Social Media and News Sources during the 2017 UK General Election

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ABSTRACT

Platforms like Twitter and sources like Wikipedia are important parts of the information diet for many citizens. In this data memo, we analyse Twitter data on bot activity and junk news for a week in the final stages of campaigning of the 2017 UK General Election and also present data on Wikipedia page consultations about those parties and leaders. (1) Content about the Labour Party strongly dominated Twitter traffic in this period. (2) Social media users in the UK shared five links to professional news and information for every one link to junk news. (3) Wikipedia queries have transitioned being mostly about the Conservative Party and Prime Minister Theresa May to being mostly about the Labour Party and the Labour leader Jeremy Corbyn. (4) In comparison to the first week of the campaign period, we find that users are sharing slightly better quality news content, that automated accounts are generating more traffic about the election, and that more of the automation uses Labour-related hashtags (though may not be from the Labour Party itself). (5) In comparison to trends in other countries, we find that UK users shared better quality information than that which many US users shared during the 2016 US election, but worse quality news and information than was shared during the French 2017 election.

SOCIAL MEDIA AND AUTOMATION

Social media and Wikipedia play important roles in the circulation of ideas about politics and public policy. Political actors worldwide are employing both people and algorithms to shape public life.[1], [2] Bots are software intended to perform simple, repetitive, 'robotic' tasks. They can be used to perform legitimate tasks like delivering news and information—real news as well as junk—or undertake malicious activities like spamming, harassment and hate speech. Whatever their uses, highly automated social media accounts are able to rapidly deploy messages, replicate themselves, and pass as human users. Highly automated accounts can be a pernicious means of spreading junk news over social networks of family and friends. For some voters, Wikipedia has become a crucial antidote to junk news.

Multiple media reports have investigated how "fake news" may have propelled Donald J. Trump to victory.[3]–[5] In Michigan, one of the key battleground states, junk news was shared just as widely as professional news in the days leading up to the election.[1] There is growing evidence that social media platforms support campaigns of political misinformation on a global scale. During the 2016 UK Brexit referendum it was found that political bots played a small but strategic role shaping Twitter conversations.[6] The family of hashtags associated with the argument for leaving the EU dominated, while less than 1% of sampled accounts generated almost a third of all the messages.

JUNK NEWS AND AUTOMATION

Social media platforms have served significant volumes of fake, sensational, and other forms of junk news at sensitive moments in public life, though most platforms reveal little about how much of this content there is or what its impact on users may be. The World Economic Forum recently identified the rapid spread of misinformation online as among the top 10 perils to society.[7] Prior research has found that social media favors sensationalist content, regardless of whether the content has been fact checked or is from a reliable source.[8] When junk news is backed by automation, either through dissemination algorithms that the platform operators cannot fully explain or through political bots that promote content in a pre-programmed way, political actors have powerful tools for computational propaganda.[9] Both state and non-state political actors can manipulate and amplify non-factual information online.

Junk news websites deliberately publish misleading, deceptive or incorrect information purporting to be real news about politics, economics or culture.[10] These sites often rely on social media to attract web traffic and drive engagement. Both junk news websites and political bots are crucial tools in digital propaganda attacks—they aim to influence conversations, demobilize opposition and generate false support. What kinds of political news and information are circulating over social media among UK voters? How much of it is high-quality, professional news, and how much content is extremist, sensationalist, conspiratorial, masked commentary, fake, or some other form of junk news? If Wikipedia is an alternative to junk news, what might page views reveal about public sentiments?

ANALSYS OF HASHTAGS & AUTOMATION

Our dataset contains approximately 2,489,000 tweets collected between the 27th of May and the 2nd of June 2017, using hashtags associated with the primary political parties in the UK, the major candidates, and the election itself. This week included televised debates and interviews with the Party leaders. We decided to collect data from Twitter conversations during this period due to the broadcasting of pre-election candidate debates and interviews on national television. We also compare the findings to our earlier study conducted between the 1st and 7th of May.[1]

Twitter provides free access to a sample of public tweets posted on the platform. The platform's precise sampling method is not known, but the company itself reports that the data available through the Streaming API is at most one percent of the overall global public communication on Twitter at any time.[12] In order to get the most complete and relevant data set, we consulted with country experts and used our pilot study data to identify relevant hashtags. We used two sets of hashtags. The first set was used to collect URLs that people were sharing as part of the wider election conversation (see Table 3). A subset of these hashtags (see Table 1) was then selected to collect information about how much Twitter conversation each party was generating and how much of this was automated.

Parliamentary, multi-party systems tend to have a larger variety of hashtags related to particular candidates and important political issues. So our sampling strategy may have missed minor hashtags that refer to small or short-lived conversations about particular people or issues, including tweets that may not have used our identified hashtags at all. Programming for data collection and most of the analysis was done in the R software environment developed. Selecting tweets based on hashtags has the advantage of capturing the content most relevant to the election. The Streaming API yields (1) tweets which contain the selected hashtags; (2) tweets with a link to a web source, such as a news article, where the URL or the title of the web source includes a hashtag; (3) retweets that contain a message's original text, wherein the hashtag is used either in the retweet or in the original tweet; and (4) quote tweets where the original text is not included but Twitter uses a URL to refer to the original tweet.

Our method counted tweets with the selected hashtags in a simple manner. Each tweet was coded and counted if it contained one of the specific hashtags that were being followed. If the same hashtag was used multiple times in a tweet, this method still counted that tweet only once. If a tweet contained more than one selected hashtag, it was credited to all the relevant hashtags. Contributions using none of these hashtags were not captured in this data set. It is also possible that users who used one or more of these hashtags, but were not discussing the election, had their tweet captured. Moreover, if people tweeted about the election, but did not use one of these hashtags or identify a candidate account, their contributions were not analysed here.

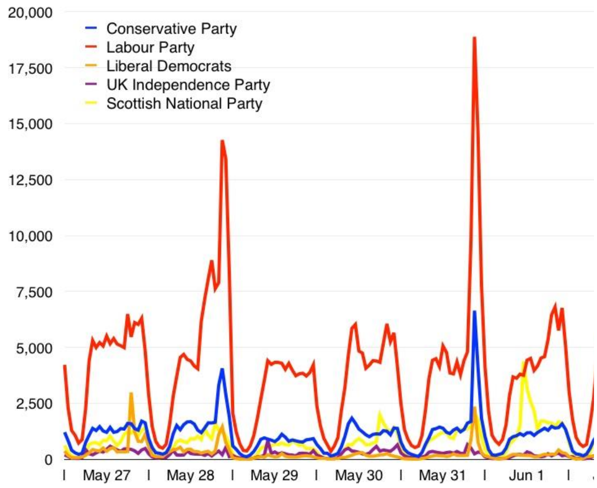
Table 1 and Figure 1 compare the use of party specific hashtags for the sample week. Hashtags about the Labour Party appeared most often,

Table 1: Twitter Conversation about the UK Election

	Number of tweets	%
Labour Party	710,191	61.9
Conservative Party	193,960	16.9
Scottish National Party (SNP)	137,931	12.0
Liberal Democrats	63,027	5.5
UK Independence Party (UKIP)	42,014	3.7
Total	1,147,123	100.0

Source: Authors' calculations from data sampled 27 May – 2 June.
Note: Tory hashtags include #TheresaMay, #Tories, #Tory, #AskTheresaMay, #Conservatives, #VoteTory, #StrongandStable, #ToryManifesto, #ConservativeManifesto, #ImVotingTory; Labour hashtags include #VoteLabour, #Labour, #IC4PM, #Corbyn, #Labourdoorstep, #JeremyCorbyn, #Corbyn4pm, #JezzWeCan, #VoteCorbyn, #LabourManifesto, #ImVotingLabour, #ForTheMany, #VoteNHS; Liberal Democrat hashtags include #LibDems, #LibDemFightBack, #LibDem, #TimFarron, #UniteforEurope, #VoteLibDem, #LibDemSurge, #LibDemManifesto; UKIP hashtags include #UKIP, #Farage , #VoteUKIP, #Nuttall, #UKIPmanifesto; SNP hashtags include #ScotRef, #IndyRef2, #VoteSNP, #SNP, #NicolaSturgeon, #SNPmanifesto.

Figure 1: Twitter Conversation about the Major Parties in the UK Election, Hourly



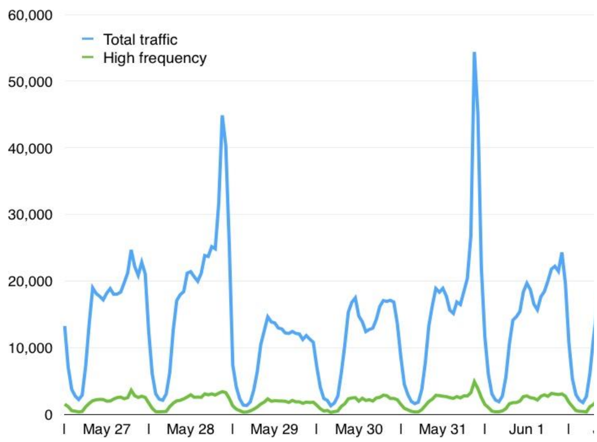
Source: Authors' calculations from data sampled 27 May – 2 June.
Note: This figure is based on the party-specific hashtags used in the tweets.

Table 2: High Frequency Tweeting about the UK Election

	N of Tweets	% of Total	N of Accounts
Labour Party	116,348	16.4	528
Conservative Party	29,710	15.3	522
Scottish National Party (SNP)	27,218	19.7	438
Liberal Democrats	10,673	16.9	372
UK Independence Party (UKIP)	5,048	12.0	389

Source: Authors' calculations from data sampled 27 May – 2 June.

Figure 2: High Frequency Tweeting on the UK Election, Hourly



Source: Authors' calculations from data sampled 27 May – 2 June.

representing 61.9% of the party-specific tweets during the week as a whole. The Conservative Party generated a lower proportion of the conversation at 16.9% and Figure 1 reveals that the Labour Party attracted consistently more conversation than the Conservative Party. At 12%, the Scottish National Party generated a disproportionally high percentage of the conversation, given the size of the party. In comparison to the first sampling period, the Liberal Democrats generated more traffic, 5.5%, attracting more Twitter conversation than UKIP, 3.7%.

Table 2 and Figure 2 reveal the rhythm of Twitter traffic about the UK General Election. We define a high level of automation as accounts that post at least 50 times a day on one of the selected hashtags during the data collection period. This detection methodology fails to capture highly automated accounts that are tweeting with lower frequencies. By political party, it appears that the Conservative Party and the Labour Party have a higher number of highly automated accounts generating traffic about them when compared to the other three parties. We found that there was a large overlap between accounts that tweeted using Labour-related hashtags and accounts that tweeted using Conservative-related hashtags. In total our analysis showed that 522 highly automated accounts were active using both Labour-related hashtags and Conservative-related hashtags. These accounts, however, generated significantly more content when using Labour-related hashtags, as shown in Table 2. We cannot know who manages these accounts, and we do not analyze content or emotional valence of particular tweets. Hence, this information alone is insufficient to determine whether the highly automated accounts are run by the campaign to promote a candidate, or run by outsiders to critique the candidate, or are in fact completely neutral.

Figure 2 reveals that the level of automation being used in UK political conversations is fairly consistent and that it flows in tandem with human-generated content during the natural waking hours of human users. On average, 16.5% of traffic about UK politics is generated by highly automated accounts that we are able to track.

Table 3: UK Political News and Information On Twitter

Type of Source	*N*	*%*	*N*	*%*
Professional News and Information				
Major News Brands	9,823	74.4		
Minor News Brands	3,385	25.6		
Subtotal	13,208	100.0	13,208	48.8
Professional Political Content				
Political Party or Candidate	2,030	78.5		
Government	167	6.5		
Experts	390	15.1		
Subtotal	2,587	100.0	2,587	9.6
Other Political Content				
Citizen or Civil Society	3,630	41.0		
Junk News	2,797	31.6		
Other Political	1,186	13.4		
Russia	239	2.7		
Humor or Entertainment	917	10.4		
Religion	37	0.4		
Political Merchandise	42	0.5		
Subtotal	8,848	100.0	8,848	32.7
Relevant Content Subtotal			24,643	91.1
Other				
Social Media Platform	584	31.1		
Other Non-Political	1,291	68.9		
Subtotal	1,875	100.0	1,875	6.9
Inaccessible				
Language	261	48.2		
No Longer Available	280	51.8		
Subtotal	541	100.0	541	2.0
Total			27,059	100

Source: Authors' calculations from data sampled 27 May – 2 June. Note hashtags include: #generalelection, #ge2017, #brexit, #ge17, #generalelection2017, #remain, #election2017, #stopbrexit, #theresamay, #toriesout, #tories, #torymanifesto, #conservativemanifesto, #imvotingtory, #weakandwobbly, #tory, #asktheresamay, #conservatives, #votetory, #strongandstable, #publicduty, #votenhs, #makejunetheendofmay, #electionfraud, #votelabour, #labour, #jc4pm, #corbyn, #labourdoorstep, #jeremycorbyn, #labourmanifesto, #imvotinglabour, #forthemany, #corbyn4pm, #jezzwecan, #votecorbyn, #libdems, #libdemfightback, #libdemmanifesto, #libdem, #timfarron, #uniteforeurope, #votelibdem, #libdemsurge, #ukipmanifesto #ukip, #farage, #voteukip, #nuttall, #scotref, #indyref2, #votesnp, #snp, #snpmanifesto, #scotland, #nicolasturgeon

ANALYSIS OF JUNK NEWS

To understand what kinds of political news and information UK users are sharing, we then analyzed the links included in the tweets that contained our selected hashtags about the UK election. After determining how often each candidate was being discussed on Twitter, the next step was to determine what information was being shared as political news and information. From our dataset of 2,488,804 tweets, we selected all of the tweets that contained URLs. Between the 27th of May and the 2nd of June, Twitter users in the UK shared 724,988 links on the platform. URLs that pointed towards another tweet were removed from our sample, as most of these tweets are generated automatically by Twitter when someone quotes a tweet. If Twitter users shared more than one URL in their tweet, only the first URL was analyzed. We then generated a random 10% sample of the dataset using a Python script, which contained 27,059 URLs. We removed duplicate URLs from our sample to classify each URL according to our classification system. The classification of each URL was carried out by a team of six coders fluent in the English language and familiar with the media landscape. They worked together over a period of two days, and to ensure consistency across coders a training period was carried out, followed by a short test of ground-truth URLs which all coders were required to pass. Once each unique URL was coded, we expanded the coding to the duplicate URLs to complete the coding for our random 10% sample.

The grounded typology of news platforms and content types that was used is as follows:

- Professional News and Information
  - Major News Brands. This is political news and information by major outlets that display the qualities of professional journalism, with fact-checking and credible standards of production. They provide clear information about real authors, editors, publishers and owners, and the content is clearly produced by an organization with a reputation for professional journalism. This content comes from branded news organizations, including locally affiliated broadcasters.
  - Minor News Brands. As above, but this content comes from small news organizations or startups displaying evidence of organization, resources, and professionalized output that distinguishes between fact-checked news and commentary.

- Professional Political Content
  - Government. These links are to the websites of branches of government or public agencies.
  - Experts. This content takes the form of white papers, policy papers, or scholarship from researchers based at universities, think tanks or other research organizations.
  - Political Party or Candidate. These links are to official content produced by a political party or candidate campaign.

- Other Political Content
  - Junk News. This content includes various forms of propaganda and ideologically extreme, hyper-partisan, or conspiratorial political news and information. This content is deliberately produced false reporting. It seeks to persuade readers about the moral virtues or failings of organizations, causes or people and presents commentary as a news product. This content is produced by organizations that do not employ professional journalists, and it uses attention grabbing techniques, lots of pictures, moving images, excessive capitalization, ad hominem attacks, emotionally charged words and pictures, unsafe generalizations and other logical fallacies.
  - Citizen, Civic, or Civil Society. Links to content produced by independent citizens, civic groups, or civil society organizations. Blogs and websites dedicated to citizen journalism, citizen-generated petitions, personal activism, and other forms of civic expression that display originality and creation more than curation or aggregation.
  - Humor and Entertainment. Content that involves political jokes, sketch comedy, political art or lifestyle- or entertainment-focused coverage.
  - Religion. Links to political news and information with distinctly religious themes and faith-based editorializing presented as political news or information.
  - Russia. This content was produced by known Russian sources of political news and information.
  - Other Political Content. Myriad other kinds of political content, including portals like AOL and Yahoo! that do not themselves have editorial policies or news content, survey providers, and political documentary movies

- Other
  - Social Media Platforms. Links that simply refer to other social media platforms, such as Facebook or Instagram. If the content at the ultimate destination could be attributed to another source, it is.
  - Other Non-Political. Sites that do not appear to be providing information but that were, nevertheless, shared in tweets using election-related hashtags. Spam is also included in this category.

- Inaccessible
  - Language: Links that led to content in foreign language that was neither English nor French, when their affiliation could not be verified through reliable source.
  - No Longer Available. These links were shared, but the content being linked to has since been removed. If some evidence from an author or title field, or the text used in a UR could be attributed to another source, it is.

Table 3 explains the distribution of content shared by UK Twitter users and reveals that the largest proportion of content being shared by Twitter users interested in UK politics comes from professional news organizations, which accounts for 53.6% of the relevant content shared. Relevant content is calculated after non-political content, spam, irrelevant social media, language and inaccessible content have been removed.

Junk news accounts for over a third of other political news and information and accounts for 11.4% of the relevant content shared. Within the professional news content that was shared, the BBC was most popular, with 22.7% of professional news coming from this source. This was followed by The Guardian with 17.7% of links directing to the newspaper's website. A high percentage of other political content that was shared comes from citizen-generated sources like personal blogs or civil society organizations. The number of links to such sources was higher than the number of links to junk news. Like in our earlier UK election study, Russian sources did not feature prominently in the sample, and no content was shared that could be attributed to WikiLeaks. This was in contrast to our project's previous memos on the US and French elections.

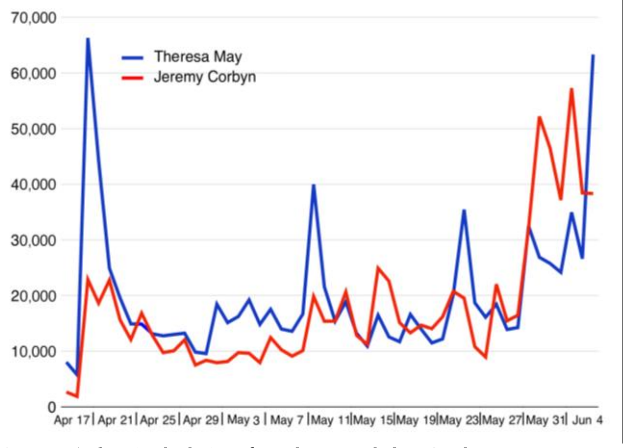
ANALYZING WIKIPEDIA USE

Direct links to Wikipedia pages are rarely shared over Twitter—barely 0.05% URLs linked to Wikipedia in the current sample. But other research has suggested that Wikipedia is an important consultative source for voters during elections and in times of political crisis.

The data are collected through the Wikipedia page views API. Previous research has shown that the volume of search queries and the traffic to articles on Wikipedia are good predictors of voters' behaviour, particularly swing voters.[11] In other words, voters may only seek information about parties and candidates when changing their vote.[12] The data are collected from the English Wikipedia site. This site is used internationally and so we cannot ensure that all visitors are eligible UK voters, this may lead to a margin of error in interpretation.

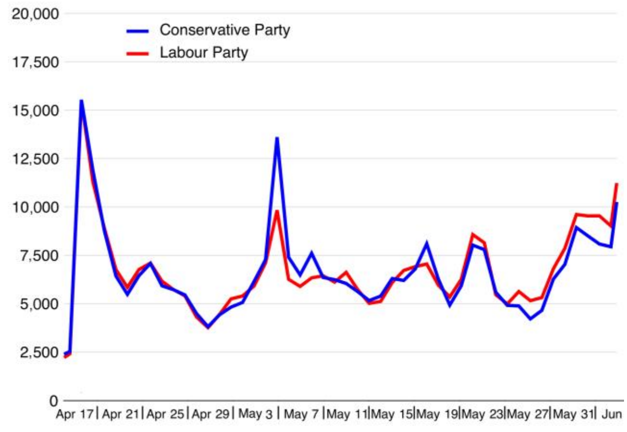
Figures 3 and 4 chart the daily page consultation rate since Prime Minister Theresa May's announcement that a general election would be held. The figures show the number of daily page views to the articles on Wikipedia for the main two parties and their leaders. In the first week of campaigning many more people looked up Theresa May than looked up Jeremy Corbyn, and the readership for pages about the Labour and Conservative parties was about the same size. In the final week of campaigning, according to Table 4, the Wikipedia entries on Jeremy Corbyn and the Labour Party were receiving the most page views.

Figure 3: Wikipedia Page Views for Theresa May and Jeremy Corbyn,



Source: Authors' calculations from data sampled 16 April – 4 June.

Figure 4: Wikipedia Page Views for the Conservative Party and Labour Party, Daily



Source: Authors' calculations from data sampled 16 April – 4 June.

Table 4: Average Wikipedia Page Views, First and Last Week of Campaign Period

	First Week	Final Week
Jeremy Corbyn	13,781	43,134
Theresa May	26,250	33,457
Conservative Party	7,555	8,470
Labour Party	7,533	9,396

Source: Authors' calculations from data sampled 16 April – 4 June.

COMPARISONS OVER TIME

Having analyzed content shared on Twitter over four major elections in the past twelve months, we can now compare the consumption of news and information across several countries. Table 5 shows the levels of automation and junk news shared on Twitter across the major global elections that have occurred so far in 2016-2017.

Earlier in the election campaign, UK social media users shared a higher percentage of junk news content than social media users who were actively discussing German politics and French politics during election periods. In the second sampling period, the proportion of relevant content shared on UK social media identified as junk news was 11.4%, compared to 12.6% during the first UK sampling period, 12.5% in Germany and 5.1% and 7.6% respectively in the two election rounds in France. We also found that UK users were not sharing as much junk news in their political conversations as US users in the lead up to the 2016 elections, where the level of junk news shared was significantly higher. In the days leading up to the US election, we did a close study of junk news consumption among Michigan voters and found users were sharing as much junk news as professional news content at around 33% of total content each.

Substantive differences between the qualities of political conversations are evident in other ways. In the US sample, 33.5% of relevant links being shared led to professional news content. In Germany this was 55.3%, and in France this was between 49.4% and 57% of relevant links across both election rounds. Similarly, in the current UK-based study we show that 53.6% of relevant links being shared led to professional news content. In the initial UK sampling period this was almost identical at 53.4%. Having compared the content shared by UK users across two sampling periods, we can show that the quality of information shared did not differ substantially over time. This is different to the other countries we had investigated, where the quality of information shared deteriorated as the election drew closer. We are also able to show that individuals discussing politics over social media in the European countries sampled tend to share more high quality information sources than US users.

CONCLUSION

The Internet has long been used both for political activism and social control.[15] The term "fake news" is difficult to operationalize, so our grounded typology reflects the diversity of organizations behind the content that was circulated over Twitter by people tweeting about UK politics.

Content about the Labour Party strongly dominated traffic on Twitter in the second sampling period, showing a substantial increase from the earlier in the campaign. Social media users in the UK shared five links to professional news and information for every one link to junk news. Wikipedia page views have gone from being mostly about the Conservative Party and Prime Minister Theresa May to being mostly about the Labour Party and the Labour leader Jeremy Corbyn. In comparison to the first week of the campaign period, we find that users are sharing slightly better quality news content, that automated accounts are generating more traffic about the election, and that more of the automation uses Labour-related hashtags (though may not be from the Labour Party itself). In comparison to trends in other countries, we find that UK users shared better quality information than that which many US users shared during the 2016 US election, but worse quality news and information than was shared during the French 2017 election.

Table 5: Automation and Junk News in Major Elections, 2016-2017							
Country	Percent of relevant content from professional news sources	Percent of relevant content from parties, government agencies, or experts	Percent of content from automated sources	Percent of relevant content that is "Junk News"	Percent of relevant content from Russian news sites	Ratio of links to professionally produced news to other political content	Ratio of links to professionally produced news to junk news
USA – Michigan. Sample, 1-11 November 2016, 22m tweets.	33.5	4.4	-	33.8	1.1	0.5:1	1.0:1.0
Germany. Sample, before voting, 1-13 February 2017, 121K tweets.	55.3	16.8	5.7	12.5	3.3	2.0:1	4.4:1
France I. Sample, before Round 1 voting, 13-19 March 2017, 842K tweets.	57.0	19.2	7.2	5.1	3.0	2.4:1	11.2:1
France II. Sample, between Round 1 and 2, 27-29 April 2017, 960K tweets.	49.4	15.4	16.4	7.6	3.9	1.4:1	6.5:1
United Kingdom. Sample, soon after election announced, 1-7 May 2017, 1.4m tweets.	53.4	11.1	12.3	12.6	1.0	1.5:1	4.2:1
United Kingdom. Sample, candidate debates, 27 May-2 June, 2.5m tweets.	53.6	10.5	16.5	11.4	1.0	1.5:1	4.7:1

Note: 'Relevant content' is calculated after other non-political content, spam, irrelevant social media, language and inaccessible content have been removed.

ABOUT THE PROJECT

The Project on Computational Propaganda (http://comprop.oii.ox.ac.uk) involves international, and interdisciplinary, researchers in the investigation of the impact of automated scripts—computational propaganda—on public life. *Data Memos* are designed to present quick snapshots of analysis on current events in a short format. They reflect methodological experience and considered analysis, but have not been peer-reviewed. *Working Papers* present deeper analysis and extended arguments that have been collegially reviewed and that engage with public issues. The Project's articles, book chapters and books are significant manuscripts that have been through peer review and formally published.

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REFERENCES

[1] M. Kaminska, J. Gallacher, B. Kollanyi, T. Yasseri, and P. N. Howard, "Social Media and News Sources during the 2017 UK General Election," Jun. 2017.

[2] M. Forelle, P. Howard, A. Monroy-Hernández, and S. Savage, "Political Bots and the Manipulation of Public Opinion in Venezuela," *ArXiv150707109 Phys.*, Jul. 2015.

[3] H. J. Parkinson, "Click and elect: how fake news helped Donald Trump win a real election," *The Guardian*, 14-Nov-2016.

[4] M. Read, "Donald Trump Won Because of Facebook," *New York Magazine*, Npvember-2016.

[5] C. Dewey, "Facebook Fake-News Writer: 'I Think Donald Trump is in the White House Because of Me,'" *The Washington Post*, 17-Nov-2016.

[6] P. N. Howard and B. Kollanyi, "Bots, #Strongerin, and #Brexit: Computational Propaganda during the UK-EU Referendum," Project on Computational Propaganda, Oxford, UK, Working Paper 2016.1, Jun. 2016.

[7] World Economic Forum, "10. The Rapid Spread of Misinformation Online," *Outlook on the Global Agenda 2014*, 2014. .

[8] M. D. Vicario *et al.*, "The Spreading of Misinformation Online," *Proc. Natl. Acad. Sci.*, vol. 113, no. 3, pp. 554–559, Jan. 2016.

[9] A. S. Kümpel, V. Karnowski, and T. Keyling, "News Sharing in Social Media: A Review of Current Research on News Sharing Users,

Content, and Networks," *Soc. Media Soc.*, vol. 1, no. 2, p. 2056305115610141, Sep. 2015.

[10] P. N. Howard, "Digitizing the social contract: Producing American political culture in the age of new media," *Commun. Rev.*, vol. 6, no. 3, pp. 213–245, 2003.

[11] T. Yasseri and J. Bright, "Can electoral popularity be predicted using socially generated big data?," *It - Inf. Technol.*, vol. 56, no. 5, pp. 246–253, 2014.

[12] T. Yasseri and J. Bright, "Wikipedia traffic data and electoral prediction: towards theoretically informed models," *EPJ Data Sci.*, vol. 5, no. 1, p. 22, Dec. 2016.