are more influential; hence, their messages or opinions are more likely to be disseminated in the networks. For instance, an influential blogger can be recognised through longer post length, higher number of inlinks in the posts and higher number of comments (Agarwal et al., 2008). These categories represent for the eloquence, recognition and follow-up activity generation of a blog. In the other words, more influential bloggers can get more attention and interests from fellow bloggers, hence their posts are more recognised. Regarding influential twitter users or twitterers, the influence is widely interpreted through popularity, indicated by the number of followers and friends. However, the number of followers or friends might not be a good indicator of influence. Conjecturing that more popular twitterers have more posts compared to less popular users, Huberman et al. (2008) acknowledge that users with a larger number of followers and friends do not necessarily have a large number of tweets. Similar results are also achieved when different measures of influence and the Twitter users passivity are taken into account (e.g., Cha et al., 2010; Romero et al., 2011).

The second strand focuses on the scale, speed and range of information dissemination in social media. Adar and Adamic (2005) propose a technique to track the routes of spreading URLs in blog space. In which, they suggest that properties of a potential infection route include blog link structure, attribution links, node properties, and historical data. Regarding information spread on Twitter, Yang and Counts

(2010) find that some properties of the tweets such as attribution links can predict the speed, scale and range of information diffusion. However, the properties of the twitterers like mentioned rates are stronger indicators. Similarly, the properties of a tweet like content features, inlinks and hashtags are strongly related to the probability of being spread (Suh et al., 2010). The users' characteristics such as the number of followers and followees as well as the age of the account are also associated with retweetability. However, past activity is not an indicator for being spread likelihood.

This study attempts to provide new insights into the issue of information dispersion on Twitter during the EU Referendum, a high-impact political event. Given the fact that Twitter bots are often used to create and spread the artificial trends, we investigate the information dissemination through the interaction between real users and political bots. By doing so, we can find out whether or not human's opinions about Brexit were driven by bots. Since humans are likely to be affected by sentiment of the text, we adopt the sentiment analysis to decompose tweets created by bots into negative and positive sentiments. Thus, it provides answer for the concern of whether the interaction between human agents and bots is affected by these components. These concerns are hypothesized as follows:

Hypothesis 2a: Humans' opinions about Brexit on Twitter are affected by bots

Hypothesis 2b: Messages with negative sentiment are more influential

3. Methodology and data

3.1. Empirical strategy

3.1.1. Forecast model

To understand the predictability of the EU Referendum result based on historical data from Twitter, we only observe posts whose users are from UK and estimate the following model:

$$Share\ of\ leavers_t = \beta_0 + \beta_1 Share\ of\ leavers_{t-1} + \beta_2 controls + \varepsilon \quad (1)$$

where *Share of leavers* is the ratio of the number of leave voters to the total number of UK voters on each day. We define a user as a leave supporter (voter) if that person solely posts or shares pro-leave tweets. Control variables include: (1) *Share of leave bots* is the ratio of the number of UK leave bots to total number of UK bots on each day; (2) first difference in the number of pro-leave tweets; (3) first difference in the number of total tweets and (4) difference in the number of pro-leave tweets and pro-remain tweets on each day.

Equation (1) is first estimated using autoregressive model, in which there is only one independent variable, lag(s) of *Share of leavers*. Next, we estimate equation (1) using both lag(s) of *Share of leavers* and different sets of control variables. Using estimated coefficients from equation (1) we then construct predicted share of leave votes for the EU Referendum outcome. The forecast exercise is given by $Predicted\_share = \beta X$ in which β is a vector of coefficients and X is vector of mean of independent variables in equation (1). We estimate model (1) using daily data up to 22 June 2016, the day before the polling day, and then forecast the share of leave votes for forthcoming days.

3.1.2. Vector autoregressive model

a. Baseline VAR model

The vector autoregressive (VAR) model is one the most flexible models for multivariate time series analysis. Since it is useful in providing evidence for the dynamic behaviour of economic and financial time series, it has been widely used in macroeconomics research (see, e.g., Dees et al., 2007; Ca'Zorzi et al., 2012). Recently, this model is also employed to examine the inter-linkages, or inter-correlations among different economic and financial factors (e.g., Chordia and Swaminathan, 2000; Hou, 2007). Being inspired from previous studies, we employ the vector autoregressive model to examine the interaction between humans Twitter agents and Twitter bots in diffusing information about Brexit. The specifications are as follows:

$$\Delta Leave\ Humans_t = \alpha + \sum_{k=1}^{K} \beta_{1k} \Delta Leave\ Humans_{t-k} + \sum_{k=1}^{K} \beta_{2k} \Delta Remain\ Humans_{t-k} + \sum_{k=1}^{K} \beta_{3k} \Delta Leave\ Bots_{t-k} + \sum_{k=1}^{K} \beta_{4k} \Delta Remain\ Bots_{t-k} + \gamma Diff_{t-1} + \text{time dummies} + \varepsilon \quad (2)$$

$$\Delta Remain\ Humans_t = \alpha + \sum_{k=1}^{K} \beta_{1k} \Delta Leave\ Humans_{t-k} + \sum_{k=1}^{K} \beta_{2k} \Delta Remain\ Humans_{t-k} + \sum_{k=1}^{K} \beta_{3k} \Delta Leave\ Bots_{t-k} + \sum_{k=1}^{K} \beta_{4k} \Delta Remain\ Bots_{t-k} + \gamma Diff_{t-1} + \text{time dummies} + \varepsilon \quad (3)$$

$$\Delta Leave\ Bots_t = \alpha + \sum_{k=1}^{K} \beta_{1k} \Delta Leave\ Humans_{t-k} + \sum_{k=1}^{K} \beta_{2k} \Delta Remain\ Humans_{t-k} + \sum_{k=1}^{K} \beta_{3k} \Delta Leave\ Bots_{t-k} + \sum_{k=1}^{K} \beta_{4k} \Delta Remain\ Bots_{t-k} + \gamma Diff_{t-1} + \text{time dummies} + \varepsilon \quad (4)$$

$$\Delta Remain\ Bots_t = \alpha + \sum_{k=1}^{K} \beta_{1k} \Delta Leave\ Humans_{t-k} + \sum_{k=1}^{K} \beta_{2k} \Delta Remain\ Humans_{t-k} + \sum_{k=1}^{K} \beta_{3k} \Delta Leave\ Bots_{t-k} + \sum_{k=1}^{K} \beta_{4k} \Delta Remain\ Bots_{t-k} + \gamma Diff_{t-1} + \text{time dummies} + \varepsilon \quad (5)$$

where Δ*Leave Humans*, Δ*Remain Humans*, Δ*Leave Bots*, Δ*Remain Bots* are the percentage changes of hourly number of leave tweets and remain tweets created by human and bots. The natural logarithm of the difference between total leave tweets and total remain tweets per hour is indicated by variable $Diff$. We also include time dummies (hour, date and month) in our models. Equations (2)-(5) are estimated with five (K=5) lags.

If hypothesis (2a) holds, the sum of slope coefficients corresponding to changes in bots' activities in equations (2) and (3) should be distinguishable from zero. Similarly, if bots do interact with humans in spreading information, the sum of slope coefficients corresponding to humans' activities in regressions (4) and (5) should be different from zero.

b. VAR model with sentiment analysis

More often, an opinion is perceived and spread not only due to its topic but also due to its sentiment. Thus, we take a further step in our analysis by adopting sentiment analysis to detect the sentiment of the tweets and incorporate sentiment analysis into VAR model to test hypothesis (2b).

Regarding sentiment analysis, we use TextBlob, a publically available text-processing tool written in Python, to get the polarity score of each tweet. TextBlob can be used to perform various tasks such as part-of-speech tagging, noun-phrase extraction, sentiment analysis, spelling correction, text translation and many more. For sentiment analysis, TextBlob will return the polarity score in range from -1 to 1. In which, the negative score represents negative sentiment, the positive score represents positive sentiment while the score of 0 refers to neutral sentiment. We employ two sentiment analysis implementations contained in TextBlob, PatternAnalyzer and NaiveBayesAnalyzer. Both implementations provide the same sentiment score for each tweet, suggesting the cross validation of our analysis. After sentiment analysis, we create four new indicators, namely, *Leave Bots (-)*, *Leave Bots (+)*, *Remain Bots (-)* and *Remain Bots (+)*. Variable *Leave Bots (-)* equals 1 if the bots' pro-leave tweet is written in negative sentiment, 0 otherwise. Similar ideas are applied for other indicators. Examples of how TextBlob works in our sample are as follows:

	Polarity score	Interpretation
I really hope British people want to stay in the EU	0.1	(Slightly) Positive

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	Positive
Brexit frees the Tories to destroy workers' right	-0.25	Negative
If we allows the 18 Albanians who arrived on our shores illegally to stay then UK faces a migrant crisis this summer	-0.5	(Highly) Negative
I'm voting leave because nobody owns allegiance to an unelected elite	0	Neutral

Regarding VAR model with sentiment analysis, the specifications are as follows:

$$\Delta Leave\ Humans_t = \alpha + \sum_{k=1}^{K}\beta_{1k}\Delta Leave\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{2k}\Delta Remain\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{3k}\Delta Leave\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{4k}\Delta Leave\ Bots\ (+)_{t-k} + \sum_{k=1}^{K}\beta_{5k}\Delta Remain\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{6k}\Delta Remain\ Bots\ (+)_{t-k} + \gamma Diff_{t-1} + time\ dummies + \varepsilon \quad (6)$$

$$\Delta Remain\ Humans_t = \alpha + \sum_{k=1}^{K}\beta_{1k}\Delta Leave\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{2k}\Delta Remain\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{3k}\Delta Leave\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{4k}\Delta Leave\ Bots\ (+)_{t-k} + \sum_{k=1}^{K}\beta_{5k}\Delta Remain\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{6k}\Delta Remain\ Bots\ (+)_{t-k} + \gamma Diff_{t-1} + time\ dummies + \varepsilon \quad (7)$$

$$\Delta Leave\ Bots\ (-)_t = \alpha + \sum_{k=1}^{K}\beta_{1k}\Delta Leave\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{2k}\Delta Remain\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{3k}\Delta Leave\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{4k}\Delta Leave\ Bots\ (+)_{t-k} + \sum_{k=1}^{K}\beta_{5k}\Delta Remain\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{6k}\Delta Remain\ Bots\ (+)_{t-k} + \gamma Diff_{t-1} + time\ dummies + \varepsilon \quad 8)$$

$$\Delta Leave\ Bots\ (+)_t = \alpha + \sum_{k=1}^{K}\beta_{1k}\Delta Leave\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{2k}\Delta Remain\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{3k}\Delta Leave\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{4k}\Delta Leave\ Bots\ (+)_{t-k} + \sum_{k=1}^{K}\beta_{5k}\Delta Remain\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{6k}\Delta Remain\ Bots\ (+)_{t-k} + \gamma Diff_{t-1} + time\ dummies + \varepsilon \quad (9)$$

$$\Delta Remain\ Bots\ (-)_t = \alpha + \sum_{k=1}^{K}\beta_{1k}\Delta Leave\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{2k}\Delta Remain\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{3k}\Delta Leave\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{4k}\Delta Leave\ Bots\ (+)_{t-k} + \sum_{k=1}^{K}\beta_{5k}\Delta Remain\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{6k}\Delta Remain\ Bots\ (+)_{t-k} + \gamma Diff_{t-1} + time\ dummies + \varepsilon \quad (10)$$

$$\Delta Remain\ Bots\ (+)_t = \alpha + \sum_{k=1}^{K}\beta_{1k}\Delta Leave\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{2k}\Delta Remain\ Humans_{t-k} + \sum_{k=1}^{K}\beta_{3k}\Delta Leave\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{4k}\Delta Leave\ Bots\ (+)_{t-k} + \sum_{k=1}^{K}\beta_{5k}\Delta Remain\ Bots\ (-)_{t-k} + \sum_{k=1}^{K}\beta_{6k}\Delta Remain\ Bots\ (+)_{t-k} + \gamma Diff_{t-1} + time\ dummies + \varepsilon \quad (11)$$

where Δ*Leave Bots (-)*, Δ*Leave Bots (+)*, Δ*Remain Bots (-)*, Δ*Remain Bots (+)* are the percentage changes of hourly number of leave tweets and remain tweets created by bots with negative or positive sentiment; Δ*Leave Humans* and Δ*Remain Humans* are the percentage changes of hourly number of leave tweets and remain tweets created by humans. Similar to the baseline regressions, we also include time dummies (hour, date and month) in our model. Equations (6)-(11) are estimated with five (K=5) lags. If hypothesis (2b) holds, $\sum_{k=1}^{K}\beta_{3k}$ and $\sum_{k=1}^{K}\beta_{5k}$ in equations (6) and (7) should be distinguishable from zero and should be higher than other sums of slope coefficients on other changes.

3.2. Data and sample

The data for analysis has been collected using Twitter Streaming API. Through this, we make a request, filter by keyword "Brexit" and leave the connection open to collect as many tweets as possible during the period between 24 May 2016 and 17 August 2016. Tweets are tracked if they contain the hashtag "#Brexit". Our sample includes about 28.9 million tweets in total, with about 3.7 million tweets created on 24 June 2016. Each retrieved tweet contains the plain text of the tweet as well as information about users (user id, user name) and other fields such as date, source, location, friend counts, follower counts, URL, retweet counts, etc. The screening and cleaning process is as follows. First, we process the tweet content to extract the relevant content and remove the irrelevant one. More specifically, we exclude special characters, link tokens (starting with "http://", "https://", "www."), hashtag tokens (starting with "#"), user identifier tokens (starting with "@") from the tweet content. Second, we delete all tweets that contained attribution links only. Third, we delete a tweet if its source is not important[2]. Finally, we delete all tweets that were not written in English. After screening, our final sample includes about 28.6 million observations.

Since the main objective of this study is to distinguish the information spread process of leave supporters and remain supporters, we restrict our observations to the ones whose tweets are either pro-leave or pro-remain. Neutral tweets are not taken into account. Adopting similar approach with Howard and Kollanyi (2016), we define pro-remain tweets and pro-leave tweets based on the hashtags used as follows.

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

In this restricted sample, we observe the presence of both human Twitter agents and Twitter bots. Bots are defined by three categories: (1) abnormal tweeting time (from 00:00 to 06:00 UK time); (2) abnormal number of tweets per day and (3) tweet sources are platforms. In our sample, the number of bots accounts for around 20 percent of the total users (Figure 1). Summarised statistics for users' characteristics (Tables 1 and 2) present the clear differences in humans' characteristics and bots' characteristics. That is, most bots accounts are newly created with large number of followers and statuses while the number of friends is significantly lower than those of humans' accounts. Although the number of total tweets created by bots accounts for only 22 percent of total observations, the number of tweets per bot is higher than the number of tweets created by each human account.

Figures 2 and 3 show the evolution of the total number of leave and remain tweets in full sample and during polling and result days, respectively. As can be seen, the number of leave tweets was significantly higher than the number of remain tweets during pre-Brexit period while the difference disappeared from July 2016. Furthermore, during the polling day, especially few hours before the polls closed the number of leave tweets jumped dramatically. Figure 4 presents the dynamic of the number of leave and remain tweets created by humans and bots. In which, Panels A and C present the number of tweets created bots while the number of tweets created by humans is showed in Panels B and D. We observe the higher number of leave tweets for both humans' tweets sample and bots' tweets sample. Moreover, the number of leave tweets created by human increased few days before the result day while the number of remain tweets increased before the polling day then decreased on the polling day. Differently, the number of tweets created by bots reached its peak on the polling day with the notable increase in the number of leave messages. Regarding hourly tweets created during Brexit period, tweets created by human followed a normal time trend: more tweets were created during daytime and working time. By contrast, tweets created by bots soared up just few hours before the polls closed, showing an abnormal trend.

[2] A source is defined as unimportant if the number of tweets using that source is less than 100.

Figures 5 and 6 indicate the number of tweets with sentiment created by bots. As we can see, during pre-Brexit period, the number of leave tweets with positive sentiment was significantly higher than the number of leave tweets with negative sentiment and the number of remain tweets while we do not observe this difference after the result day. Furthermore, during the polling day, bots attempted to spread more leave messages with positive sentiment since the number of leave tweets with positive sentiment increased dramatically while the number of remain tweets with positive sentiment dropped.

To preliminarily investigate the interaction between bots and humans in spreading messages about Brexit, we define all original tweets created by bots and humans and check the number of original tweets that were retweeted. Next, among the retweets, we define the ones that were made by bots and humans separately (Figure 7). In general, we observe that humans are more likely to retweet and they tend to retweet a bot's tweet. Considering the number of bots' tweets that were retweeted during pre-Brexit period, for each original tweet created by a bot, the number of retweets made by humans is about 2 times higher than the number of retweets made by other bots (Figure 8). For every retweeted tweet, there are about 7 retweets made by humans and 2 retweets made by bots. Furthermore, a bot's tweet will be retweeted by humans about 3 times more if it contains a leave message compared to the one contains remain message (Figure 9). In the other words, there is a sign that during pre-Brexit period, humans tend to spread the leave messages that were originally generated by bots. Since the number of bots is significantly lower than the number of humans, this influence of bots' tweets is substantial.

4. Results discussion

4.1. Could Brexit result be predicted through Twitter?

Figure 10 represents our preliminary comparison between the share of leavers/leave bots on Twitter and the actual result of the EU Referendum. As can be seen, the share of leave voters on Twitter is always higher than 50 percent, and higher than the figure of actual outcome (51.9 percent). Interestingly, nearer the date of polling day, the share of leavers on Twitter was very close to the actual result. Figure 9 also shows that the number of leavers indeed decreased when it came nearer to the polling day. Table 3 presents the share of leavers broken down into areas. When we account for both leavers and leave bots, the correlation between our results and the actual results is 83 percent and the correlation is 79 percent when we account for leavers only. Although there is variation, the correlation is quite high suggesting the predictive power of public opinions on Twitter. Further, taking into account the fact that the majority of leave voters is elderly people who are less likely to use social media, this variation is acceptable. These suggest that to some extends the examination of public opinions on Twitter can predict the result of the EU Referendum.

Forecast results from estimated coefficients in model (1) are presented in Table 4. Panel A presents results for estimations with 1 lag while Panel B presents results for estimations with 2 lags. In all cases, our forecast exercise returns the predicted share of leave votes of around 62 percent, suggesting the result in favour of leave. The confidence interval at 95 percent significance level is from 60 percent to 64 percent. Thus, although the forecast somewhat overestimates the actual result, we can still conclude that it is possible to analyse public opinions in social media like Twitter to forecast results of political events. Moreover, our forecast does predict correctly the domination of leave votes while forecasts from some online sources do not. For example, 38 polls conducted through YouGov from January 2013 to June 2016 returned the results of around 40-50 percent to remain, 25-30 percent to leave while 20-30 percent is neutral votes. Similar results are also found from 80 polls conducted from September 2010 to May 2015. Interestingly, polls results conducted on 22 June by different pollsters show no difference between leave and remain votes.

4.2. Could Brexit result be manipulated?

Regression results for VAR models are presented in Table 5. Panels A, B, C and D present results for full sample, sample of pre-Brexit period, sample of during-Brexit period and sample of after-Brexit period, respectively. Columns (1)-(5) present estimated coefficients on lagged changes in leave supporters' tweets, remain supporters' tweets, leave bots' tweets, remain bots' tweets and lagged difference in the number of leave tweets and remain tweets, respectively. We also perform a set of post-estimation tests including: (1) test for significance of exogenous variable (*Diff*); (2) test for the eigenvalue stability condition and (3) test for the sufficiency of the number of lags included. In general, we find that: (1) exogenous variable is significant in estimated system; (2) our VAR model satisfies the stability condition and (3) the optimal number of lags is 5[3].

Regarding results for estimations with full sample, we observe the interaction between humans in spreading information about Brexit. More specifically, the tweeting activity of remain supporters is affected by the activity of leave supporters: if the number of tweets created by leave supporters increase by 10 percent, the number of humans' pro-remain tweets increases by 3.36 percent. Furthermore, the sum of the coefficients on lagged changes in humans' leave tweets is higher than the sum of the coefficients on lagged changes in humans' remain tweets (0.336 versus -1.090). This suggests that leave supporters are more influential than remain supporters. Additionally, humans' tweeting activity is also influenced by bots. However, the ability of spreading leave messages of leave bots is better than the information spread ability of remain bots. In details, 10 percent increase in leave bots' tweets results in 2.62 percent increase in humans' leave messages while 10 percent rise in remain bots' posts leads to 1.56 percent increase in humans' remain messages only. By contrast, bots' activity is not affected by humans' activity since $\sum_{k=1}^{K}\beta_{1k}$ and $\sum_{k=1}^{K}\beta_{2k}$ in equations (4) and (5) are indistinguishable from zero. Indeed, bots do interact with others in disseminating artificial trends about Brexit. In which, if leave bots are more active in the past 5 hours, remain bots would also create and spread pro-remain tweets more.

When we estimate the model with the sample of pre-Brexit period, the impact of leave supporters' and remain bots' activities on remain supporters' activity disappears. However, we still acknowledge that leave supporters are indeed influenced by leave bots. In terms of leave bots' information diffusion, the results indicate that leave bots do interact with remain supporters and other bots in spreading leave messages. In details, if remain messages created by humans raises by 10 percent, the number of leave bots' posts increases by 3.72 percent. Further, leave bots are much more responsive to humans' pro-remain posts than to other bots' tweeting activities; and also adjust to the arrival of remain bots' tweets faster than the one of leave bots' tweets ($\sum_{k=1}^{K}\beta_{2k} > \sum_{k=1}^{K}\beta_{4k} > \sum_{k=1}^{K}\beta_{3k}$). Differently, during pre-Brexit period, remain bots only interact with remain supporters and other remain bots in disseminating pro-remain messages. In which, 10 percent increase in the volume of remain supporters' posts could increase the number of posts created by remain bots by 3.38 percent. Moreover, the sum of the coefficients on lagged changes in humans' remain tweets is higher than the sum of the coefficients on lagged changes in bots' remain tweets. This indicates that

[3] Details of post-estimation tests are available upon request.

the interaction between remain bots and remain supporters is stronger than the one among remain bots.

Interestingly, despite the spike in the number of tweets created on polling and result days, no interaction in spreading opinions about Brexit is observed. For post-Brexit period, again the impact of bots on other bots' activity as well as impact of bots on remain supporters' activity disappear. However, leave supporters are still affected by bots. On the one hand, the increase in tweets created by leave bots leads to the increase in the pro-leave tweets created by humans. On the other hand, pro-leave users slow down their tweeting process if the number of remain bots' tweets increases. In addition, if the number of leave tweets in the last hour is higher than the number of remain tweets, the process spreading leave tweets will be slowed down while the remain tweets will be diffused more.

Results for causality tests are presented in Table 6. Panels A-D report results for full sample, pre-Brexit, during Brexit and after Brexit samples, respectively. The results for full sample reveal the Granger causality between humans and Granger causality between bots. In other words, leave supporters and remain supporters do interact with others in spreading news and opinions about Brexit. Similarly, leave bots and remain bots do interact. However, these relationships disappear when we test the causality in different periods. In terms of interaction between humans and bots, we find that the tweeting activities of both types of bots are affected by the tweeting activities of remain supporters since the causality of ΔRemain Humans on bots is significant in all samples. Differently, leave supporters' activities mostly affect remain bots' activities and the signs are quite weak with 10 percent and 5 percent significance levels. Regarding the causal influence of bots on humans, there is strong evidence that leave supporters are more likely to be affected by bots, especially leave bots as the signs for the causality of ΔLeave Bots on leave supporters are 5 percent and 1 percent significance levels.

In general, our findings demonstrate that twitter bots, especially leave bots, do attempt to manipulate public opinions about the EU Referendum, and thus drove the result of the Referendum. As bots were mainly used for this purpose, bots are most active prior to polling and result days. In addition, to disseminate artificial trends, bots adjust the tweeting activity to the arrival of new tweets created by humans much faster than the speed of humans' adjustment to bots' activities. Furthermore, we find that leave supporters actually followed the trend created by leave bots while remain supporters were more persistent. Considering the significant lower number of bots compared to humans, this spillover effect from bots to humans is considerable.

4.3. Does sentiment matter?

Since the information spread activity of humans Twitter agents is more likely to be affected by the activity of bots, we examine whether this impact is driven by the sentiment of the tweets created by bots. We estimate equations (6)-(11) with full sample and the samples of before-Brexit period and after-Brexit period. Estimated results are presented in Table 7.

Results of estimations with full sample are consistent with the previous finding that there are interaction between leave supporters and remain supporters in spreading information about Brexit. Additionally, the information diffusion process of leave supporters is largely driven by tweets with negative sentiment created by leave bots. More specifically, if leave bots increase leave messages written in negative sentiment by 10 percent, the number of posts created leave supporters increases by 1.31 percent. This result is stronger in both magnitude and sign when we estimate our model with pre-Brexit sample (3.75 percent versus 1.31 percent, 1 percent significance level versus 10 percent significance level). Moreover, during pre-Brexit period, 10 percent increase in positively-written leave posts created by bots increases the number of leavers' posts by 2.48 percent. The higher magnitude in the sum of the coefficients on lagged changes in leave bots' negative tweets suggests that tweets with negative sentiment spread by bots are more influential. We also note that in four out of six regressions the coefficients on the dynamics of bots' negative leave messages are significant, indicating the high impact of leave bot's negative tweets. In which, 10 percent increase in leave bots' negative tweets leads to 2.15 percent increase in humans' pro-remain tweets. Results from equations (8) and (9) provide additional evidence for the interaction among leave bots in spreading leave messages. Furthermore, the speed of negative leave bots' reaction to the arrival of positive leave tweets is 0.446. It is about double the speed of adjustment of positive leave bots to the change in negative leave tweets (0.215). In contrast, we do not observe the interaction between negative remain bots and positive remain bots.

After the EU Referendum result is announced, the interaction between humans and bots in diffusing information do change. That is, after Brexit leave supporters are only affected by negative leave bots while remain supporters are affected negative remain bots. Specifically, if leave bots increase the negative messages by 10 percent, the number of pro-leave tweets created by humans increases by 1.62 percent. This influence seems to be weaker compared to the influence in previous period in both sign (10 percent significance level versus 1 percent significance level) and magnitude. Further, if remain bots increase the negative posts by 10 percent, the number of remain supporters' posts increases by 2.22 percent. Interestingly, during post-Brexit period, leave bots seem to be affected by humans' tweeting activity: if remain supporters increase their number of posts by 10 percent, leave bots spread negative messages more with the change of 5.44 percent. This interaction is very strong since the sum of coefficients on tweets of remain supporters is highest among all sums of coefficients.

Performing Granger causality tests for VAR model with sentiment, we find additional evidence for the high influence of leave tweets with negative sentiment (Table 8). More specifically, although the tweeting activities of leave supporters are affected by leave bots' tweets, the impact of tweets with negative sentiment is significantly stronger than the impact of tweets with positive sentiment in terms of signs. Moreover, the way in which remain supporters are affected by remain bots is also different in different period. In pre-Brexit period, remain supporters are more likely to be influenced by remain tweets with positive sentiment while after Brexit, they are more likely to be affected by tweets with negative sentiment.

Results from vector autoregressions with sentiment provide answers for the concern of what extend humans' opinion is affected by bots. We find that negative messages created and disseminated by leave bots are most influential. In addition, this influence is stronger during pre-Brexit period, supporting the finding that leave bots do attempt to manipulate humans' views about the EU Referendum. Furthermore, although humans do adjust their tweeting activity corresponding to different sentiment, the speed of reaction to negative messages is more rapidly than the speed of adjustment to positive tweets.

5. Conclusions

Social media is a powerful tool for influencing public opinion in information era. For instance, views and opinions about key political events are created, spread, and widely discussed in social networks like Twitter or Facebook. The main purpose of this paper is to investigate whether the EU Referendum result could be predicted through Twitter social networking service. Furthermore, the mechanism of information diffusion on Twitter is explored. We process the data on sharing Brexit information by humans and bots to investigate whether public opinions could be manipulated. Additionally, we distinguish the sentiment of tweets to examine whether these sharing activities are driven by the sentiment.

Our data are collected from Twitter Stream API and include about 28.6 million tweets with "Brexit" hashtag from 24 May 2016 to 17 August 2016. Our key results and implications can be summarized as follows. First, the result in favour of leave could indeed be predicted through Twitter. In our sample, we also identify the locations of users in different geographical areas and measure the shares of leave votes in each location. Our findings are highly correlated to the actual results with the correlation of about 80 percent. Since our results suggest that the political outcomes could be predicted through social networks like Twitter, social media could be used in high-impact events to track public opinions and predict future reactions or predict results.

Second, public opinions about Brexit could be shaped by bots. Although the number of bots accounts for only 20 percent of total results, bots' tweets are largely retweeted by humans, generating a huge contribution on all traffic on Twitter about the EU Referendum. This finding is similar to Howard and Kollanyi (2016) who explore the activities of political bots during Brexit event. However, they cannot provide evidence for the role of bots in manipulating humans' opinions while our VAR estimates reveal that leave supporters are indeed affected by the artificial trend created by leave bots. In contrast, remain supporters tend to interact with other remain supporters and resist to the trend created by bots. As bots indeed formed public opinions rather than just promoting innocuous political events as documented by Forelle et al. (2015), a legal framework to control the use of bots in future high-impact events should be considered.

Third, the interaction between humans and bots might be driven not only by the topic of the tweets but also the sentiment. Deploying sentiment analysis, we find that humans actually react more rapidly to negative information. This is in line with results from previous studies which investigate impacts of news sentiment on market reaction (e.g., Smales, 2014a; Smales, 2014b). The result suggests that we can make use of sentiment in information diffusion process.

Table 1. Summary statistics for users' characteristics in full sample

	P10	P25	Mean	P75	P90	SD	Obs.
Age	5.591	6.751	7.076	7.769	7.902	0.972	635,995
Friends	4.127	5.043	5.853	6.770	7.561	1.410	629,635
Statuses	4.860	6.526	7.844	9.421	10.471	2.200	635,993
Followers	3.258	4.477	5.613	6.742	7.792	1.833	624,449
No. of tweets per user	1.000	1.000	4.492	2.000	5.000	78.170	635,995
No. of Bots	0.000	0.000	0.144	0.000	1.000	0.351	635,995

Age is the natural logarithm of days from created date till 23 June 2016. Friends is the natural logarithm of number of friends. Statuses is the natural logarithm of total number of statuses from the created date. Followers is the natural logarithm of number of followers. No. of tweets per user is the natural logarithm of number of tweets with "Brexit" hashtag created in the examined period. No. of Bots is the number of users which are defined as bots.

Table 2. Summary statistics for users' characteristics of bots and humans

	Humans		Bots		Difference
	Mean1	SD1	Mean2	SD2	Mean1-Mean2
Age	7.098	0.937	6.949	1.147	0.149 ***
Friends	5.870	1.313	5.736	1.897	0.135 ***
Statuses	7.754	2.132	8.362	2.513	-0.608 ***
Followers	5.545	1.763	6.027	2.178	-0.482 ***
No. of tweets per user	4.088	26.652	6.901	195.660	-2.813 ***

Age is the natural logarithm of days from created date till 23 June 2016. Friends is the natural logarithm of number of friends. Statuses is the natural logarithm of total number of statuses from the created date. Followers is the natural logarithm of number of followers. No. of tweets per user is the natural logarithm of number of tweets with "Brexit" hashtag created in the examined period. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table 3. Share of leavers by area

Area	Share of leavers on Twitter		Actual votes
	Bots and Humans	Humans only	
East	50.4%	50.1%	56.5%
East Midlands	51.1%	51.3%	58.8%
London	44.5%	44.2%	40.1%
North West	50.0%	49.9%	53.7%
Northern Ireland	46.7%	47.1%	44.2%
Scotland	46.0%	46.0%	38.0%
South East	50.0%	50.1%	51.8%
South West	46.8%	46.2%	52.6%
Wales	48.0%	47.7%	52.5%
West Midlands	49.5%	49.0%	59.3%
Yorkshire	53.6%	53.3%	57.7%

Table 4. Forecast model

	(1)	(2)	(3)	(4)
	AR	OLS	OLS	OLS
		Panel A. 1 lag		
Share_leavers(t-1)	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
Forecast	62.39	62.14	62.14	62.39
Confidence interval (95%)	(61.00; 63.78)	(60.20; 64.09)	(60.39; 63.89)	(60.90; 63.88)
$\overline{R^2}$	0.695	0.741	0.761	0.799
Obs.	29	28	28	29
		Panel B. 2 lags		
Share_leavers(t-1;t-2)	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
Forecast	62.14	61.94	61.94	62.14
Confidence interval (95%)	(60.41; 63.87)	(59.57; 64.31)	(59.63; 64.25)	(59.91; 64.37)
$\overline{R^2}$	0.664	0.763	0.778	0.783
Obs.	28	27	27	28

Predicted share of leave votes is measured based on autoregressive estimation and OLS estimation with 1 lag and 2 lags. Column (1) presents results from AR model, regressing share of leave votes on its own lag(s). Column (2)-(4) present results from OLS estimations with different independent variables including lag(s) of share of leave votes, lag(s) of share of leave bots, lag(s) of first difference in the number of pro-leave tweets, lag(s) of first difference in the number of total tweets and lag(s) of difference in the number of pro-leave tweets and pro-remain tweets on each day.

Table 5. Baseline VAR model

	(1)	(2)	(3)	(4)	(5)
	Panel A. Full sample				
	ΔLeave Humans (t-1:t-5)	ΔRemain Humans (t-1:t-5)	ΔLeave Bots (t-1:t-5)	ΔRemain Bots (t-1:t-5)	Diff (t-1)
ΔLeave Humans	-0.710***	0.104	0.262***	0.014	-0.046***
	(0.110)	(0.101)	(0.085)	(0.072)	(0.012)
ΔRemain Humans	0.336**	-1.090***	-0.014	0.156*	-0.002
	(0.134)	(0.114)	(0.096)	(0.090)	(0.014)
ΔLeave Bots	0.012	0.040	-1.177***	0.067	-0.047***
	(0.110)	(0.096)	(0.107)	(0.076)	(0.013)
ΔRemain Bots	0.002	0.141	0.295**	-1.727***	0.004
	(0.164)	(0.146)	(0.127)	(0.121)	(0.019)
	Panel B. Before Brexit				
	ΔLeave Humans (t-1:t-5)	ΔRemain Humans (t-1:t-5)	ΔLeave Bots (t-1:t-5)	ΔRemain Bots (t-1:t-5)	Diff (t-1)
ΔLeave Humans	-0.936***	-0.045	0.235**	0.078	-0.063**
	(0.209)	(0.148)	(0.109)	(0.106)	(0.031)
ΔRemain Humans	0.161	-1.136***	-0.079	0.100	0.037
	(0.241)	(0.153)	(0.139)	(0.149)	(0.029)
ΔLeave Bots	0.407	0.372*	-1.468***	-0.416**	-0.122***
	(0.262)	(0.215)	(0.193)	(0.186)	(0.044)
ΔRemain Bots	0.042	0.338*	0.133	-1.525***	0.064*
	(0.250)	(0.179)	(0.159)	(0.178)	(0.033)
	Panel C. During Brexit				
	ΔLeave Humans (t-1:t-5)	ΔRemain Humans (t-1:t-5)	ΔLeave Bots (t-1:t-5)	ΔRemain Bots (t-1:t-5)	Diff (t-1)
ΔLeave Humans	-0.091	1.494	0.354	-0.636	-0.015
	(0.418)	(0.433)	(0.181)	(0.181)	(0.006)
ΔRemain Humans	-7.788	-6.158	4.217	-2.588	-0.116
	(1.916)	(1.984)	(0.832)	(0.829)	(0.030)
ΔLeave Bots	0.999	-4.075	2.462	1.399	-0.189
	(11.150)	(11.547)	(4.840)	(4.826)	(0.173)
ΔRemain Bots	0.712	-1.576	-0.145	1.029	-0.067
	(4.202)	(4.352)	(1.824)	(1.819)	(0.065)
	Panel D. After Brexit				
	ΔLeave Humans (t-1:t-5)	ΔRemain Humans (t-1:t-5)	ΔLeave Bots (t-1:t-5)	ΔRemain Bots (t-1:t-5)	Diff (t-1)
ΔLeave Humans	-0.715***	0.096	0.397***	-0.397***	-0.102***
	(0.185)	(0.134)	(0.122)	(0.110)	(0.021)
ΔRemain Humans	0.009	-1.097***	-0.067	-0.032	0.023
	(0.248)	(0.229)	(0.143)	(0.145)	(0.026)
ΔLeave Bots	0.135	0.254	-1.530***	-0.055	-0.087***
	(0.234)	(0.175)	(0.194)	(0.128)	(0.030)
ΔRemain Bots	0.466	-0.035	-0.307	-1.688***	0.015
	(0.322)	(0.266)	(0.197)	(0.198)	(0.035)

All regressions are estimated using VAR model. *Leave Humans* is the natural logarithm of the number of leave tweets created by human per hour. *Remain Humans* is the natural logarithm of the number of remain tweets created by human per hour. *Leave Bots* is the natural logarithm of the number of leave tweets created by bots per hour. *Remain Bots* is the natural logarithm of the number of remain tweets created by bots per hour. *Diff* is the natural logarithm of the difference in number of leave and remain tweets per hour. Three sub-samples include before, during and after Brexit. Before Brexit period is the period from 24/05/2016 to 22/06/2016. During period includes 23-24/06/2016. After Brexit period is the period from 25/06/2016 to 25/07/2016. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table 6. Granger causality tests for baseline VAR model

	(1)	(2)	(3)	(4)
	Granger causality of ΔLeave Humans	Granger causality of ΔRemain Humans	Granger causality of ΔLeave Bots	Granger causality of ΔRemain Bots
		Panel A. Full sample		
ΔLeave Humans		0.000	0.000	0.743
ΔRemain Humans	0.000		0.480	0.004
ΔLeave Bots	0.040	0.074		0.451
ΔRemain Bots	0.098	0.003	0.125	
		Panel B. Before Brexit		
ΔLeave Humans		0.014	0.029	0.736
ΔRemain Humans	0.578		0.407	0.261
ΔLeave Bots	0.479	0.009		0.107
ΔRemain Bots	0.094	0.000	0.378	
		Panel C. During Brexit		
ΔLeave Humans		0.040	0.016	0.086
ΔRemain Humans	0.837		0.489	0.300
ΔLeave Bots	0.286	0.049		0.436
ΔRemain Bots	0.032	0.088	0.457	
		Panel D. After Brexit		
ΔLeave Humans		0.066	0.001	0.001
ΔRemain Humans	0.111		0.310	0.172
ΔLeave Bots	0.185	0.279		0.892
ΔRemain Bots	0.156	0.034	0.275	

Columns (1)-(4) report p-values for the tests of Granger causality ΔLeave Humans, ΔRemain Humans, ΔLeave Bots, ΔRemain Bots in equations (2)-(5), respectively. *Leave Humans* is the natural logarithm of the number of leave tweets created by human per hour. *Remain Humans* is the natural logarithm of the number of remain tweets created by human per hour. *Leave Bots* is the natural logarithm of the number of leave tweets created by bots per hour. *Remain Bots* is the natural logarithm of the number of remain tweets created by bots per hour. *Diff* is the natural logarithm of the difference in number of leave and remain tweets per hour. Three sub-samples include before, during and after Brexit. Before Brexit period is the period from 24/05/2016 to 22/06/2016. During period includes 23-24/06/2016. After Brexit period is the period from 25/06/2016 to 25/07/2016.

Table 7. VAR model with sentiment analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Full sample							
	Humans	Humans	Bots	Bots	Bots	Bots	
	Δleave (t-1;t-5)	Δremain (t-1;t-5)	Δleave (t-1;t-5)	Δleave (t-1;t-5)	Δremain (t-1;t-5)	Δremain (t-1;t-5)	Diff (t-1)
			(-)	(+)	(-)	(+)	
ΔLeave Humans	-0.870***	0.232***	0.131*	0.125	0.020	-0.033	-0.035***
	(0.121)	(0.089)	(0.068)	(0.097)	(0.064)	(0.075)	(0.011)
ΔRemain Humans	0.272*	-0.997***	0.064	0.100	0.073	-0.109	-0.005
	(0.162)	(0.129)	(0.080)	(0.112)	(0.082)	(0.094)	(0.013)
ΔLeave Bots (-)	0.350*	0.194	-1.395***	0.058	-0.021	0.064	-0.025
	(0.179)	(0.141)	(0.105)	(0.140)	(0.089)	(0.110)	(0.016)
ΔLeave Bots (+)	0.120	0.281**	0.159*	-1.188***	0.081	-0.047	-0.023*
	(0.151)	(0.113)	0.082	(0.118)	(0.080)	(0.094)	(0.013)
ΔRemain Bots (-)	-0.116	0.622***	0.155	0.396**	-1.563***	-0.284**	0.005
	(0.206)	(0.189)	(0.119)	(0.164)	(0.111)	(0.139)	(0.018)
ΔRemain Bots (+)	0.201	0.198	0.037	-0.014	0.185*	-1.476***	-0.005
	(0.194)	(0.155)	(0.103)	(0.143)	(0.107)	(0.120)	(0.015)
Panel B. Before Brexit							
	Humans	Humans	Bots	Bots	Bots	Bots	
	Δleave (t-1;t-5)	Δremain (t-1;t-5)	Δleave (t-1;t-5)	Δleave (t-1;t-5)	Δremain (t-1;t-5)	Δremain (t-1;t-5)	Diff (t-1)
			(-)	(+)	(-)	(+)	
ΔLeave Humans	-1.205***	-0.090	0.375***	0.248*	-0.020	-0.068	-0.057**
	(0.225)	(0.145)	(0.110)	(0.145)	(0.083)	(0.098)	(0.029)
ΔRemain Humans	-0.053	-1.046***	0.215*	0.046	-0.089	-0.162	0.026
	(0.269)	(0.188)	(0.115)	(0.167)	(0.093)	(0.112)	(0.029)
ΔLeave Bots (-)	-0.119	0.116	-1.118***	0.446*	-0.121	0.001	-0.074*
	(0.352)	(0.272)	(0.178)	(0.241)	(0.142)	(0.173)	(0.044)
ΔLeave Bots (+)	-0.110	0.032	0.215*	-1.186***	0.105	0.039	-0.039
	(0.279)	(0.217)	(0.123)	(0.181)	(0.101)	(0.130)	(0.030)
ΔRemain Bots (-)	-0.279	0.607*	0.308	0.270	-1.632***	-0.301	0.034
	(0.511)	(0.313)	(0.213)	(0.299)	(0.170)	(0.225)	(0.053)
ΔRemain Bots (+)	0.233	0.226	0.066	-0.190	-0.021	-1.228***	0.012
	(0.293)	(0.237)	(0.142)	(0.208)	(0.119)	(0.158)	(0.035)
Panel C. After Brexit							
	Humans	Humans	Bots	Bots	Bots	Bots	
	Δleave (t-1;t-5)	Δremain (t-1;t-5)	Δleave (t-1;t-5)	Δleave (t-1;t-5)	Δremain (t-1;t-5)	Δremain (t-1;t-5)	Diff (t-1)
			(-)	(+)	(-)	(+)	
ΔLeave Humans	-0.722***	0.011	0.162*	0.035	0.015	-0.122	-0.063***
	(0.210)	(0.143)	(0.093)	(0.133)	(0.096)	(0.119)	(0.019)
ΔRemain Humans	-0.056	-1.334***	0.022	-0.030	0.222*	-0.008	0.030
	(0.259)	(0.239)	(0.116)	(0.168)	(0.135)	(0.155)	(0.023)
ΔLeave Bots (-)	0.176	0.544**	-1.414***	-0.396*	0.043	0.056	-0.008
	(0.368)	(0.271)	(0.181)	(0.215)	(0.161)	(0.195)	(0.036)
ΔLeave Bots (+)	0.152	0.005	0.292**	-1.170***	0.060	-0.250	-0.045*
	(0.280)	(0.217)	(0.133)	(0.182)	(0.141)	(0.162)	(0.026)
ΔRemain Bots (-)	0.023	0.518	0.161	-0.099	-1.463***	-0.069	-0.011
	(0.341)	(0.371)	(0.172)	(0.234)	(0.202)	(0.233)	(0.040)
ΔRemain Bots (+)	0.574	0.086	0.074	-0.036	0.050	-1.614***	-0.031
	(0.355)	(0.324)	(0.164)	(0.229)	(0.180)	(0.225)	(0.033)

All regressions are estimated using VAR model. *Leave Humans* is the natural logarithm of the number of leave tweets created by human per hour. *Remain Humans* is the natural logarithm of the number of remain tweets created by human per hour. *Leave Bots (-)* is the natural logarithm of the number of leave tweets with negative sentiment created by bots per hour. *Leave Bots (+)* is the natural logarithm of the number of leave tweets with positive sentiment created by bots per hour. *Remain Bots (-)* is the natural logarithm of the number of remain tweets with negative sentiment created by bots per hour. *Remain Bots (+)* is the natural logarithm of the number of remain tweets with positive sentiment created by bots per hour. *Diff* is the natural logarithm of the difference in number of leave and remain tweets per hour. Two sub-samples include before and after Brexit. Before Brexit period is the period from 24/05/2016 to 22/06/2016. After Brexit period is the period from 25/06/2016 to 25/07/2016. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table 8. Granger causality tests for VAR model with sentiment

	(1)	(2)	(3)	(4)	(5)	(6)
	Granger causality of ΔLeave Humans	Granger causality of ΔRemain Humans	Granger causality of ΔLeave Bots (-)	Granger causality of ΔLeave Bots (+)	Granger causality of ΔRemain Bots (-)	Granger causality of ΔRemain Bots (+)
			Panel A. Full sample			
ΔLeave Humans		0.000	0.016	0.075	0.226	0.891
ΔRemain Humans	0.000		0.093	0.430	0.030	0.517
ΔLeave Bots (-)	0.010	0.046		0.400	0.094	0.477
ΔLeave Bots (+)	0.000	0.000	0.001		0.243	0.536
ΔRemain Bots (-)	0.458	0.000	0.298	0.010		0.190
ΔRemain Bots (+)	0.000	0.007	0.285	0.003	0.009	
			Panel B. Before Brexit			
ΔLeave Humans		0.159	0.000	0.069	0.617	0.012
ΔRemain Humans	0.376		0.057	0.934	0.172	0.017
ΔLeave Bots (-)	0.096	0.256		0.114	0.800	0.943
ΔLeave Bots (+)	0.824	0.032	0.105		0.530	0.353
ΔRemain Bots (-)	0.545	0.023	0.316	0.772		0.445
ΔRemain Bots (+)	0.058	0.660	0.076	0.112	0.726	
			Panel C. After Brexit			
ΔLeave Humans		0.554	0.001	0.005	0.879	0.671
ΔRemain Humans	0.032		0.405	0.074	0.090	0.958
ΔLeave Bots (-)	0.712	0.091		0.096	0.417	0.231
ΔLeave Bots (+)	0.002	0.098	0.000		0.143	0.456
ΔRemain Bots (-)	0.396	0.042	0.753	0.490		0.796
ΔRemain Bots (+)	0.007	0.150	0.320	0.030	0.506	

Columns (1)-(6) report p-values for the tests of Granger causality of ΔLeave Humans, ΔRemain Humans, ΔLeave Bots (-), ΔLeave Bots (+), ΔRemain Bots (-), ΔRemain Bots. *Remain Humans* is the natural logarithm of the number of remain tweets created by human per hour. *Leave Bots (-)* is the natural logarithm of the number of leave tweets with negative sentiment created by bots per hour. *Leave Bots (+)* is the natural logarithm of the number of leave tweets with positive sentiment created by bots per hour. *Remain Bots (-)* is the natural logarithm of the number of remain tweets with negative sentiment created by bots per hour. *Remain Bots (+)* is the natural logarithm of the number of remain tweets with positive sentiment created by bots per hour. Two sub-samples include before and after Brexit. Before Brexit period is the period from 24/05/2016 to 22/06/2016. After Brexit period is the period from 25/06/2016 to 25/07/2016.

Figure 1. Number of humans and bots

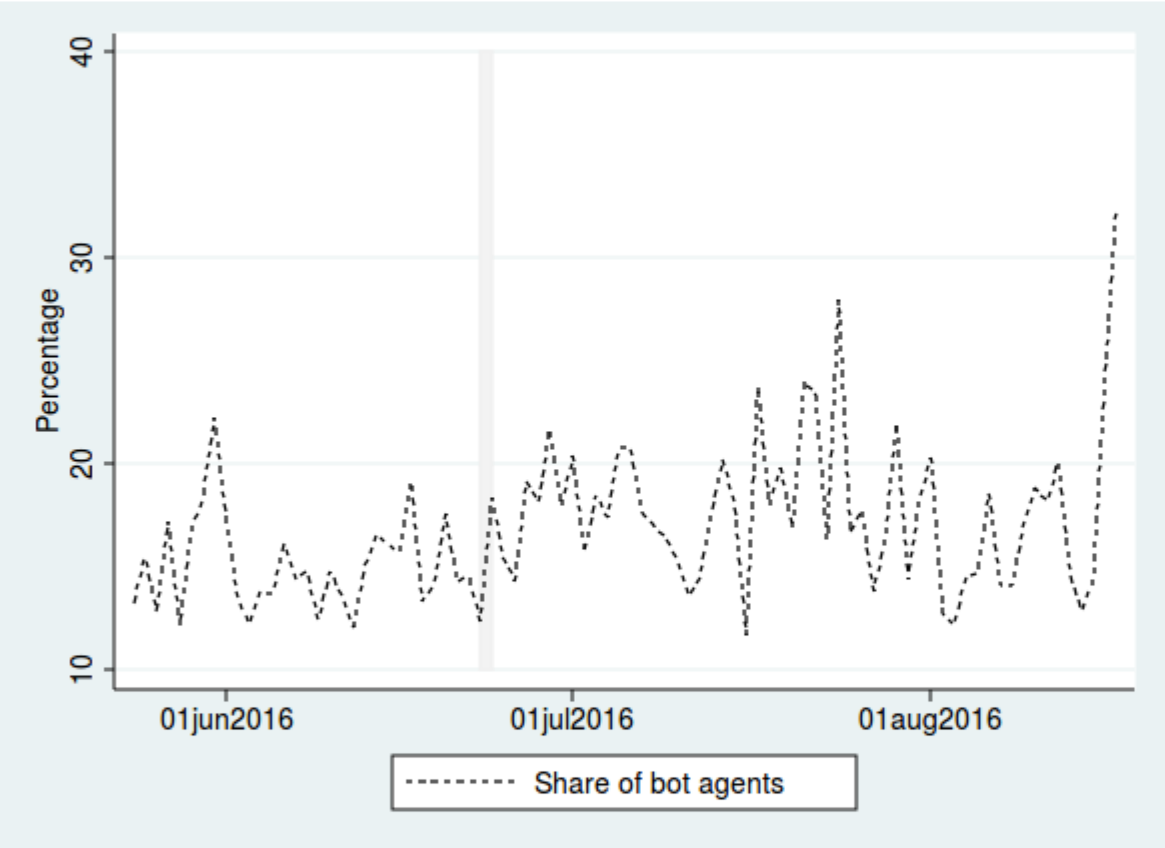


Figure 2. Evoluation of all tweets in full sample

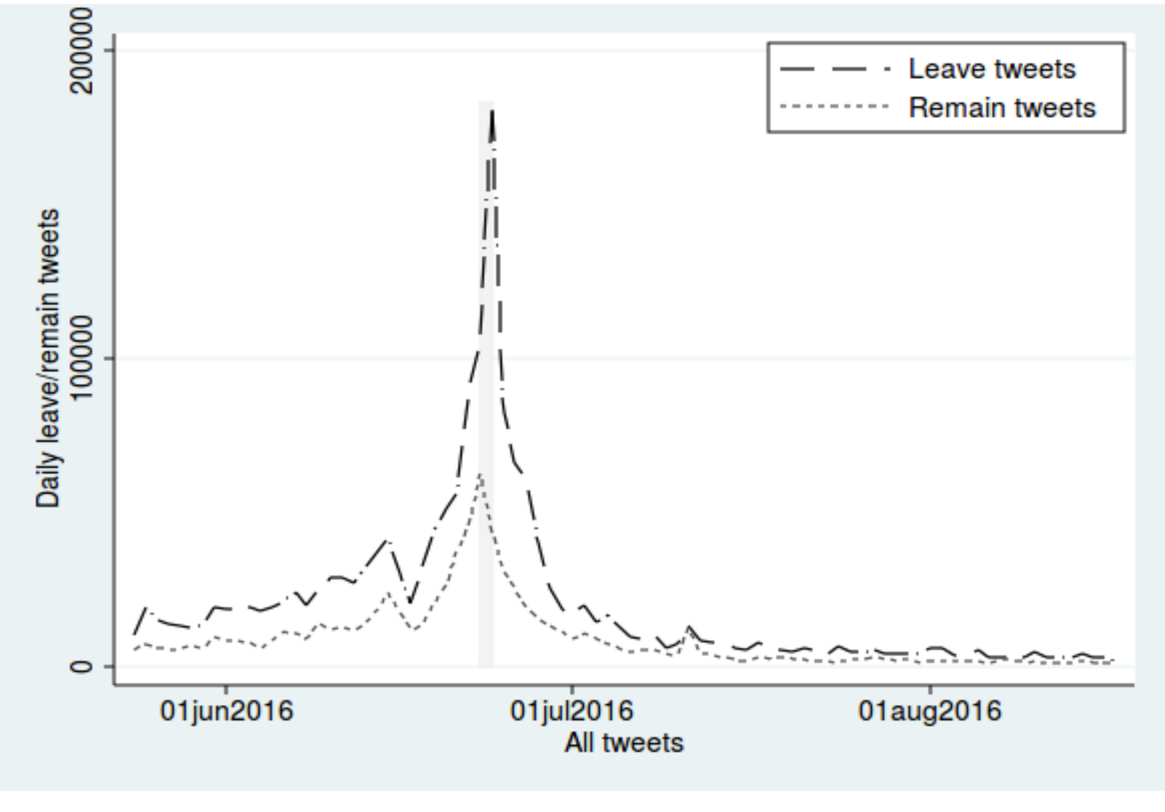


Figure 3. Evoluation of all tweets during Brexit

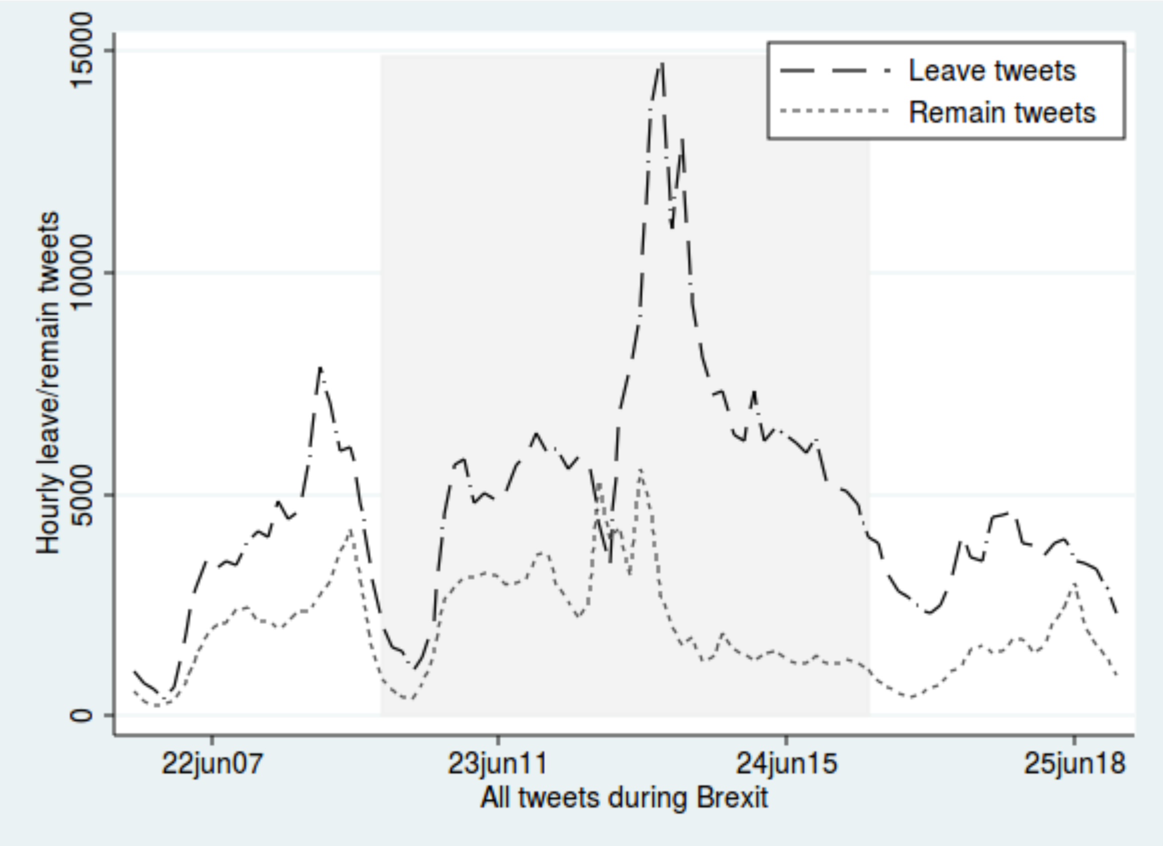


Figure 4. Evolution of tweets created by bots and humans

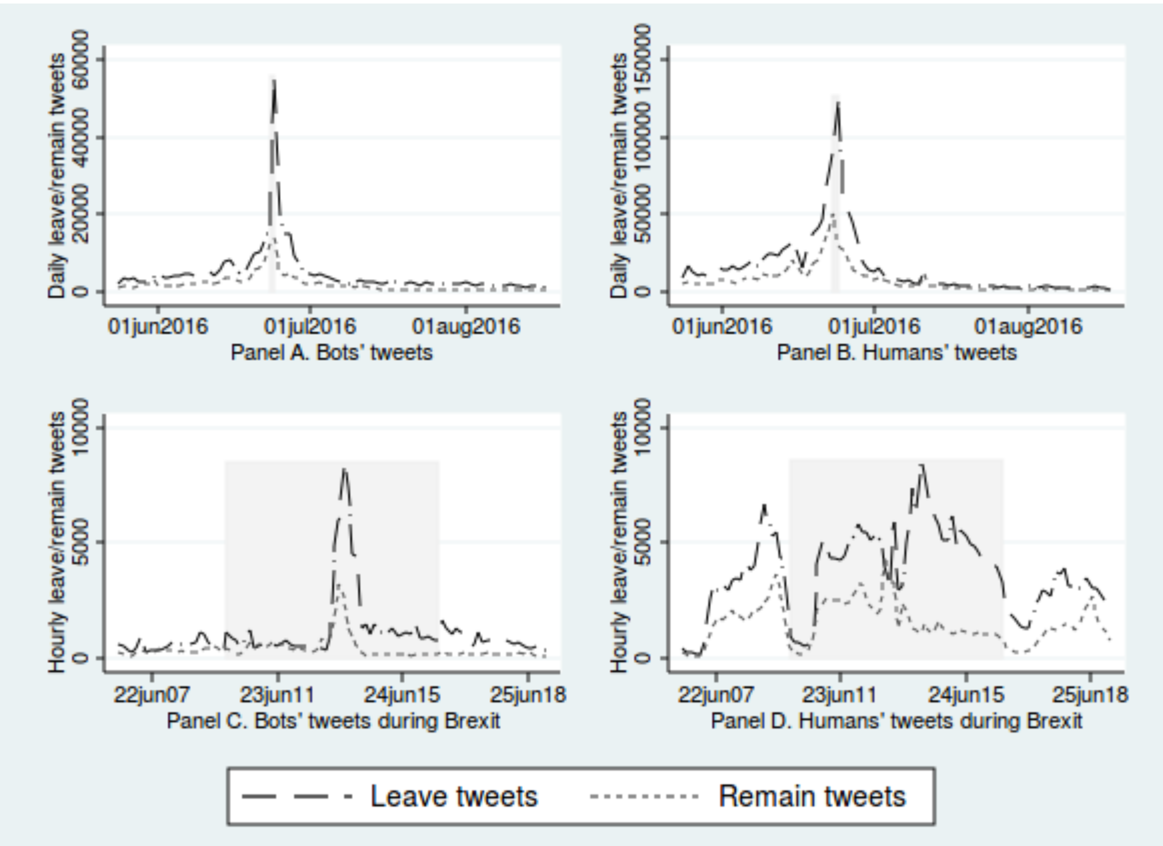


Figure 5. Evolation of bots' tweets with sentiment in full sample

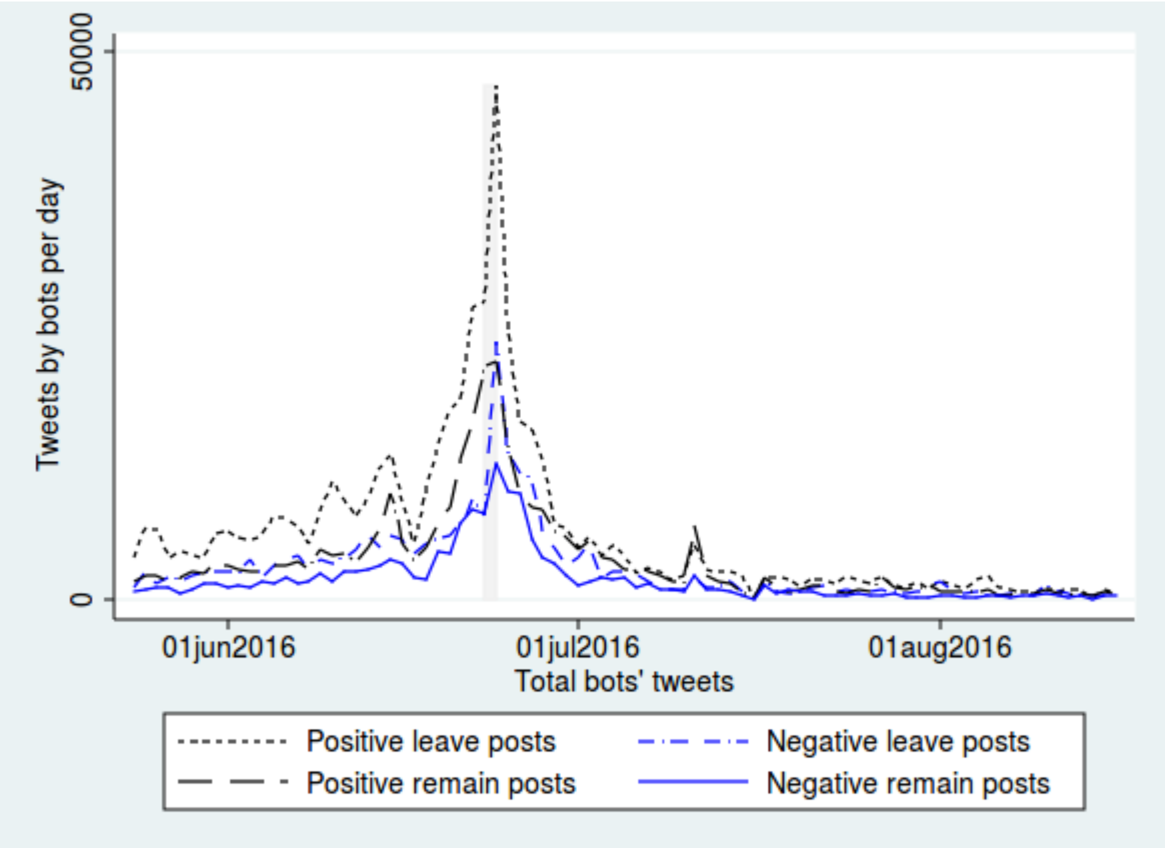


Figure 6. Evolation of bots' tweets with sentiment during Brexit

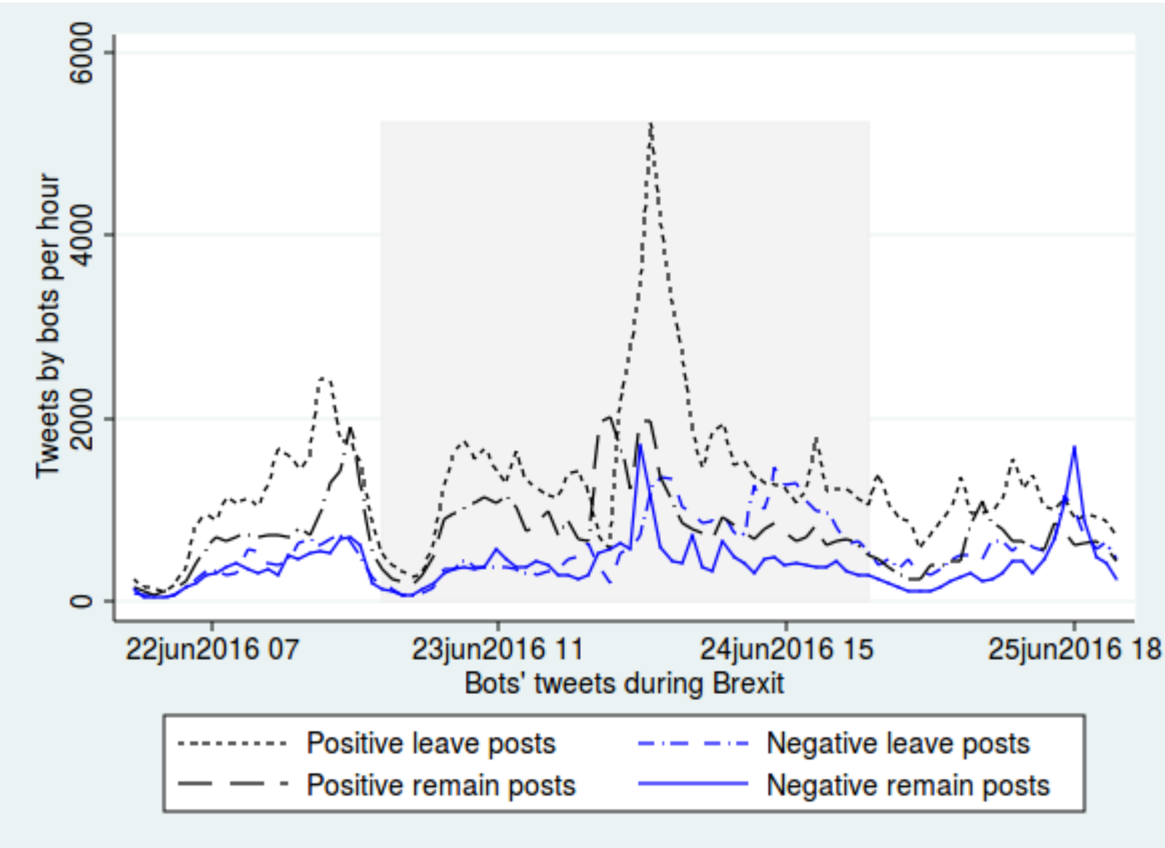


Figure 7. Retweets made by humans and bots

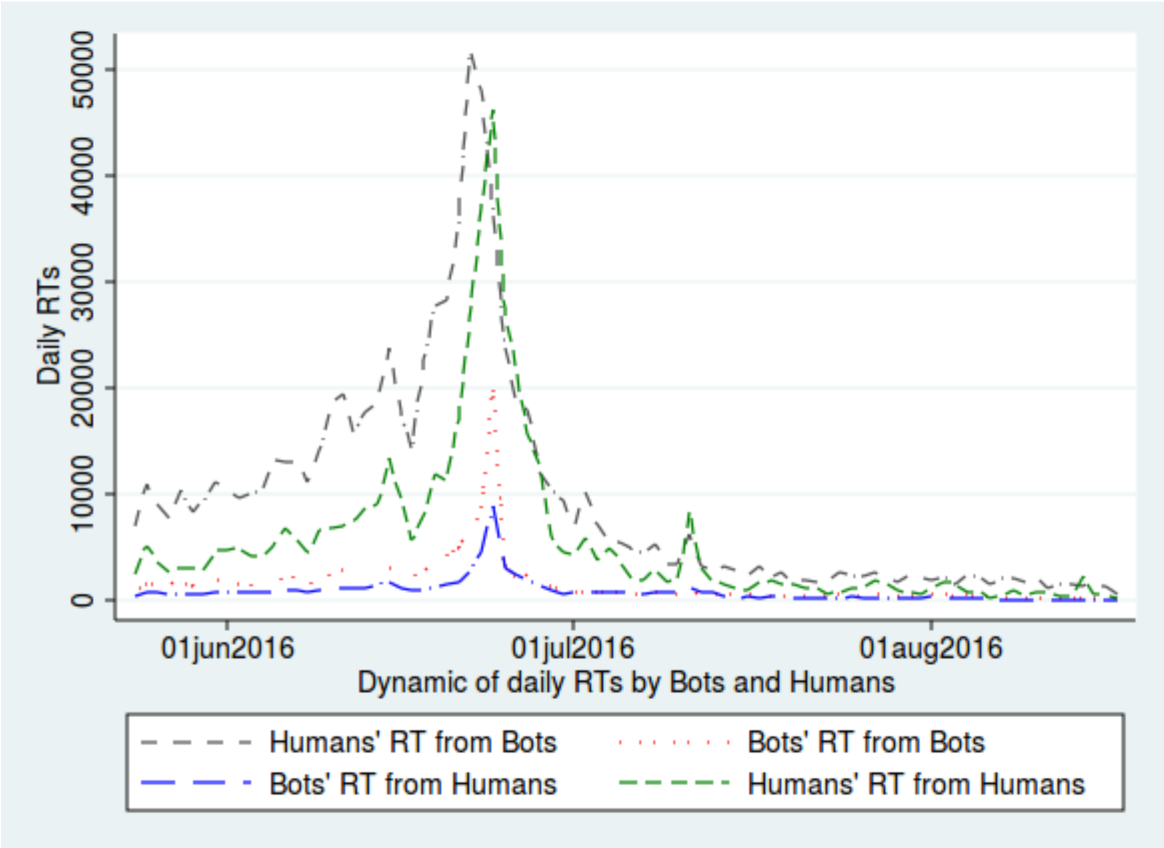


Figure 8. Average bots' tweets that are retweeted by humans and bots before Brexit

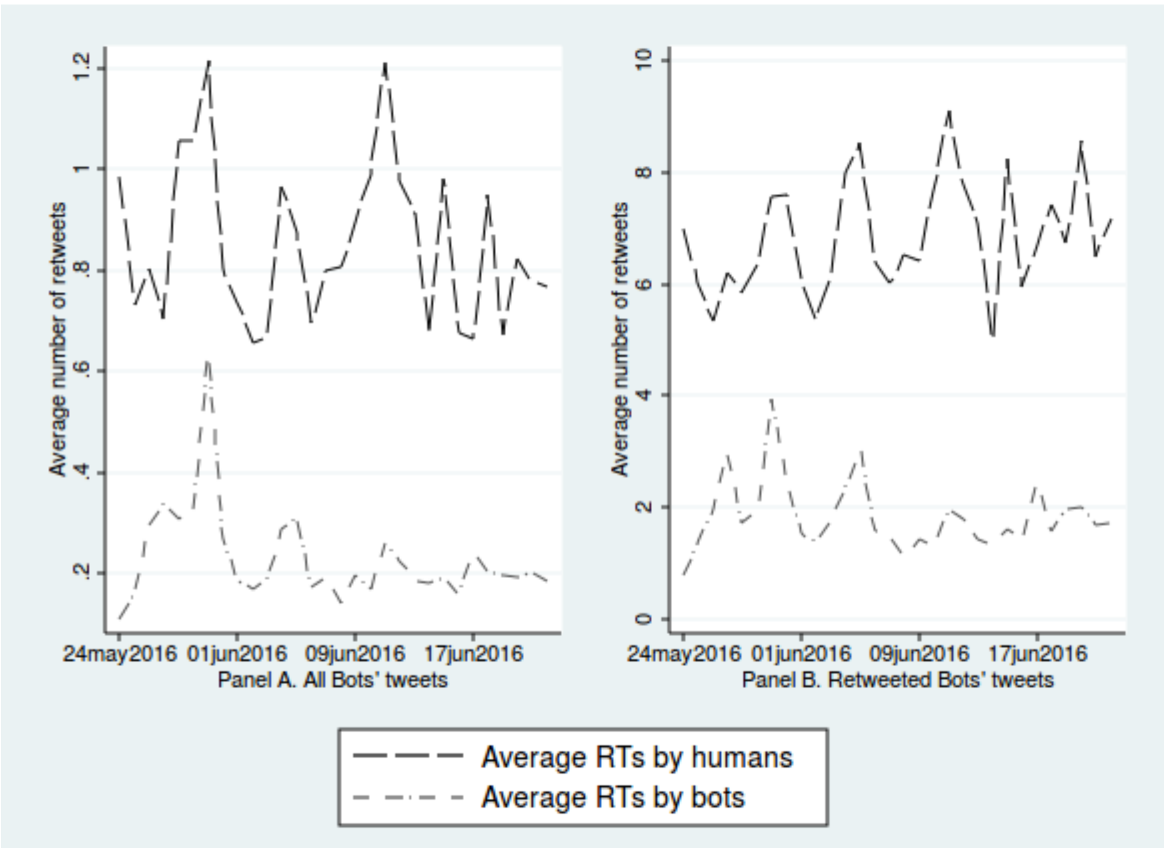


Figure 9. Average bots' leave and remain tweets that are retweeted by bots before Brexit

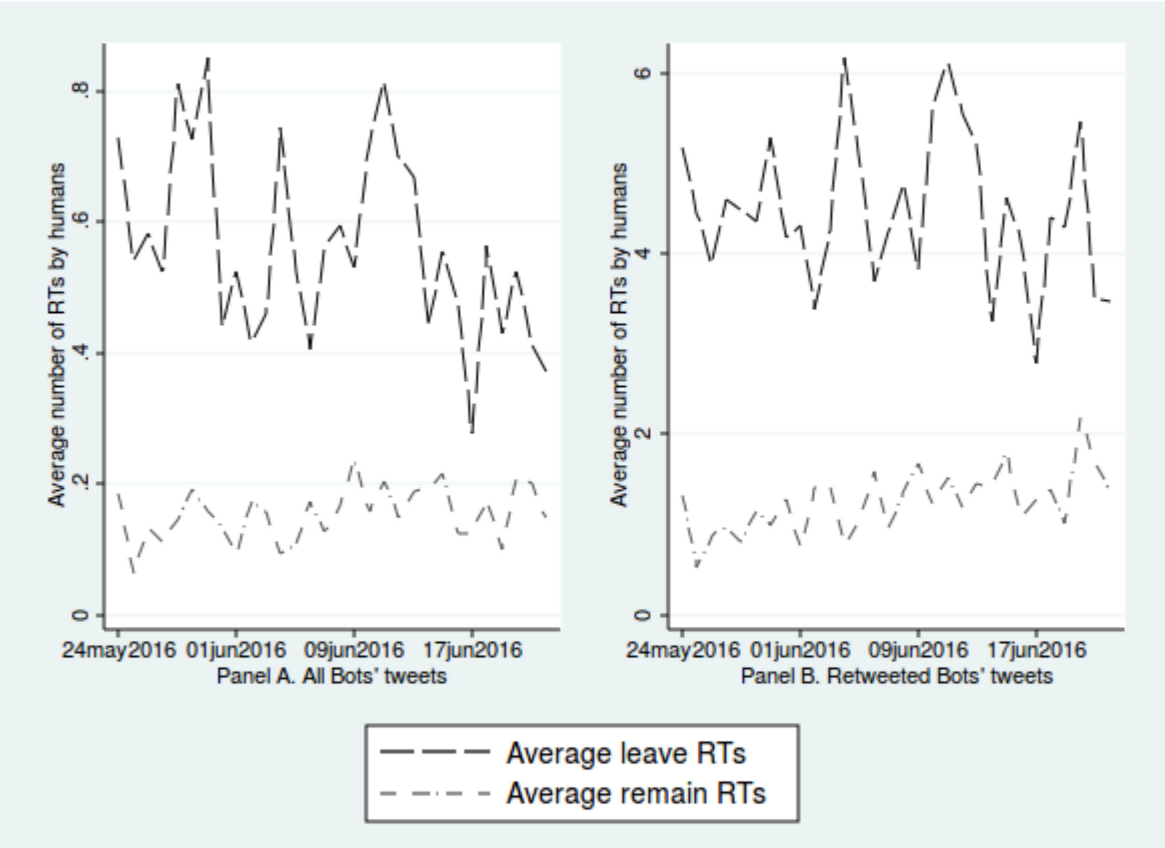
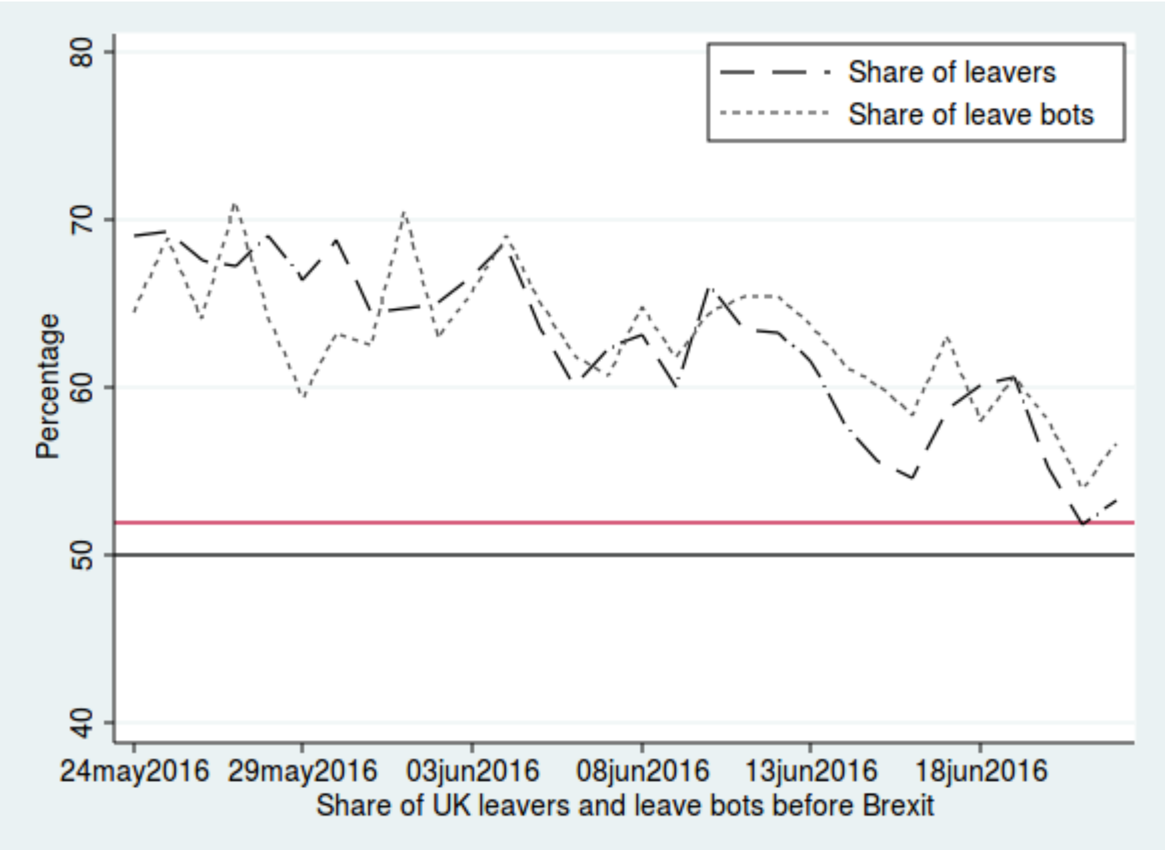


Figure 10. Change in share of leave voters and share of leave bots before Brexit



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