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Article

Calculated vs. Ad Hoc Publics in the #Brexit Discourse on Twitter and the Role of Business Actors

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Abstract: Mobilization theory posits that social media gives a voice to non-traditional actors in socio-political discourse. This study uses network analytics to understand the underlying structure of the Brexit discourse and whether the main sub-networks identify new publics and influencers in political participation, and specifically industry stakeholders. Content analytics and peak detection analysis are used to provide greater explanatory values to the organizing themes for these sub-networks. Our findings suggest that the Brexit discourse on Twitter can be largely explained by calculated publics organized around the two campaigns and political parties. Ad hoc communities were identified based on (i) the media, (ii) geo-location, and (iii) the US presidential election. Other than the media, significant sub-communities did not form around industry as whole or around individual sectors or leaders. Participation by business accounts in the Twitter discourse had limited impact.

Keywords: social media; Brexit; mobilization theory; normalization theory; network analytics

1. Introduction

Social media allows individuals and organizations to create and share content, consume content created by other users, and facilitate connections between users [1]. As a predominantly open social network, Twitter has attracted widespread attention from a marketing and communications perspective due to its large global user base and electronic word of mouth potential. In particular, the ability for users to identify and/or connect with others with similar and/or opposing views and thus rapidly form identifiable issue-centered publics or sub-networks on Twitter has attracted significant attention from political and social sciences researchers worldwide [2–5]. Mobilization theory posits that the Internet generally, and Web 2.0 and social media specifically, lead to new forms of democratic and civic participation through enhancing political knowledge and facilitating discussion [6,7]. Bruns and Burgess [8] highlight the central role of hashtags in coordinating publics on Twitter. They differentiate between ad hoc and calculated publics by referencing the extent to which a community is self-organized (ad hoc), or organized by one or more institutional actors (e.g., media, government or not-for-profit organizations) who offer an additional layer of coordination and institutionalization (calculated) [8].

On 22 February 2016, the Prime Minister of the United Kingdom (“UK”) announced a referendum to be held on 23 June 2016 regarding UK membership of the European Union (“Brexit”). The result of Brexit was a vote to leave the European Union (51.89%). As well as the formal campaigns, Britain Stronger in Europe (Remain) and Vote Leave (Leave), campaigns were initiated by political stakeholders (e.g., Conservatives In, Labour in for Britain, Labour Leave), industry (e.g., National Outsourcing Association, European Federation of Pharmaceutical Industries and Associations,

Business for Britain) and civic society stakeholders (e.g., Scientists for EU, Universities for Europe, Economists for Brexit). Both the leave and remain campaigns were active on Twitter. A number of studies have been published on the use of Twitter in Brexit. These have focused on outcome prediction [9]; opinion analysis [10,11], influential identification [12,13], and mood and sentiment analysis [14–16]. This study examines the Brexit referendum discourse on Twitter through the lens of mobilization theory using network analytics. This paper analyzes a dataset of over 10 million tweets featuring the hashtag #Brexit published from February 2016 to July 2016. We ask two research questions:

RQ1: *Is the #Brexit discourse on Twitter dominated by calculated publics or ad hoc publics?*

RQ2: *What role did non-media business accounts play in the #Brexit discourse on Twitter?*

The paper makes use of network analytics to identify calculated and ad hoc publics, rank the relative prominence of sub-networks in the dataset, and identify influential users and key brokers within these sub-networks. Content analytics and peak detection analysis are used to provide greater explanatory value to the potential organizing themes for these sub-networks. The empirical context for this study is both novel and topical. Firstly, there are few studies on mobilization theory (a) focusing on non-media business organizations, (b) using referendums as an empirical context, and (c) using network analytics as a primary methodology. Secondly, Brexit is still a relatively recent event and its context is evolving. Thirdly, few referendums have been as significant to business as Brexit while at the same time substantially lacking societal consensus. Thus, the participation of businesses in the Brexit discourse on social media provides a potentially rich source of data for understanding who, how and why businesses engage in socio-political discourse. The findings from this initial study extend our understanding of the role of different actors in the Brexit discourse, the prominence of calculated and ad hoc publics in political and societal discourses on Twitter, and insights on the role of Twitter in stakeholder and civic engagement.

The remainder of this paper is organized as follows. The next section provides a brief overview of the related literature on social media usage in social and civic discourse, and specifically socio-political involvement by firms. Following an overview of the empirical context and the methods for collecting and analyzing data, the results of the analysis are presented. This is followed by a brief discussion. The paper concludes with a summary of key findings and a discussion on the limitations of the research and avenues for future research.

2. Background and Theoretical Context

While oft-referenced, social media has a wide range of meanings. Lynn et al. [17] identify three main definitional perspectives—the application view, the communications views and the integrated view. The applications view defines social media with reference to the Internet-based software applications that allow the creation and exchange of user generated content [18]. In contrast, the communications view defines “social media as communication systems that allow their social actors to communicate along dyadic ties” [19]. This paper follows the integrative view as per Kietzmann et al. [20], which defines social media as comprising both the conduits and the content disseminated through interactions between individuals and organizations. Kaplan and Haenlein [18] identify six categories of social media: (i) collective projects (e.g., Wikipedia), (ii) blogs and microblogs (e.g., WordPress and Twitter), (iii) content communities (e.g., YouTube), (iv) social networks (e.g., Facebook), (v) massively multi-player online role-playing games (e.g., World of Warcraft) and (vi) social virtual worlds (e.g., Second Life). However, as social media has evolved, researchers have pointed to the blurred lines between different types of social media and social networking sites [17,21]. More nuanced frameworks for examining social networks have emerged. Kietzmann et al. [20] identify seven functional building blocks of social media which can be used to categorize social media services—(i) identity, (ii) presence, (iii) relationships, (iv) reputation,

(v) groups, (vi) conversations, and (vii) sharing. Others suggest that the application or thematic focus (news, entertainment, document sharing etc.) or user type (individual or enterprise) may also provide insights [17].

Twitter is one of the largest social networking sites worldwide, with over 186 million monetizable daily active users [22]. It is historically and primarily a micro-blogging site and thus enables users to send and read short posts instantaneously [23]. Originally limited to 140 characters of text, Twitter has evolved to support a wide range of content including longer text, private messaging, multiples images, audio, live and recorded video, URLs and other resources. While Kaplan and Haenlein [18] categorize blogs and microblogs together, Java et al. [24] point to the predominantly short nature of posts combined with the relative instantaneous nature of microblogging as key differentiators which result in higher update frequencies and more real-time updates. Twitter is used to provide updates on a user's personal life, post real-time information and gather interesting and useful information for work or personal interests [25]. One of the most popular mechanisms for information sharing on Twitter is the ability to forward the message of another user to your followers, an activity known as retweeting [26]. Hashtags are a prominent feature of Twitter and are used by users to identify users with similar or opposing views, collate information from these users or on a topic, and interact with them [3]. It is worth noting that Twitter is largely an open network where the majority of interactions are in the public domain and can be accessed by following a user, search or hashtags. Unlike Facebook or LinkedIn, where users typically authorize the connection with another user based on a pre-existing relationship or some other criteria, Twitter typically requires no such approval. As such, it is distinctive in that it connects strangers through following and content, in the form of hashtags.

One can view the role of social media in the public sphere at different levels. Social networking sites (SNS) like Twitter, play a macro-level role as part of the wider media ecology which act as spaces for public discourse for individuals at a micro-level. Bruns and Burgess [3] argue that the hashtag on Twitter plays an important coordinating role on Twitter, by facilitating the formation of issue-centered publics, which may or may not correspond to and correspond with related issue-centered publics in other public spheres, both online and offline. They posit that the relatively real-time and short-form format of Twitter makes it particularly effective in rapidly responding to emerging issues and events when compared to other media channels which may be subject to more formal editorial considerations [3]. Such publics may form communities around a shared interest, represented by a specific hashtag for the purpose of engagement and/or knowledge gathering [8]. These topical hashtag communities may be characterized as ad hoc or calculated. Ad hoc hashtag communities can be formed in an instant without necessarily any additional coordination other than the use and reuse by others of a hashtag [3]. In contrast, calculated communities can be formed praetor hoc in anticipation of a foreseeable event or some time later once the significance of an event has been established, often by mainstream media and traditional actors in socio-political discourse [3]. As such, topical hashtag communities can be distinguished by their spontaneity.

Since the advent of accessible Internet and the acceleration of adoption resulting from ubiquitous connectivity, mobile technologies and social media, two primary hypotheses have been posited by researchers. Proponents of mobilization theory posit that the Internet, in all its guises, should lead to new actors and new forms of democratic and civic participation [27–29]. Enjolras [30] suggests that the low cost of participation online will mobilize civic and political engagement at the micro-level. Papacharissi [7] highlights the power of social media to enable many-to-many communication and the connectivity of both private and public spheres for political discourse. In contrast, normalization theorists posit that the Internet and Web 2.0 largely reproduce and reinforce the existing social biases in social and civic discourse [31,32]. The reality is most likely some place in between. The overlap of private and public spheres, both offline and online, are being both enabled and exploited by a 'hybrid media system' and new 'hybrid mobilization movements' [33,34]. In the context of Twitter, empirical evidence suggests that candidates and campaigns use Twitter to influence coverage of political topics in the media [33,35] and that the media use Twitter as a source of content [36,37]. Similarly, participation

by non-traditional actors has been identified in campaigns [38], supporters [39], and socio-political events [40]. A topical example is the use of Twitter by the Trump campaign in the 2016 US presidential election and media consumption of such content [5]. While this case, at first glance, may be perceived to support the normalization theory, emerging research on the presidential campaign suggests that part of the Trump campaign's success was mobilizing new participants, often disparate groups with only democrat opposition in common, through social media use, and through the use of bots and other forms of automated accounts [41,42]. Research on the use of Twitter in referendums from a mobilization perspective is limited. Suiter et al. [43] present evidence of new actors being mobilized in three Irish constitutional referendums (including small- to medium-sized organizations), but little difference in the content being discussed.

While the primary focus of this paper is a study of the network structure of the Brexit discourse on Twitter, a secondary focus is the participation of business organizations in this discourse. This is interesting as an empirical context, as Twitter is used widely by businesses, large and small [44–46]. While there are numerous studies on the use of Twitter to meet a variety of business objectives, there is a relative dearth on the use of Twitter for socio-political objectives. Corporate participation in civic discourse can be categorized into three primary categories: corporate social responsibility (CSR), corporate political activities (CPA) and socio-political involvement (SPI). CSR is typically given to refer to the integration by a corporation of responsibilities to society and the environment into their business operations and interactions with stakeholders [47]. CPA differs from CSR in that rather than responding to societal needs, firms attempt to shape government policy in ways favorable to the firm [48]. While both CSR and CPA have a socio-political dimension, the linkage between a firm's business objectives and the socio-political activity remains. In contrast, SPI involves firms taking positions on issues that are characterized as lacking societal consensus, having low information rationality, and evolving viewpoints and issue salience [49]. As a result, SPI is considered riskier and more controversial than CSR and even CPA. Participating, and specifically taking a position, in a discourse that lacks societal consensus may be viewed in two ways by stakeholders. Stakeholders may perceive the firm acting ethically or virtuously, responding to stakeholder pressures, and/or reflecting the ideologies of senior management. Alternatively, the firm may alienate stakeholders with opposing views for limited or no operational benefits [49]. Nalick et al. [49] view social media as a key enabler of SPI, as corporate leaders can share their views on socio-political issues for little or no cost [50].

3. Research Method

3.1. Empirical Context

This paper explores the participation of different publics in the Twitter discourse on Brexit. As such, the empirical context is informed by referendums in general, the British political context, and Twitter. In a referendum, the electorate vote on a public issue that is more or less specific and determined [51,52]. While referendums interact with the mechanisms and decision-making processes of representative democracy and government, they are discrete mechanisms in themselves, and as a result may represent a tension between these two mechanisms [52,53]. Constitutional referendums, in particular, can be viewed as a unique feature in the modern political landscape in which civic duty and political dissatisfaction drive participation [54]. The United Kingdom is a parliamentary sovereignty. As a result, constitutional referendums presented to the whole of the United Kingdom are relatively rare and not legally binding. To date, there have only been three such referendums, the first related to continued membership of the European Community (EC) in 1975, the second, in 2011, related to electoral reform, and the most recent and subject of this study was Brexit in 2016. As discussed, the result of Brexit was a narrowly won vote to leave the European Union, and this reflects a lack of societal consensus. Indeed, reporting in the media suggests that the Brexit campaign featured significant information asymmetries and low information structures, as well as a high degree

of shifting views over the period of the referendum. As such, Brexit contains all the elements of a socio-political issue as per Nalick et al. [49].

Twitter is a suitable empirical context for a variety of reasons. As discussed earlier, Twitter is largely an open network, widely used in political discourse by wide variety of stakeholders, and has a range of features and functionality that allow for analysis of topic-based communities. In the context of the UK, social media was used by over 63% of UK adults in 2016 [55], and while Twitter does not release country-level statistics, sources report that approximately 17% of the UK population used Twitter daily at the time of the Brexit referendum [56].

3.2. Methodology

GNIP, Twitter's enterprise API platform, was used to prepare a dataset of all English language tweets featuring the hashtag '#Brexit' from the announcement of the referendum on 23 February 2016 until 23 July 2016, one month after the vote. These data were augmented to include supplemental data, including Klout Score (a Social Network Influencer Score), geographic location and URL expansion. The final dataset used in the study comprised 10,651,454 tweets generated from 2,137,807 unique screen-names (accounts). The dataset featured 206,032 unique hashtags.

Descriptive analytics involved the use of statistical and data mining techniques to develop and visualize descriptive statistics and were carried out using R, an open source data science programming language. To identify communities, the prominence of sub-networks, and key brokers within these sub-networks, network analytics were carried out using the Gephi open graph visualization platform. The ForceAtlas-2 algorithm was used to construct a graphical representation of the overall network topology and the topologies of sub-communities in the Brexit dataset. The network topology was designed by grouping all the vertices into communities using Blondel et al.'s community detection algorithm in Gephi [57]. The network for the data set was constructed using the screen-name and the reply-to-user-screen-name attributes, since they helped in establishing links between the users in the network. The network had 251,144 nodes and 436,697 edges. In line with Myers et al. [58], degree distribution, connected components, shortest path lengths, clustering coefficients, and two-hop neighborhoods were analyzed to determine whether the #Brexit dataset and prominent sub-networks represent information networks or social networks.

Centrality analysis was undertaken to measure betweenness centrality and in-degree, metrics commonly used to identify the hubs and influencers in a social network. To supplement the analysis on influential users, the most active users and most visible users were identified as per Cha et al. [59]. The activity of the users was determined by the number of tweets contributed by a user, while the number of followers was used as a metric to determine the visibility of the users.

In order to greater understand the #Brexit public as a whole and prominent sub-networks, we used content analytics and peak detection analysis to conduct preliminary analysis on the topic discourse over a calendar year. Content analytics were carried out by cross-referencing the content and structural features to identify usage patterns [60]. Word analysis and hashtag analysis were used to extract intelligence from the data set. Items attracting abnormal interest were identified by using three peak detection algorithms to validate the results as per Healy et al. [61], i.e., Du et al.'s [62] continuous wavelet transformation, Palshikar's [63] peak detection algorithm (S1) and Lehmann et al.'s [64] peak detection algorithm.

To supplement the network analytics and to gain further insights into the participation of business firms in the Brexit dataset, non-media business Twitter accounts with a Klout score greater than 75 were identified. Klout is a system-generated tool for measuring social media influence and has been found to be a good indicator for credibility in the absence of other data [65]. Overall, 239 tweets generated by only 49 discrete screen-names identified as non-media business accounts were identified and categorised by sector. These were classified manually by business objectives as per Eschenbrenner et al. [66] and extended by Lynn et al. [67], and socio-political engagement as per Nalick et al. [49]. Two coders independently interpreted the intent of each

tweet and classified each into one of the categories per coding scheme. Inter-rater reliability with Kappa coefficients of 0.99 and 0.94 were achieved for the two coding schemes respectively.

4. Findings

4.1. Descriptive Analytics

The Brexit dataset had 10,651,454 tweets, of which 3,740,846 (35 percent) were original tweets and 6,910,608 (65 percent) were retweets. Replies constituted 15 percent (565,912) of the total number of the original tweets. The dataset had 206,032 unique hashtags. There were 2,137,807 unique screen-names in the dataset. The most active and visible users were identified. The activity and visibility of users were calculated as per Chae [68]. The visibility of a user was determined by the total number of retweets and replies received by each user at 23 July 2016. The activity of a user was calculated as the sum of the number of tweets, retweets and replies which the user has contributed to the network.

Table 1 presents a list of the top 25 most visible users along with their activity count; Table 2 provides a list of the top 25 most active users along with their visibility values. It can clearly be observed from these tables that the most visible users are not the most active users, and vice versa. Interestingly, @Snowden (the second most visible user) is not among the most active users in this network. Similarly, @brexitmarch (the most active user) is not among the most visible users.

Table 1. Top 25 Visible Users and their Activity.

User Screen Name	Number of Retweets Received (A)	Number of Replies Received (B)	Visibility (A + B)	Activity (Tweets + Retweets + Replies)
BBCBreaking	54,573	1172	55,745	43
business	43,815	675	44,490	1378
Snowden	42,611	117	42,728	1
joffley	40,437	6	40,443	1
nicoleperlooth	28,555	48	28,603	4
PrisonPlanet	24,981	950	25,931	174
CNN	24,714	648	25,362	92
LeaveEUOfficial	18,994	1426	20,420	816
Nigel_Farage	13,599	4564	18,163	52
BBCNews	15,636	2190	17,826	251
DartmouthDerek	16,738	2	16,740	10
TheEconomist	15,636	807	16,443	220
benphillips76	16,359	12	16,371	10
MoDeutschmann	16,051	5	16,056	4
scottbix	15,669	14	15,683	4
McIlroyRory	15,488	35	15,523	1
LouiseMensch	13,900	1173	15,073	2600
theordinaryman2	13,935	307	14,242	3080
feminizza	13,848	6	13,854	5
Dwalingen	13,384	125	13,509	4903
billmaher	13,384	77	13,461	1
wmyeoh	12,933	15	12,948	6
sturdyAlex	12,470	127	12,597	192
RT_com	11,849	341	12,190	351
Pdacosta	11,831	87	11,918	628

Table 2. Top 25 Active Users.

User Screenname	Original Tweets (A)	Retweets (B)	Replies (C)	Activity (A + B + C)	Number of Retweets Received (D)	Number of Replies Received (E)	Visibility (D + E)
brexitmarch	37,215	0	0	37,215	371	6	377
iVoteLeave	0	34,296	0	34,296	0	74	74
Col_Connaughton	31,805	0	2	31,805	2182	33	2215
iVoteStay	0	21,560	0	21,560	0	70	70
Fight4UK	4087	5544	49	9631	5985	210	6195
RoyalNavyNews	7078	1835	4593	8913	595	27	622
MikkiL	486	8126	360	8612	897	206	1103

Table 2. Cont.

User Screenname	Original Tweets (A)	Retweets (B)	Replies (C)	Activity (A + B + C)	Number of Retweets Received (D)	Number of Replies Received (E)	Visibility (D + E)
UKIPNFKN	6447	783	632	7230	3498	211	3709
SaraPadmore	1	6510	0	6511	0	2	2
marie52d	37	6210	25	6247	9	5	14
KimKligonian	6158	0	0	6158	222	2	224
JodieActy	939	5102	118	6041	852	25	877
BrexitLive	5833	11	5	5844	327	12	339
EUVoteLeave23rd	2770	2265	241	5035	5609	215	5824
mwengway	1652	3316	1624	4968	224	12	236
Dwalingen	2806	2097	240	4903	13,384	125	13,509
BUZZ_Just_In	4741	12	0	4753	14	1	15
2053pam	506	3955	352	4461	476	29	505
richyh5712	666	3784	10	4450	668	27	695
Jeansmart45Jean	86	4194	3	4280	49	7	56
IsThisAB0t	0	4239	0	4239	0	1	1
tallison54	421	3740	282	4161	289	18	307
KeithBe1	27	4120	10	4147	83	15	98
MarkInNorthWest	2717	1411	438	4128	568	35	603
belindawood99	528	3505	54	4033	313	17	330

4.2. Network Analytics

4.2.1. Topological Analysis

The #Brexit network was built from the reply tweets. The network had 251,144 nodes and 436,697 edges. Nodes correspond to users who received at least one reply during the time period covered by our dataset. Edges represent the link between the source and the target of each reply message. The average degree of the network was found to be 1.739, suggesting that each user is engaged with at least one other user in the network. The average degree is on the lower end, and this can be attributed to the presence of many users who engage less in the network. Network diameter measures the largest distance between any two nodes in the network. A small network diameter is an indication of the presence of powerful hubs in the network. The network diameter was found to be 22. The network density which is the ratio of actual connections and potential connections in the network is 0.001; mainly due to less connected users. In other words, users in this network are not utilizing the potential connections available in the network. The average path length which measures the average distance between any two nodes was found to be 6.275, indicating the presence of powerful hubs in the network which connect different users in the network, thereby acting as facilitators. Figure 1 provides a network topology for the #Brexit network, constructed using the ForceAtlas-2 algorithm in Gephi.

Community analysis provides deeper understanding of social networks through a deeper analysis of relationships at the sub-network level. The Blondel algorithm [57] was used for this analysis due to its ability to work with real-world network data, given its computational efficiency when compared to other community detection algorithms. The algorithm found 33,788 distinct communities in the network. The modularity of a network, which measures the strength of a network when divided into communities or clusters, was found to be 0.598 (maximum being one). This suggests that nodes have moderately dense connections within communities and sparse connections with nodes from other communities. Figure 2 and Table 3 provide the network characteristics for the five largest communities in the #Brexit dataset respectively, where each community is denoted by SC1 to SC5 by degree of magnitude, with SC1 being the largest sub-community. Additional analysis was undertaken to examine the network typologies of these communities. These are presented in Figure 2. These sub-communities represent up to 30% of users participating in the #Brexit discourse on Twitter under examination.

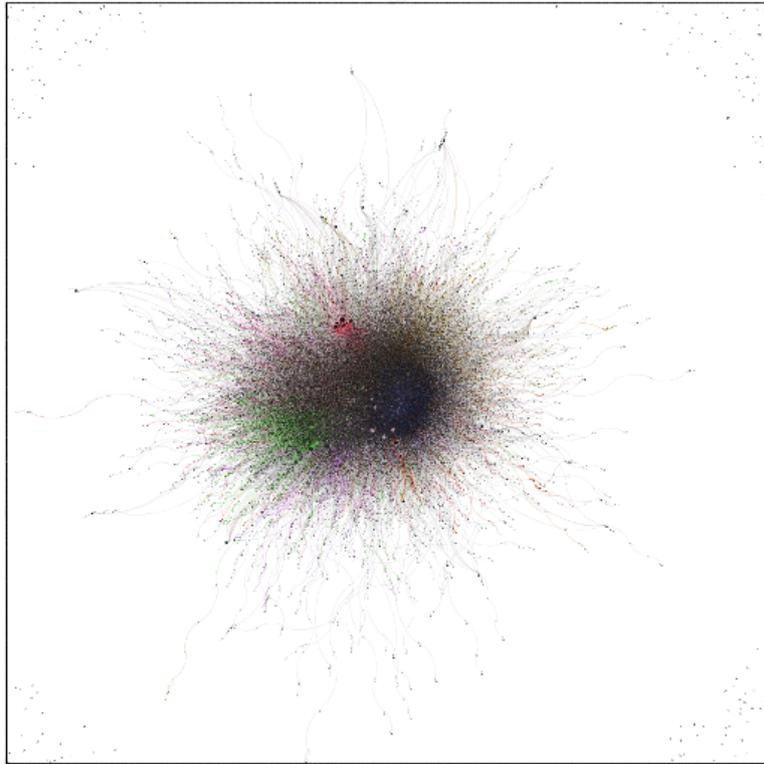


Figure 1. Analysis of the network topology for the #Brexite Network suggests that there are powerful hubs in the network that facilitate connections between a large volume of less connected users.

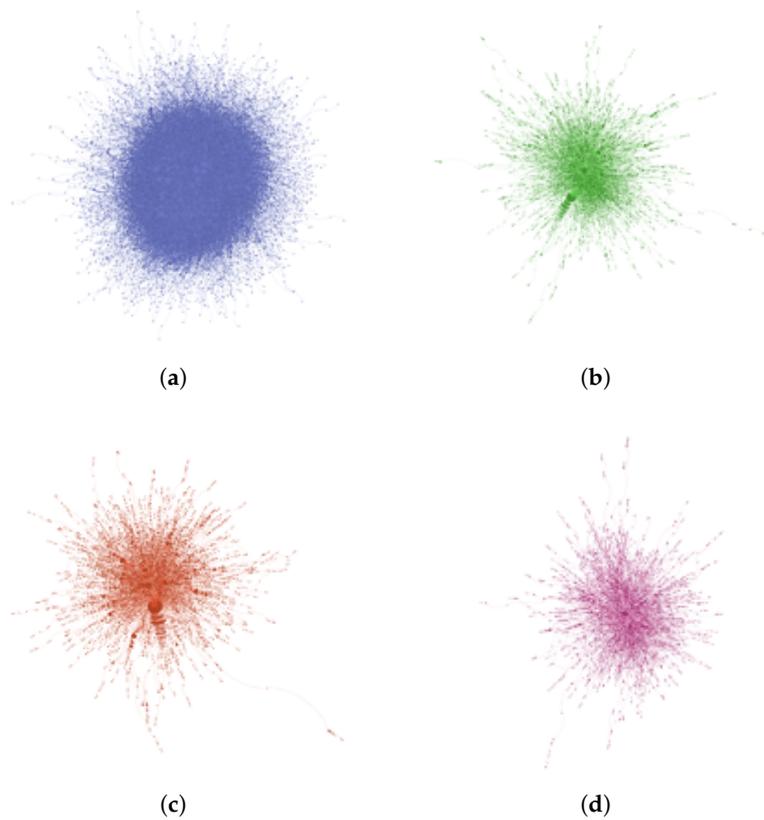
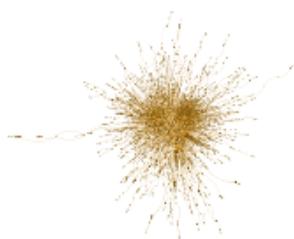


Figure 2. *Cont.*



(e)

Figure 2. Analysis of the network topology for the five largest sub-communities indicates different sub-networks. (a) SC1 is dominated by campaign accounts and high profile campaigners. (b) SC2 includes US presidential election candidates, media coverage, and supporters of those candidates. (c) SC3 is dominated by political parties and high profile politicians. (d) SC4 largely reflects media coverage of the Brexit campaign. (e) SC5 is dominated by discussion of Scotland and Brexit.

Table 3. Descriptive Network Statistics for Communities.

Network Attribute	Communities				
	SC1	SC2	SC3	SC4	SC5
Number of Nodes	31,631	13,440	10,612	10,028	9674
Number of Edges	109,782	16,048	12,531	11,960	11,530
Average Degree	3.471	1.194	1.181	1.193	1.192
Network Density	0.001	0.001	0.001	0.001	0.001
Network Diameter	15	9	7	11	19
Average Path Length	5.206	1.41	1.63	2.695	7.111
Average Clustering Co-efficient	0.012	0.003	0.004	0.005	0.006
% of #Brexit Network	13%	5%	4%	4%	3.85%

4.2.2. Centrality Analysis

Influencers (or users who attract a high number of inward connections) were identified. Both in-degree and PageRank were used to identify the key influencers in the network. In-degree for a node is defined by the number of connections coming into the node. In terms of this network, it defines the number of replies a user has received from the other distinct users. Users whose tweets are replied to more frequently will have a higher in-degree. PageRank as a network statistic considers the link propensity and centrality of those who connect and thus can be considered as a more robust measure to determine the centrality of the nodes. A list of the top 25 key influencers in the Brexit network is given in Table 4. These are dominated by the official campaign accounts, campaigners and high-profile politicians. For example, @StrongerIn (having a PageRank of 0.00594) was found to be the most influential user in the network. Other influential users included @vote_leave (0.00576), @LouiseMensch (0.00508), @Nigel_Farage (0.00502), @BorisJohnson (0.00499) and @David_Cameron (0.00491).

Hubs (sometimes termed as brokers) play an important role in any network, since they facilitate the connections between users. There are key hubs in the Brexit network, as is evident from small values for key network statistics e.g., average path length and network diameter. Key hubs in the network were identified using betweenness centrality (BC). Betweenness centrality measures how often a node falls in between the path of communication between any two nodes in the network. Key hubs tend to have a higher score for betweenness centrality. Notably, @scotpolitik, a UKIP Scotland spokesperson, was found to be the most critical hub in the Brexit network, with a betweenness centrality score of 160,991,789.23, followed by @RoyalNavyNews with a betweenness centrality score of 81,722,474.83.

Some of the other key hubs in the network were @qprmicky (77,156,173.64), @Andy_T_ (37,890,044.68), @TheTamikonelf (33,594,424.20), @thunderf00t (22,075,568.61) and so on. Table 5 lists the top 25 key hubs in the network. It should be noted that @RoyalNavyNews and @RoyalMegaTravel were later suspended by Twitter and may represent attempts to manipulate the discourse. An additional centrality analysis was undertaken at the sub-community level. This revealed specific themes as evidenced by prominent influencers and hubs. Whereas SC1 is dominated by campaign accounts and high profile campaigners (including politicians), SC3 is dominated by political parties and high profile politicians. SC2 reflected commentary by candidates in the US presidential campaign, media coverage and supporters of those campaigns. SC4 reflected media coverage of the Brexit campaign. SC5 represents a specific community focused around Scotland and Brexit. SC2 and SC5 present evidence of homophily by geo-location. Table 6 lists the top influencers and hubs by sub-community by PageRank and betweenness centrality, respectively.

Table 4. Most Influential Users.

User Screen Name	PageRank	In-Degree	Out-Degree	Degree
StrongerIn	0.00594	1362	0	1362
vote_leave	0.00576	1127	0	1127
LouiseMensch	0.00508	745	53	798
Nigel_Farage	0.00502	4564	0	4564
BorisJohnson	0.00499	2697	0	2697
David_Cameron	0.00491	4858	0	4858
DanHannanMEP	0.00440	909	0	909
LeaveEUOfficial	0.00425	1062	5	1067
DavidJo52951945	0.00364	965	0	965
realDonaldTrump	0.00356	2402	0	2402
bbclaurak	0.00342	433	0	433
JuliaHB1	0.00318	616	1	617
afneil	0.00302	589	0	589
pmalinski83	0.00274	8	0	8
montie	0.00208	523	5	528
SkyNews	0.00204	2746	1	2747
nsoamesmp	0.00171	155	0	155
BBCNews	0.00166	2190	0	2190
ajcdeane	0.00151	264	4	268
Anna_Soubry	0.00149	168	1	169
NicolaSturgeon	0.00148	1005	0	1005
LiamFoxMP	0.00145	135	0	135
RedHotSquirrel	0.00141	565	2	567
DVATW	0.00140	398	3	401
KateHoeyMP	0.00132	275	3	278

Table 5. Summary of the key hubs identified in the data set as measured by betweenness centrality.

User Screen Name	BC	User Screen Name	BC	User Screen Name	BC
scotpolitik	160,991,789.23	JonnySongs	19,495,086.55	meNabster	14,582,841.43
RoyalNavyNews	81,722,474.83	Bonn1eGreer	19,474,988.91	LeeJasper	14,455,405.44
qprmicky	77,156,173.64	TheBRexit	19,459,144.45	PoliticalNigel	14,092,739.48
Andy_T_	37,890,044.68	teachertwit2	18,067,382.05	ivanwhite48	13,999,900.36
TheTamikonelf	33,594,424.20	paradimeshift	17,493,783.00	RT_com	13,285,581.75
thunderf00t	24,075,568.61	maxkeiser	17,318,949.70		
RoyalMegaTravel	21,179,474.30	lisa_alba	16,726,826.50		
JohnSydenham	20,197,955.15	jonworth	15,823,695.47		
foolonthehillz	19,950,977.00	PrettyHatMech	15,454,931.88		
lilyallen	19,593,113.05	georgegalloway	14,731,274.57		

Table 6. Top 10 Influencers and Hubs in the Five Largest Sub-Communities.

	SC1		SC2		SC3		SC4		SC5	
	User Screen Name	Page Rank	User Screen Name	Page Rank	User Screen Name	Page Rank	User Screen Name	Page Rank	User Screen Name	Page Rank
Influencers	StrongerIn	0.00594	realDonaldTrump	0.06052	David_Cameron	0.08937	business	0.01186	NicolaSturgeon	0.02275
	vote_leave	0.00576	CNN	0.01243	jeremycorbyn	0.01397	Reuters	0.00880	eddieizzard	0.00556
	LouiseMensch	0.00508	HillaryClinton	0.01099	Number10gov	0.01396	FT	0.00852	georgegalloway	0.00527
	DanHannanMEP	0.00440	FoxNews	0.00806	George_Osborne	0.0128	WSJ	0.00628	theSNP	0.00346
	LeaveEUOfficial	0.00425	POTUS	0.00770	Lord_Sugar	0.01242	washingtonpost	0.00578	BBC_HaveYourSay	0.00300
	DavidJo52951945	0.00364	BBC	0.00482	MayorofLondon	0.01162	zerohedge	0.00523	RuthDavidsonMSP	0.00272
	bbclaurak	0.00342	thehill	0.00396	UKLabour	0.01024	ianbremmer	0.00407	carlbildt	0.00252
	JuliaHB1	0.00318	SadiqKhan	0.00388	bbcquestiontime	0.00885	AJStream	0.00378	davidschneider	0.00247
	afneil	0.00302	cnni	0.00344	BarackObama	0.0083	CNBC	0.00365	Bonn1eGreer	0.00241
	pmalinski83	0.00274	IngrahamAngle	0.00320	theresa_may	0.00546	jimcramer	0.00328	British_Airways	0.00236
Hubs	Screen-name	BC	Screen-name	BC	Screen-name	BC	Screen-name	BC	Screen-name	BC
	LouiseMensch	12,287,456.18	Chriscarroll50	834	MarkInNorthWest	2,422.33	RudyHavenstein	5986.5	teachertwit2	876,468.56
	lasancmt	11,263,094.78	ElianaBenador	427	ComedyDignitas	1,053.00	JediEconomist	4633	scotpolitik	709,779.13
	JAFF3	9,070,600.67	SpecialKMB1969	352	AntiAssessment	642	HamishP95	3161	ivanwhite48	475,672.82
	sandieshoes	8,420,343.85	roxylloveslucy	328	Citizensmif21	576	BTabrum	2767	DiligentTruth	474,183.49
	UKIPNFKN	7,758,927.04	AlwayanAmerican	291	lucid_dementia	488.33	TimBendover	2710	PrettyHatMech	402,834.67
	BeverleyTruth	6,929,259.67	Writeonright	223	HortopJames	410.33	GTCost	1833	RogueCoder250	399,291.55
	BrexitNoww	6,647,642.16	AMTrump4PRES	143	VictoriaLIVE	252	FedPorn	1275	bcomininvisible	381,116.42
	SimonGosden	5,864,353.54	dawngpsalm63	138.5	ScottJonesy	181	Nzallblack	1218	georgegalloway	377,326.22
	Brexpats	5,249,210.79	noblebarnes87	137	narrowwaychurch	177	jrhopkin	1211	PoliticalNigel	374,852.55
stardust193	5,229,101.85	PDN_Spring	114	dougalSW19	169	isave2invest	1201	moodvik1	371,055.47	

4.3. Content Analytics

Content analytics is primarily concerned with uncovering the patterns hidden inside the content. For this study, n-gram word analysis, hashtag analysis, and peak detection analysis were undertaken.

4.3.1. Word Analysis

Spark’s Machine Learning (ML) library was used to identify the frequently co-occurring words in the Brexit dataset. Table 7 lists the top 25 frequently co-occurring words in the Brexit dataset.

Table 7. Top 25 Frequently Co-occurring Words.

Co-occurring Words	Frequency	Co-occurring Words	Frequency	Co-occurring Words	Frequency
brexit vote leave	112,372	euref leave eu	29,730	brexit leave	18,137
post brexit	51,031	david cameron	28,028	leaving eu	15,587
leave eu	44,457	brexit impact	23,670	brexit result	15,400
vote brexit	41,806	referendum vote leave	23,157	brexit mean	15,186
brexit remain	38,310	brexit referendum vote leave	22,832	brexit campaign	15,105
leave eu vote leave	34,188	brexit leave eu	21,541		
strongerin no2eu	33,232	strongerin no2eu euref leaveeu vote leave	20,069		
leave brexit	31,088	brexit euro2016	19,958		
no2eu euref	30,826	boris johnson	19,400		
vote leave	29,804	voted brexit	19,077		

The majority of these co-occurring words were related to campaigns, the implications of leaving and the final result. There are three outliers relating to the dominant political personalities in the two campaigns (‘David Cameron’ and ‘Boris Johnson’) and England’s exit from the Euro 2016 soccer championships, which was widely used as a reference point to Brexit in a humorous or ironic manner.

4.3.2. Hashtag Analysis

The dataset featured 206,032 unique hashtags. Interestingly, #euref is the most frequently used hashtag, appearing 285,575 times. Moreover, #voteleave is the second most frequently used hashtag, having been mentioned 216,243 times across both original tweets and retweets. Other popular hashtags included #remain (90,539), #strongerin (88,161), #leaveeu (84,958), #leave (58,920), #euro2016 (40,352) and #no2eu (37,707). Table 8 lists the top 25 hashtags appearing in the tweets in the Brexit dataset. Again, hashtag analysis suggests that the discourse was dominated by the campaigns with ad hoc discussions relating to Euro 2016, Donald Trump’s participation in the discourse and claims regarding the NHS by the leave campaign.

Table 8. Most Popular Hashtags.

Hashtag	Frequency	Hashtag	Frequency	Hashtag	Frequency
#brexit	1,982,983	#referendum	47,422	#europe	22,073
#euref	285,575	#euro2016	40,352	#ivoted	17,037
#voteleave	216,243	#eurefresults	39,691	#brexitvote	16,863
#eu	199,658	#no2eu	37,707	#cameron	16,741
#uk	95,065	#ukip	27,760	#votein	14,748
#remain	90,539	#britain	24,979		
#strongerin	88,161	#trump	23,782		
#leaveeu	84,958	#voteremain	23,613		
#eureferendum	75,195	#bremain	22,241		
#leave	58,920	#nhs	22,118		

4.3.3. Peak Detection Analysis

Three peak detection algorithms were used and implemented in R to identify events of significance in the data set, as per Healy et al. [61]. Du et al.’s [62] continuous wavelet transform algorithm (CWT) identified 4 true peaks. Palshikar’s [63] peak detection algorithm (S1) and Lehmann et al.’s [64]

algorithm (Lehmann) did not identify any true peak from the temporal distribution of tweets. Figure 3 visualizes each of the peaks identified with details for each of the peaks, including the timestamp of the peak and the number of the tweets which constituted the peak.

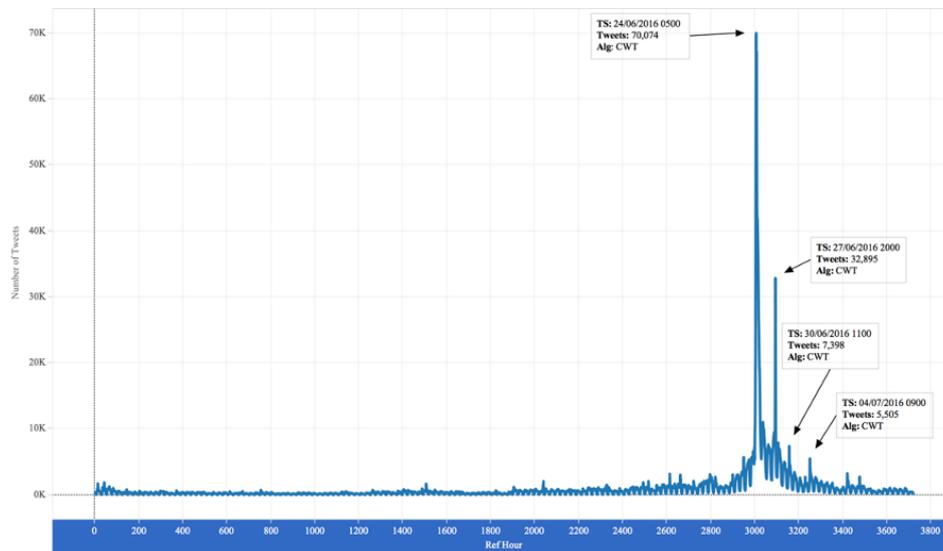


Figure 3. True Peaks Detected.

The tweets contained in each of these peaks were manually investigated to identify the trending topics. Table 9 summarizes the topics identified from the true peaks within the data set.

Table 9. Peaks and Corresponding Events.

Timestamp	Reference Hour	Number of Tweets	Topic/Event
24 June 2016 0500	3005	70,074	Brexit became a reality
27 June 2016 2000	3093	32,895	England lost to Iceland in round of 16 and hence, were eliminated from Euro2016
30 June 2016 1100	3156	7398	Boris Johnson rules himself out of Tory leadership race
4 July 2016 0900	3250	5505	UKIP leader Nigel Farage resigns

4.3.4. Analysis of Non-media Business Twitter Activity

Twitter accounts representing non-media businesses with a Klout score of greater than 75 were identified and manually coded. Overall, 239 such tweets generated from 49 screen-names (accounts) were identified. The majority of the tweets (82%) were generated by business services firms (91), banking and other financial services firms (59), and IT and telecoms firms (43). The insurance sector had the highest average activity. Table 10 summarizes the Twitter activity by industry sector.

Table 10. Twitter Activity by Industry.

Industry	Tweets				No. of Users
	N.	Avg.	Min.	Max	
Automotive Manufacturing	2	2	2	2	1
Non-food Consumer Goods Manufacturing	3	1	1	1	3
Business Services	91	1.71	1	55	8
Banking and Other Financial Services	59	5.36	1	32	11
IT and Telecommunications	43	4.3	1	29	10
Leisure Services	24	1.71	1	19	14
Insurance	17	8.5	3	14	2
Total	239	4.88	1	55	49

Twitter posts were further classified by business objectives based on Eschenbrenner et al. [66], as extended by Lynn et al. [67]. As can be seen from Table 11, the majority of tweets focused on knowledge sharing e.g., links to reports, articles, webinars etc. A smaller number focused on either marketing for events relating to Brexit or for advisory services. As can be seen, few tweets were identified where the business account was specifically seeking to influence societal or political change.

Table 11. Business Objectives of Non-Media Businesses.

Business Objectives	Tweets				No. of Users
	N.	Avg.	Min.	Max	
Recruitment and Selection	0	0	0	0	0
Socialization and Onboarding	0	0	0	0	0
Training and Development	0	0	0	0	0
Knowledge Sharing	173	5.97	1	40	29
Branding and Marketing	47	2.61	1	15	18
Creativity and Problem Solving	6	1.5	1	2	4
Influencing Organizational Culture/Change	3	1	1	1	3
Influencing Societal or Political Change	2	1	1	1	2
Automated	0	0	0	0	0
Other	8	1	1	1	8
Total	239	3.73	1	40	49

Table 12 presents the analysis of tweets by non-media business accounts in the #Brexit discourse on Twitter by socio-political engagement type. As can be seen, there is very little evidence of CSR or CPA. In line with earlier findings, the vast majority of engagement reflects links or the reporting of non-partisan expertise (67–70%) by a firm e.g., scenario analysis, impact assessments etc. In addition, there is a smaller number of tweets that share third party content e.g., newspaper articles or announcements by institutions.

Table 12. Socio-Political Engagement of Non-Media Businesses.

Activities	Tweets				No. of Users
	N.	Avg.	Min.	Max	
Corporate Social Responsibility	1	1	1	1	1
Corporate Political Activity	1	1	1	1	1
Socio-Political Involvement	1	1	1	1	1
Other Socio-Political Engagement (of which):	212	3.15	1	44	44
(a) Socio-political Curation with Opinion	26	2.36	1	11	11
(b) Other Socio-Political Discourse without Opinion	18	2.57	1	8	7
(c) Other Socio-Political Discourse with Opinion	1	1	1	1	1
(d) Non-partisan First Party Expertise	167	6.68	1	44	25
Other	24	1.5	1	8	16
Automated	0	0	0	0	0
Total	239	3.79	1	44	49

5. Discussion

5.1. RQ1: Is the #Brexit Discourse on Twitter Dominated by Calculated Publics or Ad Hoc Publics?

The results of the analyses undertaken suggest that the #Brexit discourse on Twitter was unsurprisingly organized around the two campaigns—leave and remain. The substantial influence of calculated publics on the overall discourse is supported by the analysis presented above. The network analysis presented in Section 4.2 suggests that the largest and third largest communities in the data set were campaign and party-driven. This does not mean to say that ad hoc publics did not form during the discourse, but merely that they had less prominence and impact or remained tied to core

campaigns, campaigners or parties. For example, an analysis of the fifth largest community suggests an element of self-organization around location, i.e., Scotland. The second largest community (SC2) is also noteworthy in that it has the characteristics of an ad hoc public in the context of Brexit, but may be calculated when viewed from the perspective of the US presidential election. It is unlikely that the US presidential campaigns did not plan to address Brexit during the campaign. An analysis of SC2 suggests a more event-driven public organized around the pronouncements of the various US presidential candidates and their views on Brexit and/or each other. The content analysis presented in Section 4.3 further supports this interpretation. An analysis of co-occurring words suggests that the discourse was overwhelmingly focused on the campaigns, which is supported by the hashtag analysis, suggesting that the discourse was primarily calculated. While some hashtags and common themes feature e.g., UKIP claims regarding the NHS or England's exit from the Euro 2016 soccer tournament, these were relatively short-lived. Similarly, the peak detection analysis presented in Section 4.3.4 only identified four events of significance, all occurring after the vote, and as such, the discourse was not abnormally impacted by the dynamics of ad hoc communications driven by events and crises, as posited by Bruns and Burgess [8].

In line with network theory, the sub-communities identified can be explained by homophily—the tendency for people to be attracted to others similar to themselves [69]. In the case of SC2 and SC5, the use of common hashtags suggests a significant effect around homophily through self-categorization. Shen and Monge [70] suggest that, as social attributes cannot be identified easily on Twitter, homophily is more likely to be operated on through attributes more easily identified on social media, e.g., popularity and geo-location. Word analysis of sub-communities, and specifically hashtag analysis, finds evidence supporting such behavior, whether it is by campaign (*#voteleave*, *#remain*, *#no2eu* etc.) and party (*#ukip*) in SC1 and SC3, topic in SC2 (*#Trump*) or location in SC5 (*#scotland*). SC1 and SC3 also demonstrate the power of hashtags to identify others with similar and opposing views and to form publics or communities that feature both. In addition to homophily effects, the network structures suggest influence heterogeneity in that it is clear that more influential accounts are connecting with less influential accounts. While many of these accounts are influential offline as well as online, the role of hubs with less public prominence offline is noteworthy. Strategic selection may play a role in explaining network behavior, with more influential and more active accounts being more likely to be mentioned [71]. As per Wang and Chu [71], our results suggest that activity does not equate to legitimacy and indeed some more active accounts identified were subsequently suspended by Twitter.

5.2. RQ2: What Role Did Non-Media Business Accounts Play in the #Brexit Discourse on Twitter?

Descriptive analytics of visible and active users (Section 4.1) combined with network analytics of influencers and hubs (Section 4.2) suggest a discourse dominated by campaign accounts, high profile politicians, and media. While a small number of high profile business people feature, for example Lord Sugar, non-media business accounts did not play a significant role as a hub or influencer in the main sub-communities in the discourse. Additional analyses of Twitter accounts with high Klout scores suggest that, while non-media business accounts did participate, it was at a very low level and dominated by a number of small sectors, namely those in financial and business services. This participation focused on reputation building through knowledge sharing using relatively neutral and conservative approaches to participation in social and civic discourse, and as a result can be considered to have relatively little political influence, at least on Twitter. Very few commercial organizations examined engaged in CSR, CPA or SPI. Given the lack of consensus, it is unsurprising that the majority of the corporate discourse on Twitter was either objective or neutral, thus avoiding the alienation of existing or potential clients and influential stakeholders. It would seem that on Twitter, while corporate accounts were mobilized to participate in the Brexit discourse, the participation was largely opportunistic and reflected a commercial motivation rather than a socio-political one.

6. Conclusions

In this paper, we present a preliminary analysis of the Brexit discourse on Twitter. Specifically, we investigate: (1) whether the #Brexit discourse on Twitter was dominated by calculated publics or ad hoc publics, and (2) the role of non-media business accounts in the #Brexit discourse on Twitter. We found that the overwhelming majority of the #Brexit discourse on Twitter could be explained through the lens of the established campaigns or the media, and this is reflected in both the network structure and content in the dataset. We found that while non-media business organizations, as represented by their Twitter accounts, participated in the discourse, their participation lacked political influence and reflected an opportunistic inflection rather than a societal one. As such, our findings present weak support of mobilization theory in respect to business participants in civic and political discourse. While firms are participating, the impact of this participation is negligible from a socio-political perspective.

This paper makes a number of contributions. It extends the research base on mobilization theory and corporate engagement in non-market activities, and specifically socio-political issues. It contributes to our understanding of the Brexit debate and result and the role that various stakeholders played in this debate on social media, and specifically business stakeholders. It also makes use of a suite of novel analytical techniques that brings together social sciences and information science traditions. Notwithstanding these contributions, further analysis of the more complete dataset is likely to find evidence of a long tail of sub-communities which reflect ad hoc publics with niche interests and motivations, but also greater non-media business participation. Evidence of homophily by geo-location and self-categorization was identified, as well as strategic selection. Analysis in this vein on a greater number of sub-communities may provide new insights on how communities are formed on social media in political contexts. Furthermore, analysis of less high-profile business Twitter accounts representing smaller businesses is likely to present greater evidence of socio-political engagement, and SPI in particular, possibly reflecting the political perspectives of the business founder or senior management. In addition, this study was limited to both Brexit and Twitter. A wider study of corporate participation in (i) other elections and referendums, and (ii) on other social media, and indeed traditional media, may provide fruitful insights into the wider role of non-media firms in socio-political discourse.

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Abbreviations

The following abbreviations are used in this manuscript:

BC	Betweenness centrality
Brexit	The referendum regarding UK membership of the European Union
CPA	Corporate political activity
CSR	Corporate social responsibility
CWT	Continuous wavelet transform
EC	European community
EU	European Union
IC4	Irish Centre for Cloud Computing and Commerce
IDA	Industrial Development Authority
ML	Machine learning
NHS	UK National Health Service

SPI Socio-political involvement
 UK United Kingdom
 UKIP United Kingdom Independence Party

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