information

MDPI

*Article*

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

**Theo Lynn [1,†], Pierangelo Rosati [1,*,†] and Binesh Nair [2,†]**

[1] Irish Institute of Digital Business, Dublin City University, Collins Avenue, 9 Dublin, Ireland; theo.lynn@dcu.ie
[2] Irish Centre for Cloud Computing and Commerce, Dublin City University, Collins Avenue, 9 Dublin, Ireland; binesh.nair2@mail.dcu.ie
* Correspondence: pierangelo.rosati@dcu.ie
† These authors contributed equally to this work.

Received: 12 August 2020; Accepted: 7 September 2020; Published: 10 September 2020

**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, forms 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 |
| nicoleperlroth | 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.

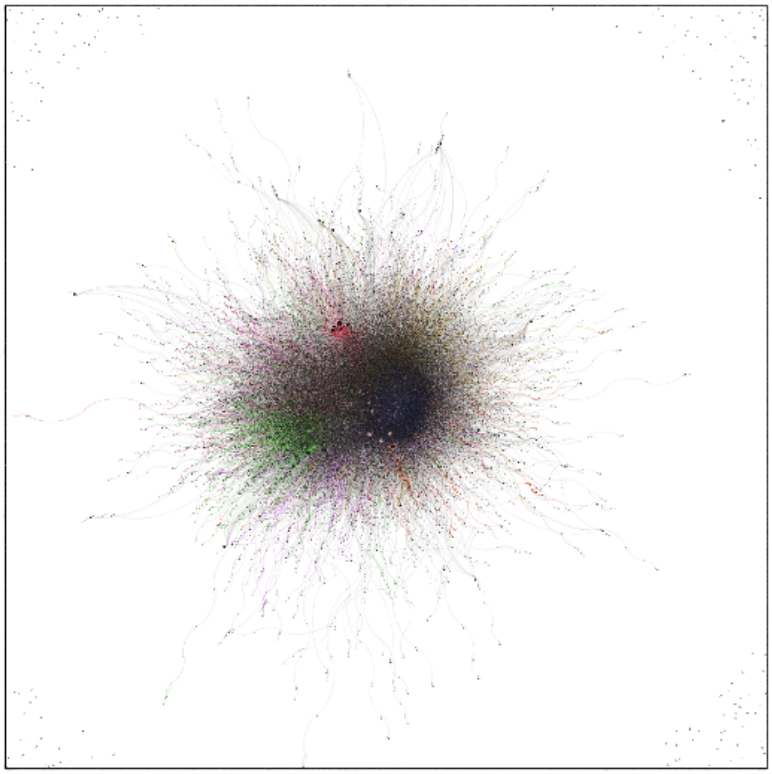
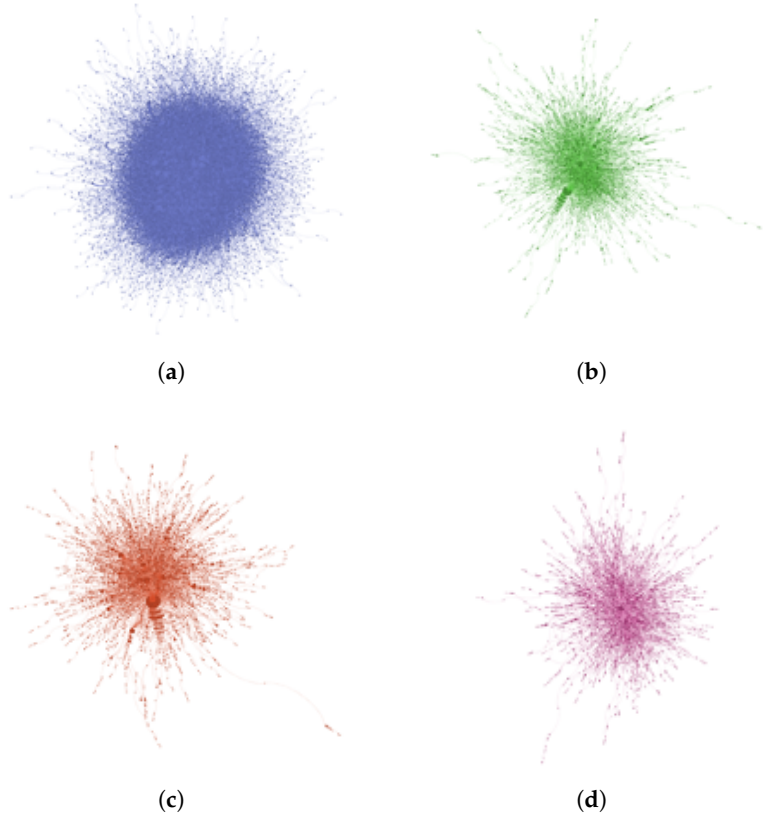


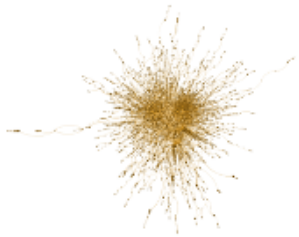
**Figure 1.** Analysis of the network topology for the #Brexit Network suggests that there are powerful hubs in the network that facilitate connections between a large volume of less connected users.



(**a**) (**b**)

(**c**) (**d**)

**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 | roxyloveslucy | 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.

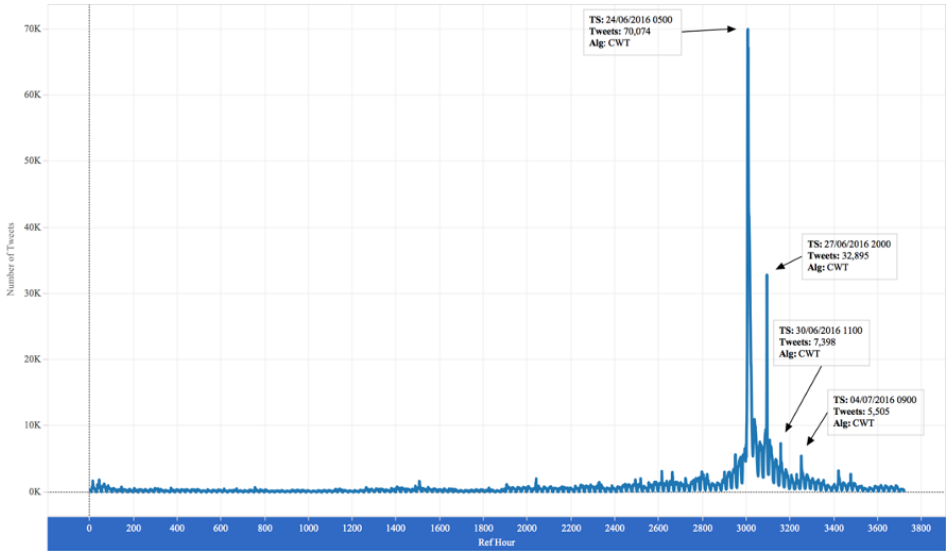



**Figure 3.** True Peaks Detected.

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.

**Author Contributions:** Conceptualization, T.L., P.R.; methodology, T.L., P.R. and B.N.; data collection, P.R. and B.N.; analysis, T.L., P.R. and B.N.; resources, T.L.; discussion, T.L. and P.R.; writing- original draft preparation, T.L., P.R. and B.N.; writing—review and editing, T.L. and P.R. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work is partially funded by the Irish Institute of Digital Business, and by the Irish Centre for Cloud Computing and Commerce (IC4), an Enterprise Ireland/IDA technology centre.

**Conflicts of Interest:** The authors declare no conflict of interest.

## 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 |

## References


1. Hoffman, D.L.; Novak, T.P. Social Media Strategy. In *Handbook of Marketing Strategy*; Venkatesh, S., Carpenter, G.S., Eds.; Edward Elgar: Cheltenham, UK, 2012; pp. 198–216.
2. Ausserhofer, J.; Maireder, A. National politics on Twitter: Structures and topics of a networked public sphere. *Inf. Commun. Soc.* **2013**, *16*, 291–314. [CrossRef]
3. Bruns, A.; Burgess, J.E. The use of Twitter hashtags in the formation of ad hoc publics. In Proceedings of the 6th European Consortium for Political Research (ECPR) General Conference, Reykjavik, Iceland, 24–27 August 2011.
4. Small, T. What the Hashtag? A Content Analysis of Canadian Politics on Twitter. *Inf. Commun. Soc.* **2011**, *14*, 872–895. [CrossRef]
5. Wells, C.; Shah, D.V.; Pevehouse, J.C.; Yang, J.; Pelled, A.; Boehm, F.; Lukito, J.; Ghosh, S.; Schmidt, J.L. How Trump drove coverage to the nomination: Hybrid media campaigning. *Political Commun.* **2016**, *33*, 669–676. [CrossRef]
6. Chadwick, A. Digital network repertoires and organizational hybridity. *Political Commun.* **2007**, *24*, 283–301. [CrossRef]
7. Papacharissi, Z. *A Private Sphere: Democracy in a Digital Age*; Polity Press: Cambridge, UK, 2010.
8. Bruns, A.; Burgess, J. Twitter hashtags from *ad hoc* to calculated publics. In *Hashtag Publics: The Power and Politics of Discursive Networks*; Peter Lang Publishing Inc.: New York, NY, USA, 2015; pp.13–28.
9. Khatua, A.; Khatua, A. Leave or Remain? Deciphering Brexit Deliberations on Twitter. In Proceedings of the 2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW), Barcelona, Spain, 12–15 December 2016; pp. 428–433.
10. Llewellyn, C.; Cram, L. Brexit? Analyzing Opinion on the UK-EU Referendum within Twitter. In Proceedings of the THE 10th International AAAI Conference on Web and Social Media (ICWSM-16), Cologne, Germany, 17–20 May 2016; AAAI Press: Palo Alto, CA, USA, 2016; pp. 760–761.
11. Mangold, L. Should I Stay or Should I go: Clash of Opinions in the Brexit Twitter Debate. Master's Thesis, University of Oxford, Oxford, UK, September 2016.
12. Digital Repository of Slovenian Research Organisations. Available online: https://dirros.openscience.si/Dokument.php?id=6351&lang=eng (accessed on 9 September 2020).
13. Mora-Cantallops, M.; Sánchez-Alonso, S.; Visvizi, A. The influence of external political events on social networks: The case of the Brexit Twitter Network. *J. Ambient. Intell. Humaniz. Comput.* **2019**, 1–13. [CrossRef]
14. Byrne, D.; Cavallini, A.; McDermott, R.; Hürlimann, M.; Caroli, F.; Khaled, M.B.; Freitas, A.; Zarrouk, M.; Vasiliu, L.; Davis, B.; et al. In or out? In Proceedings of the Real-Time Monitoring of BREXIT Sentiment on Twitter, SEMANTiCS, Leipzig, Germany, 12–15 September 2016.
15. Handschuh, S.; Hürlimann, M.; Cortis, K.; Freitas, A.; Davis, B.; Fernández, S. A Twitter sentiment gold standard for the Brexit referendum. In Proceedings of the SEMANTiCS, Leipzig, Germany, 12–15 September 2016.
16. Lansdall-Welfare, T.; Dzogang, F.; Cristianini, N. Change-point Analysis of the Public Mood in UK Twitter during the Brexit Referendum. In Proceedings of the 2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW), Barcelona, Spain, 12–15 December 2016; pp. 434–439.
17. Lynn, T.; Kilroy, S.; van der Werff, L.; Healy, P.; Hunt, G.; Venkatagiri, S.; Morrison, J. Towards a general research framework for social media research using big data. In Proceedings of the IEEE Professional Communication Conference (IPCC) 2015, Limerick, Ireland, 12–15 July 2015; pp. 1–8.
18. Kaplan, A.M.; Haenlein, M. Users of the world, unite! The challenges and opportunities of Social Media. *Bus. Horizons* **2010**, *53*, 59–68. [CrossRef]
19. Peters, K.; Chen, Y.; Kaplan, A.M.; Ognibeni, B.; Pauwels, K. Social media metrics-A framework and guidelines for managing social media. *J. Interact. Mark.* **2013**, *27*, 281–298. [CrossRef]
20. Kietzmann, J.H.; Hermkens, K.; McCarthy, I.P.; Silvestre, B.S. Social media? Get serious! Understanding the functional building blocks of social media. *Bus. Horizons* **2011**, *54*, 241–251. [CrossRef]

21. Kane, G.C.; Alavi, M.; Labianca, G.J.; Borgatti, S. What's different about social media networks? A framework and research agenda. *MIS Q.* **2012**, *38*, 275–304. [CrossRef]
22. Twitter. Selected Company Metrics and Financials. Available online: https://s22.q4cdn.com/826641620/files/doc_financials/2020/q2/Q2-2020-Selected-Financials-and-Metrics.pdf (accessed on 1 September 2020).
23. Jansen, B.J.; Zhang, M.; Sobel, K.; Chowdury, A. Twitter power: Tweets as electronic word of mouth. *J. Am. Soc. Inf. Sci. Technol.* **2009**, *60*, 2169–2188. [CrossRef]
24. Java, A.; Song, X.; Finin, T.; Tseng, B. Why we twitter: Understanding microblogging usage and communities. In Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis, San Jose, CA, USA, 12 August 2007; pp. 56–65.
25. Zhao, D.; Rosson, M.B. How and Why People Twitter: The Role That Micro-Blogging Plays in Informal Communication at Work. In Proceedings of the ACM 2009 International Conference on Supporting Group Work, Sanibel Island, FL, USA, 10–13 May 2009; pp. 243–252.
26. Stieglitz, S.; Dang-Xuan, L.; Bruns, A.; Neuberger, C. Social Media Analytics. *Wirtschaftsinformatik* **2014**, *56*, 101–109. [CrossRef]
27. Boulianne, S. Does Internet use affect engagement? A meta-analysis of research. *Political Commun.* **2009**, *26*, 193–211. [CrossRef]
28. Hirzalla, F.; Van Zoonen, L.; De Ridder, J. Internet use and political participation: Reflections on the mobilization/normalization controversy. *Inf. Soc.* **2010**, *27*, 1–15. [CrossRef]
29. Norris, P. *Democratic Phoenix: Reinventing Political Activism*; Cambridge University Press: Cambridge, UK, 2002.
30. Enjolras, B.; Steen-Johnsen, K.; Wollebæk, D. Social media and mobilization to offline demonstrations: Transcending participatory divides? *New Media Soc.* **2013**, *15*, 890–908. [CrossRef]
31. Dalton, R.J. Partisan mobilization, cognitive mobilization and the changing American electorate. *Elect. Stud.* **2007**, *26*, 274–286. [CrossRef]
32. Gibson, R.K.; Lusoli, WAnd, Ward, S. Online Participation in the UK: Testing a 'Contextualised' Model of Internet Effects. *Br. J. Polit. Int. Relat.* **2005**, *7*, 561–583. [CrossRef]
33. Chadwick, A. *The Hybrid Media System: Politics and Power*; Oxford University Press: Oxford, UK, 2013.
34. Chadwick, A.; Dennis, J. Social media, professional media and mobilisation in contemporary Britain: Explaining the strengths and weaknesses of the Citizens' Movement 38 Degrees. *Polit. Stud.* **2017**, *65*, 42–60. [CrossRef]
35. Kreiss, D. Seizing the moment: The presidential campaigns' use of Twitter during the 2012 electoral cycle. *New Media Soc.* **2016**, *18*, 1473–1490. [CrossRef]
36. Broersma, M.; Graham, T. Social media as beat: Tweets as a news source during the 2010 British and Dutch elections. *J. Pract.* **2012**, *6*, 403–419. [CrossRef]
37. Parmelee, J.H. The agenda-building function of political tweets. *New Media Soc.* **2014**, *16*, 434–450. [CrossRef]
38. Freelon, D.; Karpf, D. Of big birds and bayonets: Hybrid Twitter interactivity in the 2012 Presidential debates. *Inf. Commun. Soc.* **2015**, *18*, 390–406. [CrossRef]
39. Jungherr, A. The logic of political coverage on Twitter: Temporal dynamics and content. *J. Commun.* **2014**, *64*, 239–259. [CrossRef]
40. Quinn, M.; Lynn, T.; Joll, S.S.; Nair, B. Domestic Water Charges in Ireland-Issues and Challenges Conveyed through Social Media. *Water Resour. Manag.* **2016**, *30*, 3577–3591. [CrossRef]
41. The Atlantic. Available online: https://www.theatlantic.com/technology/archive/2016/11/election-bots/506072/ (accessed on 1 September 2020).
42. Persily, N. Can Democracy Survive the Internet? *J. Democr.* **2017**, *28*, 63–76. [CrossRef]
43. Suiter, J.; Nair, B.; Lynn, T. The role of social media in driving participation and engagement in referendums. ECIU Workshop—Menace or Blessing? In Proceedings of the Role of Direct Democracy in the Process of Political Representation, Frankfurt, Germany, 6 April 2017.
44. Lugovi, S.; Ahmed, W. An Analysis of Twitter Usage Among Startups in Europe. In Proceedings of the May 5th International Conference The Future of Information Sciences (INFuture), Zagreb, Croatia, 11–13 November 2015; pp. 299–308.
45. Rybalko, S.; Seltzer, T. Dialogic communication in 140 characters or less: How Fortune 500 companies engage stakeholders using Twitter. *Public Relat. Rev.* **2010**, *36*, 336–341. [CrossRef]

46. Wamba, S.F.; Carter, L. Social media tools adoption and use by SMEs: An empirical study. In *Social Media and Networking: Concepts, Methodologies, Tools, and Applications*; Wamba, S.F., Carter, L., Eds.; IGI Global: Philadelphia, PA, USA, 2016; pp. 791–806.
47. Dahlsrud, A. How corporate social responsibility is defined: An analysis of 37 definitions. *Corp. Soc. Responsib. Environ. Manag.* **2008**, *15*, 1–13. [CrossRef]
48. Baysinger, B.D. Domain maintenance as an objective of business political activity: An expanded typology. *Acad. Manag. Rev.* **1984**, *9*, 248–258. [CrossRef]
49. Nalick, M.; Josefy, M.; Zardkoohi, A.; Bierman, L. Corporate Sociopolitical Involvement: A Reflection of Whose Preferences? *Acad. Manag. Perspect.* **2016**, *30*, 384–403. [CrossRef]
50. van Dijck, J. *The Culture of Connectivity: A Critical History of Social Media*; Oxford University Press: Oxford, UK, 2013.
51. Butler, D.; Ranney, A. *Referendums Around the World: The Growing Use of Direct Democracy*; American Enterprise Institute: Washington, DC, USA, 1994.
52. Uleri, P.V.; Gallagher, M. (Eds.) *The Referendum Experience in Europe*; Palgrave Macmillan: London, UK, 2016.
53. Gallagher, M. Elections and referendums. In *Comparative Politics*; Caramani, D., Ed.; Oxford University Press: Oxford, UK, 2011; pp. 181–197.
54. Schuck, A.R.-T.; de Vreese, C.H. Public support for referendums in Europe: A cross-national comparison in 21 countries. *Elect. Stud.* **2015**, *38*, 149–158. [CrossRef]
55. Office of National Statistics. Internet Access—Households and Individuals: 2016. Available online: https://www.ons.gov.uk/peoplepopulationandcommunity/householdcharacteristics/homeinternetandsocialmediausage/bulletins/internetaccesshouseholdsandindividuals/2016 (accessed on 1 September 2020).
56. Statista. 2017. Age Distribution of Twitter Users in Great Britain From May 2013 to July 2016. Available online: https://www.statista.com/statistics/278320/age-distribution-of-twitter-users-in-great-britain/ (accessed on 1 September 2020).
57. Blondel, V.D.; Guillaume, J.L.; Lambiotte, R.; Lefebvre, E. Fast unfolding of communities in large networks. *J. Stat. Mech. Theory Exp.* **2008**, *10*, 1–12. [CrossRef]
58. Myers, S.A.; Sharma, A.; Gupta, P.; Lin, J. Information network or social network?: The structure of the Twitter follow graph. In Proceedings of the 23rd International Conference on World Wide Web, Seoul, Korea, 7 April 2014; pp. 493–498.
59. Cha, M.; Haddadi, H.; Benevenuto, F.; Gummadi, P.K. Measuring user influence in Twitter: The million follower fallacy. In Proceedings of the 4th Int'l AAAI Conference on Weblogs and Social Media, Washington, DC, USA, 23–26 May 2010; pp. 10–17.
60. Jones, C.; Hesterly, W.S.; Borgatti, S.P. A general theory of network governance: Exchange conditions and social mechanisms. *Acad. Manag. Rev.* **1997**, *22*, 911–945. [CrossRef]
61. Healy, P.; Hunt, G.; Kilroy, S.; Lynn, T.; Morrison, J.P.; Venkatagiri, S. Evaluation of peak detection algorithms for social media event detection. In Proceedings of the 2015 10th International Workshop on Semantic and Social Media Adaptation and Personalization (SMAP), Trento, Italy, 5–6 November 2015.
62. Du, P.; Kibbe, W.A.; Lin, S.M. Improved peak detection in mass spectrum by incorporating continuous wavelet transform-based pattern matching. *Bioinformatics* **2006**, 22, 2059–2065. [CrossRef] [PubMed]
63. Palshikar, G. Simple algorithms for peak detection in time-series. In Proceedings of the 1st International Conference Advanced Data Analysis, Business Analytics and Intelligence 2009, Ahmedabad, India, 6–7 June 2009; pp. 1–13.
64. Lehmann, J.; Gonçalves, B.; Ramasco, J.J.; Cattuto, C. Dynamical classes of collective attention in twitter. In Proceedings of the 21st International Conference on World Wide Web, Lyon, France, 16–20 April 2012; pp. 251–260.
65. Edwards, C.; Spence, P.R.; Gentile, C.J.; Edwards, A.; Edwards, A. How much Klout do you have… A test of system generated cues on source credibility. *Comput. Hum. Behav.* **2013**, *29*, A12–A16. [CrossRef]
66. Eschenbrenner, B.; Nah, F.F.-H.; Telaprolu, V.R. Efficacy of social media utilization by public accounting firms: Findings and directions for future research. *J. Inf. Syst.* **2015**, *29*, 5–21. [CrossRef]
67. Lynn, T.; Rosati, P.; Quinn, M.; Murphy, B. #Brexit: The Role of Accounting Firms in the Brexit Discourse on Twitter. In Proceedings of the 11th ENROAC Conference, Naples, Italy, 29–30 June 2017.

68. Chae, B.K. Insights from hashtag #supplychain and Twitter Analytics: Considering Twitter and Twitter data for supply chain practice and research. *Int. J. Prod. Econ.* **2015**, *165*, 247–259.
69. McPherson, M.; Smith-Lovin, L.; Cook, J.M. Birds of a feather: Homophily in social networks. *Annu. Rev. Sociol.* **2001**, *27*, 415–444.[CrossRef]
70. Shen, C.; Monge, P. Who connects with whom? A social network analysis of an online open source software community. *First Monday* **2011**, *16*. [CrossRef]
71. Wang, R.; Chu, K.H. Networked publics and the organizing of collective action on Twitter: Examining the #Freebasel campaign. *Convergence* **2017**, *25*, 393–408.