A Network Approach to Understanding Public Attention, Public Opinion, and Communication Flows in the Digital Media System

Abstract

How do various actors use digital media to influence the flows of political communication and what are the social consequences of their practices? Treating media as a space of actions and building on network theories, this dissertation argues that public attention and opinion on social media can be understood and analyzed through networks of social interactions among social actors. Ultimately, this approach traces the multifaceted flows of attention and opinion to the sources of their origins in an increasingly complex media system and holds the potential of revealing patterns of interactions between networks of social actors, and between social networks and institutional networks like news media. Results show that embedded in networks of online affinity relations (i.e., following relationships), social actors within a Twitter "flock" exhibit homogenous attention and opinion patterns, and that such flocks interact with each other and can influence news media coverage. Moderate and center-left news media network still possesses significant power in driving the attention and setting the agenda for partisan news media networks and Twitter flocks, though there are some bottom-up flows of communication from Twitter flocks to news media networks. Also, the interaction between partisan news media networks and partisan/activist Twitter flocks gives rise to partisan media ecosystems, with the conservative and progressive media ecosystems reacting to each other differently. Furthermore, activism discourses on Twitter can originate from vastly different Twitter flocks situated in networks of communications and exhibit varying attention dynamics. These results speak to the continuing splintering of the public into passionate and engaged networked publics. Such networks aggregate attention and synthesize opinions, exerting direct influence on powerful legacy news media via networked visibility and power. However, homogenous networks on social media and the oppositional reactiveness between the partisan ecosystems reflect a deepening partisan divide in the digital media system.

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> If the fundamental battle about the definition of the norms of society, and the application of these norms in everyday life, revolves around the shaping of the human mind, communication is central to this battle. … [The] process of communication operates according to the structure, culture, organization, and technology of communication in a given society. The communication process decisively mediates the way in which power relationships are constructed and challenged in every domain of social practice.
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> —Manuel Castells, Communication Power

Shaping the human mind and underlying power and counterpower, communication is central to any society (Castells, 2013). For social actors who strive to maintain or challenge power, their success hinges on the ability to communicate ideas to the public effectively, including attracting public attention and molding public opinion and ultimately driving communication flows. As those actors influence the process of communication in society, they can challenge those in power and thereby alter existing power relationships. At the same time, actors and processes of communication are shaped by existing power structures, particularly the media system that enables and constrains actors and their communications.

While existing studies have examined the media system in the early decades of the 21st century by focusing on shifts in its structures, norms, cultures, and audiences (e.g., Benkler, 2006; Chadwick, 2017; Prior, 2007; Stroud, 2010), there is yet a systematic framework for understanding and tracing communication flows to reveal the dynamics of the media system and power relations. Treating media as a space of actions (Couldry, 2012), I examine how social actors use social media to signal attention and express opinion, and how their practices are related to communication flows in the larger media system. Building on network theories (Castells, 2013; McPherson et al., 2001; Latour, 2012), I propose a network approach that positions social actors on social media in the networked space of social interactions and places social interactions on social media in the networked space of social actors. I apply computational methods, including network sampling and analysis (Chen, Zhang, & Rohe, 2019) to detecting networks of social actors and interactions so as to track public attention and opinion expression; employ time series modeling (Wells et al., 2019) to formally analyze their interaction with news media; and use natural language processing to map out the patterns of public opinion and media content. Results provide empirical support for the network approach and reveal complex patterns of interaction between social and news media networks. Implications for the media system, the public, power relations, and democratic processes are discussed.

A shifting media system

A media system can be defined as an elastic and evolving assemblage of interconnected actors whose practices are governed by institutions and norms (Chadwick 2017; Jungherr, Rivero & Gayo-Avello, 2020). Before the internet, mass media dominated the media system (Blumler and Kavanagh, 1999). With the popularization of the internet, digital outlets and social media have entered the system and increasingly compete for audiences by operating on the logics of inexpensive production, niche targeting, and network distribution (Klinger & Svensson, 2015). The coexistence, competition, and cooperation between older and newer media give rise to a hybrid media system (Chadwick, 2017).

With changes in the composition of media come changes in practices of social actors, evidenced in a shift from a mass society to a network society. In the mass society, for social actors striving to reach the public with their messages, passing the media gate and molding media discourses were critical (Shoemaker & Vos, 2009). Therefore, the logics of mass media deeply shaped the practices of other social actors (Couldry & Hepp, 2013, 2018; Hjarvard, 2013). In the network society, people use new media technologies like social media to connect with each other and form online networks that have the potential to create, distribute, and amplify content independent of mass media (Benkler, 2006; Bruns, 2008b; Ritzer, Dean, & Jurgenson, 2012; Tufekci, 2013), resulting in changing patterns of information consumption, political participation, social interaction, and strategic communication (e.g., Bennett, 2012; Hermida, Fletcher, Korell & Logan, 2012; Kreiss, Lawrence & McGregor, 2018; Rainie and Wellman, 2012; Webster, 2014). The gatekeeping role of mass media has attenuated and new roles emerge such as a gate watcher, amplifier, and credential giver (Bruns, 2008a; Chadwick, 2017).

While existing literature on the media system rightly centers around its structural and technological features and its implications for individual choices and collective actions (e.g., Bennett & Segerberg, 2013; Chadwick, 2017; Tufekci, 2018; Wu, 2017), I study the concrete processes of mediated communication embedded in the media system (Carr, 2020).

Media as practices

Media can be seen as a space for actions, where social actors strive to “connect what is separated” (Zielinski, 2008, p.7) and where “power is decided” (Castells, 2007, p.242). Couldry (2012) treats media in light of its relation to social actions and argues for a socially oriented approach to media that foregrounds “the social processes that media constitute and enable” (p.8). Specifically, this approach focuses on the process and consequences of social actors’ use of “media technologies and media contents,” both of which can be understood by examining media-related practices (Couldry, 2012, p.8; Schroeder, 2018). Practice, according to Couldry (2012), is regular action constructed socially and fulfilling social needs. Through examining media-related practices and the impacts on communication flows, we can gain a deeper understanding not only of media, but also of agency and power in society (Castells, 2007; Chadwick, 2017; Couldry, 2012; Schroeder, 2018).

In the media system deeply influenced by the internet and social media, “the key dimensions of social organization and practices” are composed of networks (Castells, 2010, p. xviii). While mass media of the industrial age connect people by creating audiences with shared mediated experience (Livingstone, 2005; Thompson, 2005), digital platforms structure social interactions through digital connectivity (Castell, 2011; Tufekci, 2017). This gives rise to a networked public sphere, alongside the mass-mediated public sphere, and marks the shift from centralized to distributed control of information and communication (Benkler, 2006).

As people play a more active and participatory role in the production, circulation, and consumption of information (Benkler, 2006; boyd, 2010; Webster, 2014), the ways they pay attention to and express opinions about issues of public interest shift dramatically.

Though mass media have long shaped and created public attention (Napoli, 2011; Webster, 2014; Wu, 2017), various members of the public have become increasingly powerful in driving public attention through the “programming” and “switching” of networks (Castells, 2007). Social actors can take advantage of connective communication technologies like social media to program networks by attracting the attention of like-minded others. For example, the activation of self-expression through personalizable action frames during an online movement can lead to widespread dissemination of the movement through online networks (Bennett and Segerberg, 2013). Social actors can connect multiple networks, such as fusing social media attention and traditional media attention (Freelon et al., 2018; Wells et al., 2016), driving communication flows and accumulating communicative power.

Similarly, while public opinion is shaped by mass media, public opinion articulated on social media differs from opinion collected by survey-based opinion polls. Social media platforms like Twitter have emerged as one key battleground of public discourse, where people from different backgrounds actively comment on current events and public issues, and strive to exert influence (Conway, Kenski & Wang, 2015; Tufekci, 2013; Kim et al., 2015). This leads to naturally occurring, temporally sensitive, and inherently social opinions (Anstead & O'Loughlin, 2015; boyd, 2010; McGregor, 2019). Social media public opinion can influence journalistic work in subtle yet significant ways. Journalists rely on "objective" audience metrics to guide their judgment and give legitimacy to their product (Parmelee, 2014). They see intrinsic news value in content produced by audiences on social media (McGregor & Molyneux, 2018), embedding such content as "vox populi" (McGregor, 2019) and treating retweets as a sign of newsworthiness (Wells et al., 2016).

A network approach

I propose a network approach to understanding and measuring the practices of attention signaling and opinion expression in the emerging media system. Latour (2012) argues that an actor consists of a network of attributes and that "the more you wish to pinpoint an actor, the more you have to deploy its network" (p.3). The reverse holds true as well: to understand a network is to investigate actors that compose the network for "a network is fully defined by its actors" (p.3).

Through social media, social actors are directly connected with each other, forming networked publics (boyd, 2010). Existing evidence shows that tie formation in online networks is largely driven by homophily and peer influence, resulting in homogeneous networks (Aral, Muchnik & Sundararajan, 2009; Bakshy, Rosenn, Marlow & Adamic, 2012). Connectivity between networked publics also creates a potentially boundless network of interactivity between them, thus changing the context of social action (Benkler, 2006; Couldry, 2012). These suggest that connections between individuals can be deployed to understand their actions; their actions can be used to understand their connections.

In the current media system driven by the attention economy, networks possess agency by connecting social actors, organizing their communication, and holding the potential to draw attention and prompt actions from other actors in society. Networks of attention are the attention of the engaged, speaking directly to the programming of a network by an object, a person or an idea, and the agentic power of the network programmed by it (Benkler, 2006; Castells, 2011). Networks of attention are also the attention of scale, which affords visibility. Individuals within the networks are aggregated to be seen and thereby gain visibility, which "constitutes a powerful new form of agency" (Webster, 2014, p.26). Similar to networks of attention, networks of opinion also constitute a form of agency. Public opinion that is synthesized and organized can be seen and can influence media coverage and public policy (Benkler, 2006).

In sum, the network approach entails positioning social actors in the networked space of social interactions and situating social interactions in the networked space of actors. It also considers networks of media, which sort themselves in the competition for audience attention and interact to drive communication flows. The dynamics of the digital media system and power relations can be revealed through the lens of interactive networks, including both networks of social actors/interactions and networks of media outlets. This is a process similar to Castell's

(2011, p.782) assertion that “[networks] interact with networks in the shared process of network making.”

In what follows, I present three studies. The first one examines how attention and opinion on Twitter can be measured by identifying networks of homogeneous actors. The second one studies how Twitter networks interact with news media networks, revealing media system dynamics. The third one investigates networks of actors in online activism by focusing on patterns of attention and expression.

Study I: Networked Public Attention and Public Opinion on Twitter

Can public attention and opinion be captured by networks on social media? In this study, my collaborators and I supply empirical evidence for the argument that attention and opinion can be predicted by the structure of online social networks, encoded in flocks (AUTHORS). Drawing on the idiom that birds of a feather flock together, I define a flock identified via flock members’ social network ties as a homogeneous, interactive and stable group. This is shown in the tendency for flock members to follow each other, be followed by shared audiences, and interact with each other, all in a consistent manner over time. Furthermore, attention and opinion are embedded in the techno-social context of a flock, making it reasonable to collapse the attention and opinions of flock members into attention and opinion of the flock for issues relevant to the flock.

Method

In August 2018, 59 seed nodes, including activists, pundits, journalists and media outlets spanning the whole political spectrum in the United States, were used to sample elite Twitter accounts who actively expressed political opinions on Twitter via personalized PageRank (PPR) sampling. This yielded a sample of 193,120 Twitter accounts, who followed a total of 1,310,051 accounts, after filtering. In August 2019, the same sampling procedure was taken after removing inactive seed nodes (such as @RealAlexJones and @RichardBSpencer) and adding new seeds that figured prominently in the 2018 pull (Appendix I).

A tweet sample containing all tweets of the identified flocks on Mondays from October 1, 2018 to October 1, 2019 was constructed. It yielded 30,028,074 tweets (15,846,255 being retweets), which were used to analyze opinion expression of flocks. Among our sample of retweets, 7,379,555 (46.6%) were originally posted by accounts in the 50 flocks, which is then used to examine the retweeting relationship among flocks.

Two contentious political issues were selected to examine the attention of flock members of 9 media and partisan flocks (Table 1): the passing of abortion laws in the first half of 2019 and the final phase of the Mueller investigation from November 1, 2018 to July 31, 2019. Two comprehensive lists of keywords yielded 748,448 tweets for the abortion laws and 3,354,903 tweets for the Mueller investigation (Appendix I).

A Vintage Spectral Principal component analysis (VSP) was performed to detect 100 communities, i.e., “flocks,” in our sample. The VSP is a spectral clustering technique that estimates the latent factors in multivariate data. The simplest version of this algorithm consists of two steps: a low-rank singular value decomposition (SVD) and a varimax rotation on the singular vectors (Kaiser, 1958). Using the loadings output by VSP, we assigned each Twitter account to one of the 100 flocks. We interpreted and labeled each flock based on the profile descriptions of its member accounts.

Results

Flocks are homogenous, stable and networked groups

Based on the observed following network in the 2018 sample, we identified 100 flocks covering various social, cultural, political and geographical entities. We excluded most regional flocks and selected 50 flocks of interest for downstream analysis. In addition, we considered the 1000 most central accounts from each flock, i.e., accounts with the highest coefficients, to control for the effect sizes of individual flocks. We evaluated the effectiveness of flock identification through (i) shared followers, (ii) retweeting relationship, (iii) stability and fidelity of flock membership. Taken together, evidence indicates that our approach to flock identification discovers communities with high accuracy and resolution and that the identified flocks are meaningful technology-organized groups.

First, member accounts of a flock demonstrate homogeneity because they share more followers than do accounts from different flocks. As followers of a Twitter account constitute its imagined audience with whom in mind it creates messages, similar accounts should attract similar audiences. Aggregating the number of shared followers between any pairs of accounts, as observed in our sample, we found markedly more followers were shared by members of the same flock (Figure 1a). In addition, flocks of the same category also shared more followers (e.g., "mainstream media" and "national political journalists" under the "media" category), revealing an inter-flock structure. To quantify this pattern, we calculated an "in-and-out ratio" to measure the average number of shared followers by two accounts within a flock over the average number of shared followers by one from the flock and one outside it. Overall, we observed an average in-and-out ratio of 15.628 across 50 selected flocks, with a minimum of 5.52. Notably, an account of the "#uniteblue" flock shared on average 35.2 fold more followers with accounts within the flock than accounts outside the flock; similar results hold for the "Christian constitutionalists" and "national political journalists" flocks with 31.4 and 20.2 folds respectively.

Second, interaction in the form of retweeting is concentrated among member accounts of a flock, showing the parallel between flocks and online social networks. Using the Monday tweets, we quantified the proportion of retweeting that occurred between accounts within each flock and found that retweeting patterns were consistent with flock structures. Among the 7,379,555 retweets between all accounts in the 50 flocks, on average 44.1% of retweets were between accounts within a flock, with the "Brexit" flock having as high as 80.8% of within-flock retweeting (Figure 1b). In fact, we found strong statistical evidence in the correlation between an account retweeting other accounts in the sample and the retweeted post originating from other accounts within the flock: p-value < 2.2*10-16 in $\chi 2$ test, after multiplicity correction with Benjamini-Hochberg (BH) procedure. For the flocks with low levels of within-flock retweeting, we found that they retweeted a large number of tweets from flocks of the same category. For example, 50.6% of the retweeted tweets posted by "#uniteblue" originated from accounts in similar flocks, i.e., flocks under the "liberals" category; and 52.1% of the retweets by "Christian constitutionalists" were posted by accounts under the "conservatives" category. Given that retweeting reflects existing ties or is conducive to new tie formation, such evidence might further suggest redundant ties between flock members.

Third, the flock structure we identified is stable and consistent even after one year. Unlike fluid groups organized by communication, flocks, based on the following network, should be relatively stable social groups. This means that despite the ability to freely follow additional accounts or unfollow existing ones, flock members should exhibit relative consistency in accounts they follow, which we investigate here. To this end, we conducted sampling in August of 2018 and 2019 separately and compared the 100 flocks from 2018 and 2019 respectively. Specifically, we evaluated each of the 100 flocks on its (i) stability: the percentage of flock members that remained in the sample after one year and (ii) fidelity: the percentage of recurring flock members that were classified into a similar flock. We first observed that flocks exhibit stability. On average, 60.3% (median 71.6%) member accounts across the 100 flocks of 2018 reoccurred among the 100 flocks of 2019 (Figure 2a). Particularly, 68 flocks in 2018 saw more than half of their members reappear after one year and only 18 flocks less than 30%. The fidelity of flocks provides further assurance. Among the accounts that reappeared in 2019, on average 75.9% accounts across 100 flocks of 2018 were recovered in 2019 (i.e., classified into a similar flock that matches the original flock). In particular, as many as 60 flocks matched a new flock of 2019 (with more than 90% shared account) (Figure 2b).

Flocks predict attention

As shown above, member accounts of a flock are similar and connected, and exhibit stable network patterns, suggesting that a flock is a meaningful techno-social group. Situated in a shared group context, accounts within a flock are expected to signal their attention to social issues in a relatively uniform manner, possibly due to a combination of homophily and peer influence. To explore this relationship, I used the two event datasets to examine how members of the 9 flocks paid attention to the issues. I operationalize attention as the daily counts of tweets concerning a particular issue by a certain account.

An examination of the correlations of the time series between accounts within a flock and between accounts from different flocks provides evidence showing that attention patterns of accounts within flocks are more similar than those of accounts between flocks (Table 2). For all 9 flocks across both cases, the within-flock correlations are always positive and between-flock correlations are always negative.

Flocks predict opinion expression

Besides attention, we also expect flocks to share topical focus in opinion expression. For this analysis, we again relied on the Monday tweets. Given that hashtags are semantic markers of full tweets, we focused on the pattern of hashtags used across the 50 flocks. The most frequently used hashtags were grouped into 6 categories and their occurrences in tweets were computed by flock. For illustration, we present the use of selected hashtags in Figure 3. Overall, we found a high level of correspondence between hashtags and the flocks that used them, suggesting the predictability of opinion expression by flock structure.

Hashtags presumably used by liberals appeared most frequently in liberal flocks' tweets. Similarly, hashtags often used by conservatives to indicate conservative values, or by Trump supporters to show their allegiance, or by conspiracy believers, appeared most frequently in conservative flocks' tweets. So were the issue and topic-specific hashtags: #syria and #iran were overwhelmingly used by "Middle East correspondents." Hashtags even validated the distinction between similar flocks: #bernie2020 and #notmeus were nearly exclusively used by the "Bernie Bros" flock. However, some seemingly discriminative hashtags failed to neatly align with their corresponding flocks. For example, the use of #maga, a hashtag presumably indicating support of Trump's presidential campaign, was split among liberal, conservative and Trump supporter flocks. Similarly, #resistance and #resist, used to express opposition toward the Trump presidency also appeared saliently in tweets from "the Trump train" flock. Such idiosyncratic hashtags being used by heterogeneous flocks might be explained by hashjacking, a practice of infiltrating into opponents' networks (Bode et al., 2015). This suggests that the nuance that cannot be picked up by patterns of hashtag use can be revealed through the following network encoded in flocks.

Study II: Interaction between Twitter Flocks and News Media

To examine the relationship between networked attention and networked opinion of Twitter flocks on the one hand and news media coverage on the other hand, I focus on the same two cases as above: the passing of abortion laws mostly restricting access to abortion, and the final phase of the Mueller probe. The selection of these two cases was balanced on ideology, as the first case can be seen as driven mainly by Republicans and the second case by Democrats. In the abortion law case, several states started to take action and pass new laws to limit or expand access to abortion since early 2019. However, laws restricting access to abortion outnumbered laws expanding access. In the Mueller investigation case, special counsel Robert Mueller was appointed by the then Deputy Attorney General Rod Rosenstein to investigate the Trump campaign's potential link to or coordination with the Russian government during the 2016 presidential election. Several high-profile moments preceded and followed the conclusion of the investigation, such as the trial of Trump's former lawyer Michael Cohen, the sentencing of Trump's former National Security Advisor Michael Flynn, the sentencing of Trump's former campaign manager Paul Manafort, the release of the redacted Mueller report, and the testimony of Mueller before congress. To answer the two questions about the flow of public attention and public opinion between Twitter flocks and news media, I applied time series modeling to analyzing the interrelations between Twitter and news attention over time while controlling for key events, used topic modeling to investigate the content of tweets, and summarized news headlines based on keywords.

Method

Data

Based on legislation databases like Ballotpedia, public policy research sites such as Guttmacher.com, and reports from mainstream news media, I compiled a timeline containing 17 events regarding the passage of abortion laws in various states from January 1, 2019 to June 30, 2019. The timeline of Mueller investigation, which contains 39 key developments during the time frame, was created by cross-referencing multiple existing timelines compiled by major media outlets, including Newsweek, ABC, Vox, Reuters and Axios.

News data were retrieved from the open-source platform mediacloud using its public API. Mediacloud collects news from RSS feeds of a wide range of media outlets in the U.S. and around the world. I selected a total of 18 media outlets based on the Faris et al.'s (2017) report to represent progressive and far-left, moderate and center-left, and conservative and far-right news media networks. Using the parallel search terms and time frames for the Twitter pulls, I collected 8168 news stories containing in the headline the abortion-related terms, and 38,637 news stories for the Mueller investigation (see Appendix II for details on media outlet selection).

Measures

The daily total number of tweets posted by each Twitter flock was computed to represent flock attention to an event (see Appendix III for details). Topic modeling using Latent Dirichlet Allocation (LDA) was applied to identify the topics in the corpus of tweets for each event. For the abortion laws corpus, I identified 9 themes: 1) debate (covering contentious arguments about what is abortion, like whether it is moral and whether abortion access is healthcare etc.); 2) legislation (laws passed regarding abortion access, mostly restricting access); 3) legal decisions (court decisions on abortion cases); 4) politics (politicians' positions and comments regarding abortion, and abortion as an issue in elections); 5) advocacy (advocating certain ideas or course of action); 6) Democrat-bashing (conservatives criticizing Democrats' speech or action related to abortion); 7) conservative reaction (conservatives commenting on abortion-related events); 8) miscellaneous (other topics related to abortion, like public opinion on abortion); 9) mixed (topics that are not interpretable or contain multiple ideas). For the Mueller investigation corpus, I identified 8 themes: 1) conservative reaction; 2) advocacy; 3) Congress (Congressional hearings regarding the investigation); 4) media (fake news, media coverage etc.); 5) the report (calls for releasing the full Mueller report or the interpretation of the findings in the report); 6) the investigations (arrests, court trials, and sentencing of Trump affiliates); 7) miscellaneous (other topics like the Whitaker's appointment, controversies surrounding Attorney General Barr, and conspiracy theories); and 8) mixed (see Appendix IV for details).

To reflect the difference in the time series of each media outlet and the significant variation in the total number of stories of each outlet, I standardized the daily count of stories of each media outlet during the entire period and then aggregated the standardized stores by day for progressive and far-left, moderate and center-left, and conservative and far-right news media networks (see Appendix V for details).

To study media coverage, I focused on headlines, which succinctly convey the key messages of news stories. For each case, given limited corpus sizes, I examined the most frequent bigrams as well as the most unique words in the headlines of news stories from each news media network.

Time series modeling

To explore the dynamics of attention between Twitter flocks and news media networks, time series modeling was applied. The data collection process above yielded daily measures of the following variables for each case: a dummy variable indicating whether an event was present, attention of progressive and far-left news media network, attention of moderate and center-left news media network, attention of conservative and far-right news media network, and attention of the 9 Twitter flocks. The event variable was treated as exogenous given that events functioned as external shocks to attention, and all other variables were treated as endogenous to account for all potential inter-relationships.

A Vector Autoregression (VAR) model was used to determine the time-ordered relationship between the aforementioned variables. The variables in the VAR are as ordered above. In order to use a VAR model, I first-differenced the time series to identify non-stationary time series, as integrated components may result in incorrect estimates (Box-Steffensmeier et al., 2014). Information criteria suggest that a lag of 1 generates the best model fit. Impulse Response Functions (IRFs) from VAR models provide information regarding the longer-term effects of one variable (X) on another (Y), by testing the shock of X on Y (Swanson & Granger, 1997). Through IRFs we gauge by simulation what could happen to one endogenous variable if another endogenous variable changes by one standard deviation and how the impact changes over a period of time.

Results

Attention flows between Twitter and news media

Impulse response functions reveal similarities and differences between attention flows in the two cases. I focus on the consistent relationships across the two cases. These relationships are all positive, indicating that an increase in one variable could lead to an increase in another.

We can first observe the preeminent roles of moderate and center-left news media network and the national political journalists flock, which can be seen as moderate media/journalists on Twitter, in driving up the attention of both partisan news media networks and Twitter flocks (Figure 4). Specifically, increased attention in the moderate and center-left news media network to either the abortion laws or the Mueller investigation could predict spikes in attention of both partisan news media networks as well as partisan media and partisan/activist

Twitter flocks. Positively predicted by news media attention, the national political journalists flock could also raise the attention of all other flocks on Twitter. These patterns demonstrate a hydraulic flow of attention from the moderate and center-left news media network and the national political journalists flock on Twitter to other corners of the media system, suggesting their superior agenda-setting power.

Not only responding to influence from the moderate and center-left news media network and the national political journalists flock on Twitter, partisan news media networks and Twitter flocks interact within their partisan quarters, creating distinct progressive and conservative media ecosystems (Figure 5). The progressive and far-left news media network could drive attention of the #uniteblue, the resistance and Bernie Bros flocks on Twitter, in the same way that the conservative and far-right news media network influences the Christian constitutionalists, the Trump train, and the white nationalists flocks. The progressive media flock on Twitter could raise the attention of the Bernie Bros flock, so could the conservative media and pundits flock amp up the attention of all the three conservative partisan/activist flocks. These suggest a top-down dynamic of attention flow within the partisan media ecosystems, a hierarchy with partisan news media networks at the top, Twitter partisan media flocks in the middle, and the Twitter partisan/activists flocks at the bottom.

Moreover, the progressive and conservative media ecosystems interact with each other in an asymmetrical fashion (Figure 5). Only the #uniteblue and Bernie Bros flocks in the progressive media ecosystem could be impacted by the conservative and far-right news media network. In contrast, the conservative media ecosystem is fairly reactive to the progressive media ecosystem, with the progressive and far-left news media network driving the attention of the conservative and far-right news media network and most conservative flocks, and with the resistance flock driving the attention of the Christian constitutionalists and Trump train flocks.

Twitter public opinion and news media coverage

After conducting topic modeling of tweets and grouping similar topics into themes, it can be observed that in the abortion laws case the conservative media and pundits flock and the three conservative partisan/activist flocks focus on criticizing the Democrats writ large and some specific Democratic politicians regarding their actions or statements about abortion or abortion laws (Figure 6). They are also engaged more in advocacy than their progressive counterparts. In contrast, the progressive media and progressive partisan/activist Twitter flocks focus more on the legislation and legal decisions related to abortion.

Such a pattern corresponds to news media coverage on the abortion laws, as evidenced in the most frequent bigrams and the keywords in the headlines of the news stories on abortion (Appendix VI). The most frequent bigrams in the headlines of stories from the progressive and far-left news media network and the moderate and center-left media network both mainly concern the legislation and legal decisions, as do the progressives on Twitter. They also mention Fox News, 17 times and 26 times respectively. The words most unique to headlines of progressive and far-left news media network include "republican," "rightwing," and "gop," suggesting their attention to right-wing media and politics. While the conservative and far-right news media network also heavily covers the legislative moves and legal battles, they pay special attention to Democrats and their controversial moments, like Virginia's Democratic governor Ralph Northam's abortion statement, the Democratic Party and its presidential candidates, and Pennsylvania Democrat Brian Sims "harassing" pro-life activists. All these are consistent with conservatives' bashing of Democrats on Twitter.

In the case of Mueller investigation, the distribution of themes in tweets is similar for all flocks, dovetailing with heightened reactivity between the progressive and conservative flocks (Figure 7). Nonetheless, two things stand out. First, the conservative partisan/activist flocks are more engaged in advocacy than their progressive counterparts. Second, the progressive media and partisan/activist flocks emphasize the investigation more than the conservative flocks do. Top bigrams in the media coverage of the Mueller investigation are also similar across the three media networks (Appendix VI). However, the progressive and far-left news media network reacts to the conservative and far-right news media network differently than the reverse, similar to the finding in the abortion case. For the progressive and far-left news media network, “fox news” was the 8th most frequent bigram in their headlines. In fact, Daily Kos, Raw Story and Vox ran 342 stories mentioning Fox News in the headline, accounting for 4% of all stories (n = 8098) they ran about the Mueller investigation. However, for the conservative and far-right media network, “adam schiff,” “hillary clinton” and “james comey” are the 10th, 11th and 14th most frequent bigrams. This pattern is also evidenced in the keywords, with “fox”, “conservative” and “rant” among the most unique words in the headlines of the progressive and far-left news media network, and “dems,” “collusion,” “hillary,” “schiff,” “adam” and “clinton” among the most unique words in the headlines of the conservative and far-right news media network.

Study III: Networked Public Attention and Opinion in Online Activism Discourses

In studies I and II, I focus on networks based on friendship relations. In this study, I turn to networks based on communication. In the context of the #Metoo movement, I take the network approach to place social actors in the networks of communication and study retweeting flocks in the #Metoo discourses. I focus on three aspects of the #Metoo movement: participants and opponents, dynamics of attention, and patterns of opinions.

Method

Twitter data were collected from a random 1% archive of tweets, which ingests random Twitter stream using its REST API. A selection of keywords yielded 1,038,248 English tweets during the three years between 2016 and 2018, which covers the year before the #Metoo movement, the year when it took off, and the year after (Appendix VII). The overwhelming majority (73%) of the tweets were retweets, totaling 752,827. These retweets were posted by 540,267 unique users, who retweeted 123,899 unique users (i.e., features that define the retweeting users).

Based on the retweeting relationship (who retweets whom), 15 flocks were detected using the same spectral clustering method (VSP) used in Study I (Appendix VIII). I interpreted each community based on the top 50 features and their profile descriptions. Then I validated my interpretation by summarizing the profile descriptions of both users and features. For automated text analysis, each account's profile description was treated as a document and preprocessing was applied, including removing hyperlinks, special characters and stop words.

To explore the temporal pattern of their expression, I created a time series for each flock based on the daily number of tweets (original tweets or retweets) they generated. I generated autocorrelation and partial autocorrelation graphs to assess whether the underlying process contained autoregressive or moving average processes. Autocorrelation function (ACF) represents the coefficient of correlation between two values in a time series; partial autocorrelation function (PACF) is the correlation coefficient between two values in a time series after transforming the series to filter out random noise. I use these two measures to assess the ephemerality or persistence of the attention of a retweeting flock.

Results

Participants and opponents as observed through retweeting flocks

Table 3 displays each flock and the summary information about the feature accounts that each flock retweeted. The table also displays the number of feature accounts (8569 in total) for each flock, the percentage of verified accounts, and the median (due to great variance) follower/friend counts of the feature accounts.

Two flocks retweeted organizational/activist accounts: the “gender equality movement” flock that retweeted mostly official accounts associated with the gender equality and solidarity campaign “HeForShe” organized by the United Nations, and the “anti-sexual violence alliance” flock that retweeted accounts associated with organized groups combatting sexual violence. The most representative accounts that the “gender equality movement” flock retweeted included @HeforShe, @UN_Women, @WomenintheWorld, @UNWomenUK, @UN and @iHeforShe. This flock’s feature accounts have the second-highest percentage of verified accounts (53%) and third-highest median follower count. Different than the “gender equality movement” flock, the “anti-sexual violence alliance” flock retweeted more grassroots activism accounts like @PixelProject (the Twitter account of a nonprofit organization) and @DavidLeanLeano (an activist who fights against child abuse), as only 26% of feature accounts were verified. The most representative words in their profile include “awareness,” “violence” and “survivor.”

Four retweeting flocks retweeted accounts that espoused feminist ideals, such as @WeNeedFeminlsm, @projectFem4All, @ltsFeminism, @FeminismDaiIy and @feministculture, as well as individuals accounts who claimed to be (leftist) feminists or supporters of feminism. The anti-feminism flock retweeted accounts that advanced men's rights and viewed feminism as discriminative, such as @MeninistTweet, @CauseWereGuys and @TooSexist. It is noteworthy that all the feminism and anti-feminism flocks retweeted mostly grassroots accounts, with only 10% to 20% of feature accounts being verified by Twitter.

There are three partisan retweeting flocks, two progressive flocks and one Trump supporters flock. The progressive flocks retweeted accounts that declared their liberal ideology or resistance to the Trump presidency. Almost half (49%) accounts that they retweeted were verified, the highest among the feature accounts of all flocks. The Trump supporter flock retweeted the far-right, conservative or Trump surrogate accounts like @PrisonPlanet, @RealCandaceO, and @RealJamesWoods. Both the most representative and top words in their profiles concerned Trump campaign slogans and Christian religious beliefs.

Two retweeting flocks mainly retweeted celebrities in western societies like @EmmaWatson and @katyperry or K-pop accounts. Those retweeted by the celebrity followers flock have the second-highest percentage (46%) of verified accounts, while a much lower percentage (20%) of accounts retweeted by the K-pop flock were verified. Three flocks were not interpretable as they retweeted a mixture of accounts that do not fit together, therefore I classified them as "mixed" and excluded them from downstream analyses (Appendix IX).

Among all accounts classified into flocks, the majority (63%) belonged to the progressive flocks (#3 and #14). The next is the flock of Trump supporters, who compose 22% of all classified accounts. The feminism flocks are the third-largest category, though they only composed 8% of all classified accounts. The remaining groups made up merely 2% to 1% of all classified accounts. This suggests that discourses surrounding #Metoo movement and feminism were mainly driven by ideological groups. For the downstream analysis, I excluded the mixed flocks and combined flocks with the same label, which leads to eight unique flocks.

The temporal patterns of expression

Given that the majority of tweets were retweets, I aggregated the daily count of retweets separately to create 8 time series for the 8 unique flocks. It can be seen that the gender equality movement and anti-sexual violence alliance flocks were active long before the takeoff of the #Metoo movement (Figure 8). There seemed to be sustained discourses by these two advocacy flocks before and after the rise of the #Metoo movement. The discourses surrounding feminism as well as the counter-discourses that advocated men's rights also started long before the rise of the #Metoo movement and continued after it. However, their temporal patterns are more sporadic than those of the advocacies. Even more so are the time series of celebrity followers and K-pop fans, marked by a few spikes. However, the time series of the two partisan groups are different from all others. Both progressives and Trump supporters participated in the conversations before the rise of the #Metoo movement, but their activity increased substantially after it. Two events seem to have driven their activity significantly: the series of sexual assault/harassment accusations at the end of 2017 and the confirmation hearing of Justice Brett Kavanaugh in late September of 2018 where Dr. Christine Ford testified that she was sexually harassed by him.

Both ACFs and PACFs demonstrate different auto-regressive patterns (Figure 9 and Figure 10). The retweeting discourses by feminism and anti-feminism flocks were the most ephemeral, with retweeting activity only correlated within a couple of days. They are followed by the celebrity followers and K-pop fans flocks, whose retweeting activity drove itself for around 10 days. This is similar to the gender equality movement and anti-sexual violence alliance flocks. The most persistent retweeting patterns are observed among progressives and

Trump supporters: once they started to retweet, their activity can sustain itself for over 30 days. In particular, the Trump supporters' retweeting was the most persistent, with the activity of a day still correlated with the activity 30 days later at 0.3.

The content of opinion expression

What did the retweeting flocks retweet? Table 4 presents the most frequent bigrams and their frequencies among the unique retweeted tweets from the 8 unique retweeting flocks. The top 10 bigrams among all the unique retweeted tweets are about sexual abuse/assault/harassment and the #Metoo movement, suggesting that the dominance of sexual violence discourses. The majority of the retweeted tweets by the gender equality movement flock contained "gender equality" and bigrams concerning the HeForShe campaign, beyond the 10 most frequent bigrams. The anti-sexual violence alliance flock retweeted tweets mostly concerning child sexual abuse and awareness raising, though the top retweets are about #Metoo and feminism.

Most retweeted tweets by the feminism flocks, besides discussing sexual violence, also brought up the issue of intersectionality in feminism and expressed dismay that the election of Trump presented as a challenge for women. The tweets that the anti-feminism flock retweeted varied a lot, but the top retweets showed that this flock criticized feminism/feminists as sensitive and frivolous on the one hand and radical and destructive of men's lives on the other.

Tweets that progressive flocks retweeted were mostly about sexual abuse/harassment accusations against politicians like Donald Trump, Brett Kavanaugh and Roy Moore, as well as big names in the entertainment industry like Harvey Weinstein and Bill Cosby. These flocks also paid attention to debates within feminists like white feminism and intersectional feminism. Trump supporters also retweeted tweets about allegations, but mostly against Democratic politicians and those close to Democratic/progressive politics like Bill Clinton, Hillary Clinton, Harvey Weinstein, Al Franken, John Conyers and Linda Sarsour. The top retweeted tweets demonstrated this flock's deep disbelief in the veracity of women's sexual accusations and in the victimhood of men inflicted by those false accusations.

Discussion

This dissertation centers around processes of political communication in the US as impacted by digital media. I take a practice-oriented approach that prioritizes media practices, i.e., how social actors use digital media and what social consequences their practices lead to. Specifically, I focus on how social actors signal attention to issues of public interest and express their opinions on those issues through social media. Building on the actor network theory that posits the mutually constitutive relationship between actors and their networks, I argue that public attention and public opinion emerging on social media can be understood and analyzed through networks, i.e., placing social interactions in the networked space of actors and positioning social actors in the networked space of social interactions. Ultimately, this network approach traces the multifaceted flows of attention and opinion to the networks they originate from in the digital media system and holds the potential of revealing patterns of interactions between networks of social actors, and between social networks and institutional networks like media, which provides a unique angle to observe the dynamics of the media system and the contour of the public.

Focusing on Twitter, a unique social media platform that attracts various social actors and generates high-profile and heated political discussions and debates, I demonstrate that Twitter flocks are homogeneous, interactive and stable social groups and that their attention signaling and opinion expression can be predicted by flock structure, providing empirical support for treating flocks as units of analysis of attention and opinion.

I then examine interactions between news media networks and Twitter flocks. In the context of two cases, the passing of abortion laws and the Mueller investigation, a hierarchy of attention flows surfaced, moving from moderate and center-left news media network, to partisan news media networks, Twitter moderate media flock, Twitter partisan media flocks, and lastly to partisan/activist Twitter flocks. This finding speaks to the considerable power of traditional elites, i.e., mainstream journalists and media outlets, in driving communication flows in the digital media system. This suggests that traditional media elites in the internet era still possess significant power (Hindman, 2008; Langer & Gruber, 2020). However, considerable as the elite media's power was, there were some bottom-up flows from the partisan/activist Twitter flocks to the news media networks in the Mueller investigation case, suggesting the potential for ordinary people to deploy the power of networks to wield influence.

Results also reveal the coupling of the partisan news media networks and the partisan media and activists Twitter flocks, giving rise to the emergence of partisan media ecosystems in the hybrid media system. Such distinct partisan media ecosystems point to the division in the hybrid media system despite the agenda-setting power of moderate and center-left media. However, this does not mean that the two partisan ecosystems are insulated islands. In both cases, the partisan media ecosystems did interact with each other, though in an asymmetrical and reactive fashion. The conservative media ecosystem was more attentive and reactive to the progressive media ecosystem than the reverse. Such interaction was as asymmetrical as qualitatively different: while the conservative media ecosystem directed their attention to calling out Democrats and the Democratic party for their outrageous speeches or behaviors, the progressive media ecosystem primarily reacted to conservative news media. Such interaction further exacerbates partisan division and contributes to the deep chasm within the media system.

I further examine a different type of flocks, the retweeting flocks based on who retweeted whom, in the Twitter discourses about the #Metoo movement. Results show that these discourses attracted a wide variety of networks, supportive and oppositional, politically engaged and disinterested. These included Twitter users supporting gender equality, against sexual violence, for and against feminism, with strong ideological leanings and beliefs, and into celebrities and media entertainment. In contrast to the diversity of participants, the distribution of the volumes and durations of attention from those flocks was heavily skewed. These discourses were dominated by ideological and partisan groups: the partisan retweeting flocks, i.e., the progressives and the Trump supporters, accounted for the overwhelming majority of all Twitter accounts in the sample who contributed to the discourses. These partisan retweeting flocks also demonstrated persistent attention. In contrast, the retweeting flocks coalescing around organized movements and groups for gender equality and against sexual violence, and retweeting flocks rallying behind feminism and anti-feminism only made up a fraction of the Twitter users and exhibited short-lived attention spans. Moreover, the progressive flocks mainly retweeted accusations against Donald Trump, while the Trump supporters flock retweeted accusations against Democratic politicians or progressive activists. This suggests that although news media might have sustained the attention of partisans by exposing scandals, partisans on Twitter engaged in ideologically driven opinion expression about those scandals.

Both studies show that social media provide people with opportunities to connect with each other and amplify their shared voices. The Twitter flocks, seen from following relationships and retweeting relationships alike, exhibit highly consistent attention and opinion patterns within. This shows that with social media affordances that enable people to locate like-minded others, it is easier for people to program networks around shared identities, values, or bonds.

Situated within homogenous networks, they reinforce each other's beliefs and demonstrate highly similar attention and opinion patterns. At the same time, algorithmic recommendation and news media amplification make it easier for networks to see, respond to, and interact with each other, partly explaining the interactions within the Twitter flocks and between Twitter flocks and news media networks. However, as people passionately draw attention to and express opinions on public issues and news events on social media, they tend to advance beliefs and values shared by their own networks while criticizing and provoking the oppositional networks. This points to the further splintering of the public into publics, leading to the public sphere morphing into "a complex combination of multiple interlocking elements that sometimes counteract, sometimes amplify each other, and each possesses their own specific dynamics" (Bruns and Highfield, 2015, p.63).

These results further highlight the increasing differences in style and culture between progressives and conservatives in partisan media and on Twitter alike, attesting to the potential of the network approach to reveal nuanced group dynamics. Specifically, progressive media and progressives on Twitter tend to focus more on institutions on the right (i.e., conservative media), whereas the conservative media and conservatives on Twitter tend to direct their attention more to individual Democratic politicians or progressive figures. The ready posture of conservatives attacking the boogeyman might have to do with their tendency to view social media as a battleground to fight against progressives (Peck, 2019). Moreover, the greater tendency of the conservative media ecosystem to react to the progressive media ecosystem suggests underlying differences between the two political parties. With the Republican party unified by conservative values and the conservative media playing a central role in enforcing those values (Grossmann &

Hopkins, 2016), the conservative media ecosystem is well-positioned to counter progressives' efforts.

However, though the formation of distinct networks gives rise to divided publics, networks also empower various publics. Networks forged by share bonds and identities, such as flocks based on following relationships, resemble issue publics who are committed to certain issues and values and ready to defend them against challengers; and networks programmed in the process of communication, like the retweeting flocks, can take shape and dissolve quickly. It is such social media networks that aggregate attention and synthesize opinion, and it is exactly such networks that can attract public attention and influence public opinion. This is because the current media system is more likely to see and respond to engaged attention and opinion of scale (Benkler, 2006; Webster, 2014), the exact kind from the impassioned networks on social media. The institutional mechanism of news media processing and integrating social media content is being created and increasingly influencing journalistic routines (Cherubini & Nielsen, 2016; McGregor, 2019). This tendency of news media to amplify networked public attention and opinion can be linked to the attention economy and the mounting challenges brought by social media—the pressure to produce engaging content that draws eyeballs and generates clicks, and the changing normative framework of journalism that increasingly values citizen input. As a result, the process of audience making by news media takes ever more input from news audience (Webster, 2014).

Empowerment via digital networks is not limited to a certain group—all kinds of networks emerge and hold the potential to gain attention, voice, and ultimately power in the digital media system. The past couple of decades have seen the rise of progressive networks, Tea Party networks, as well as fringe groups like the Alt-right, Neo-Nazis, and Men's rights activists, all of which have gained traction in the mainstream public discursive spaces, exactly for their abilities to program their respective networks through social media and to prompt responses and amplification from news media. This presents mounting challenges for journalists and the institution of journalism, which can fuel the growth of democratically undesirable ideologies or forces by providing them with media spotlight (Philips, 2018). This further means that the publics in the digital media system are defined more by their ability to attract attention and make themselves visible than by normative expectations of rational and public-spirited citizens.

Overall, the network approach to understanding how social actors signal attention and express opinion through social media presents a complicated and nuanced portrayal of the dynamics of the media system and the public in the early 21st century. Legacy news media still wield considerable power in shaping the agenda of other news media and online networks. In the context of an increasingly divided media system, this stands as a glimmer of hope since legacy news media can drive societal attention. However, the public is splintering into various stable or fluid publics in the digital media system and their interactions might further intensify their differences. Nonetheless, in the digital media environment, person-to-person networks can be more easily programmed, information can be more easily produced and distributed, and “birds of a flock” can see and interact with each other with greater ease. As such, networked publics possess the power to project their voices, drive the attention of traditional media elites, and make themselves visible in society. In this sense, digital media both constrain and enable social actors and their capacities in moving toward a more democratic society.

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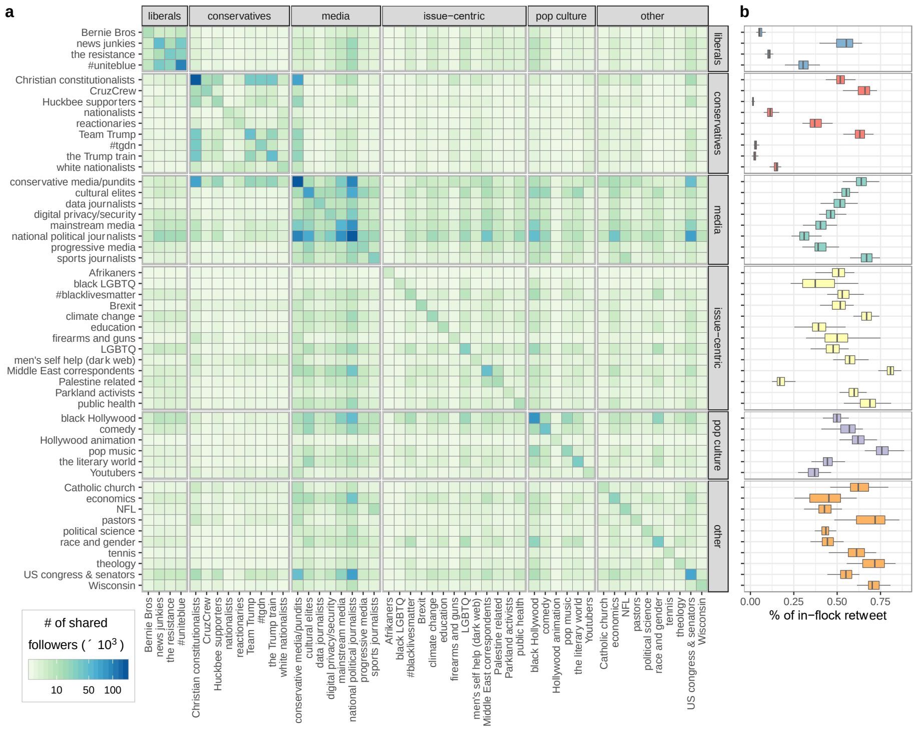


Figure 1. Shared followers and retweets are concentrated within flocks. (a) Heat map of the number of shared followers among flocks. Each row and column correspond to one flock in the same order (i.e., the shown matrix is symmetric). Rows and columns are grouped into panels by flock category, with strips on the top and right indicating the category name. The shade of color is determined by the number of shared followers between pairs of flocks. (b) Box plots showing the distribution of in-flock retweeting percentages (i.e., for each member of a flock, the percentage of retweeting that he/she initiated of tweets from another flock member was calculated). The box plots align horizontally with the rows in (a).

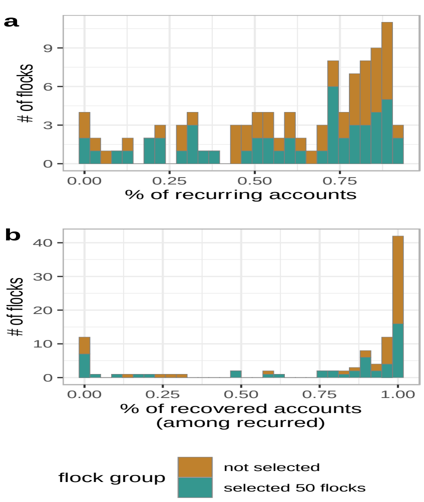


Figure 1. The percentage of flock members that recurred and recovered after one year. (a) Histogram of the percentages of flock members in the 2018 flocks that remained in the new sample in 2019. (b) Histogram of the percentages of recovered accounts in the 2018 flocks, i.e., accounts reappearing in a similar flock in 2019. In both panels, the 100 flocks are stratified by whether they belong to the 50 flocks that we selected to measure in 2018.

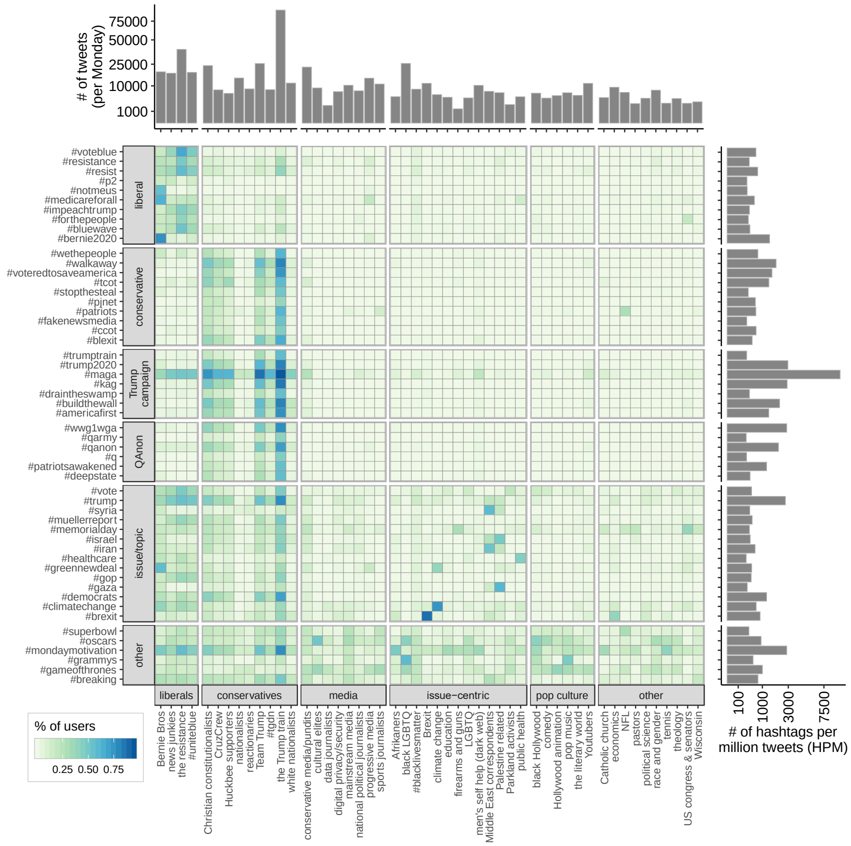


Figure 3. Heat map of 53 hashtags frequently used by 50 flocks. Each column corresponds to one flock, with column panels indicating flock category and column strips on the bottom indicating the category name. Each row corresponds to one hashtag, with row panels indicating the hashtag category and row strips on the left indicating the category name. The shade of color indicates the percentage of active accounts in the flock that utilized the hashtag. The bar plot above the heat map reports the number of daily tweets from each flock; the bar plot on the right reports the number of hashtags observed per million tweets collected.

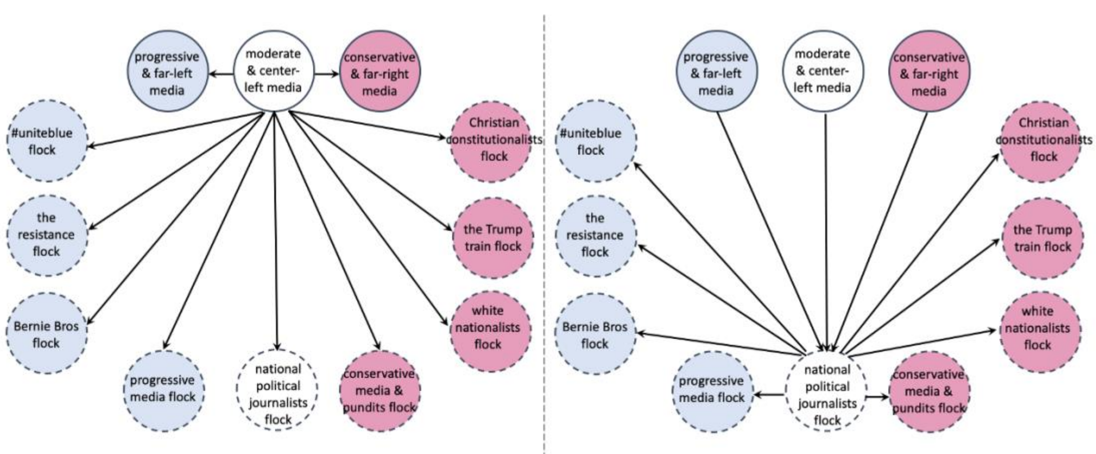


Figure 4. Consistent attention flows from the moderate and center-left news media network (left) and from and to the national political journalists flock (right).

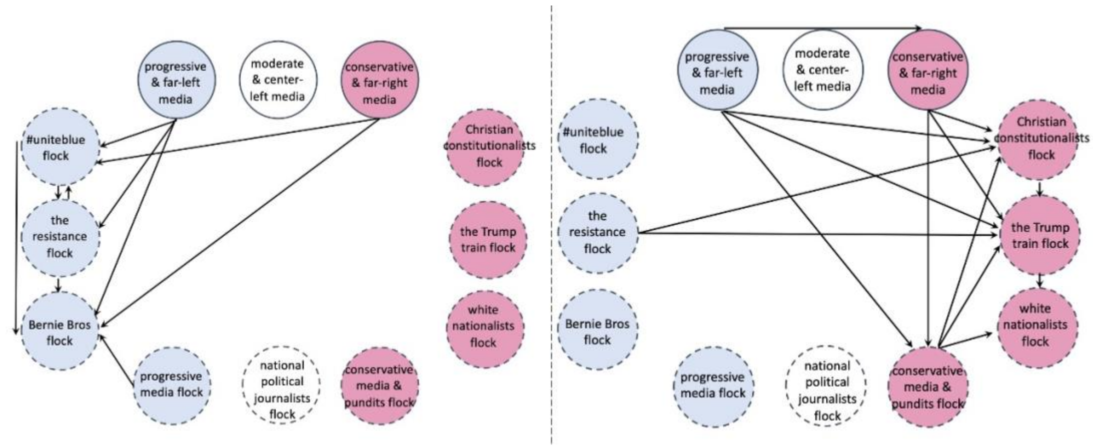


Figure 5. Consistent attention flows within the progressive media ecosystem (left) and the conservative media ecosystem (right), and between these two ecosystems.

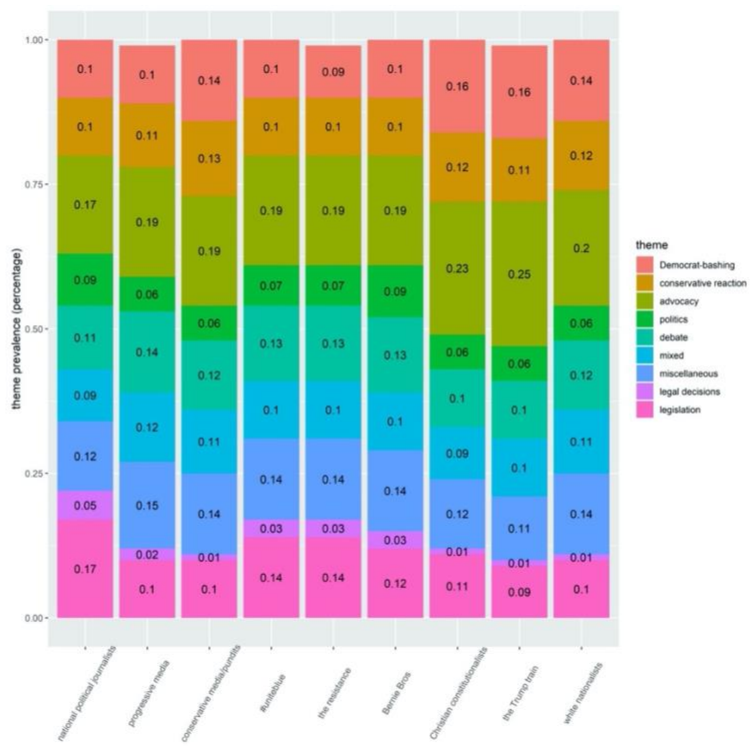


Figure 6. Theme prevalence for all tweets in the abortion laws corpus

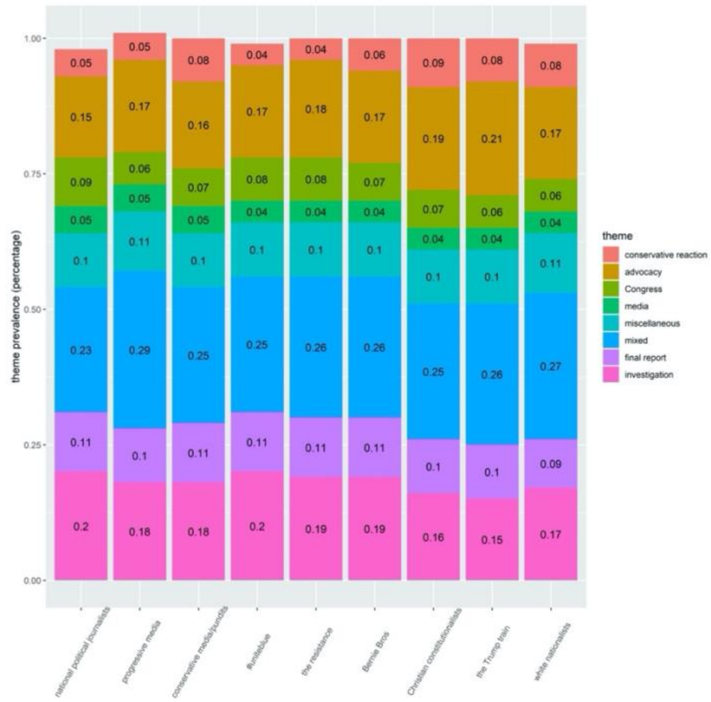


Figure 7. Theme prevalence for all tweets in the Mueller investigation corpus

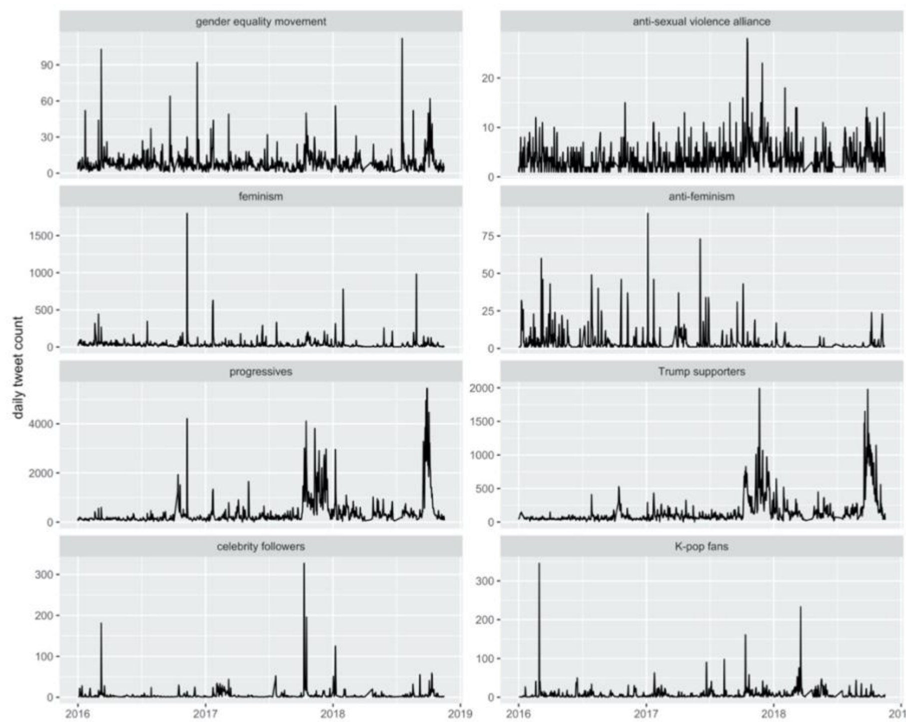


Figure 8. Daily count of tweets (retweets) from the 8 retweeting flocks

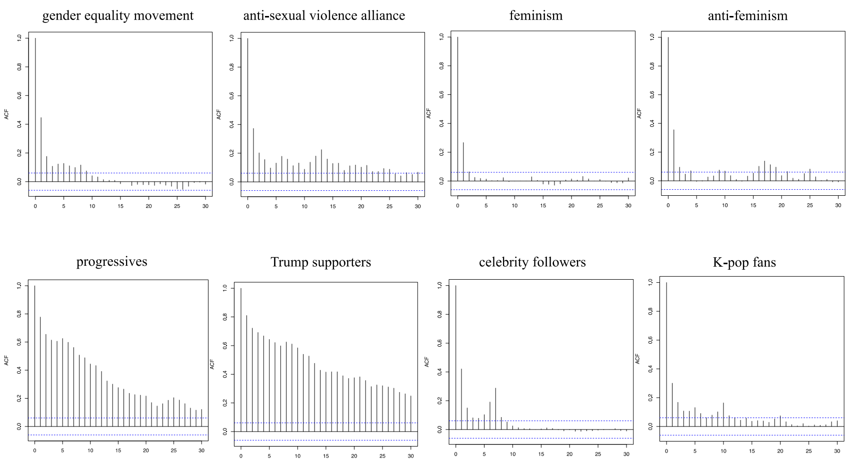


Figure 9. Auto-correlation functions (ACFs) of time series of the 8 retweeting flocks

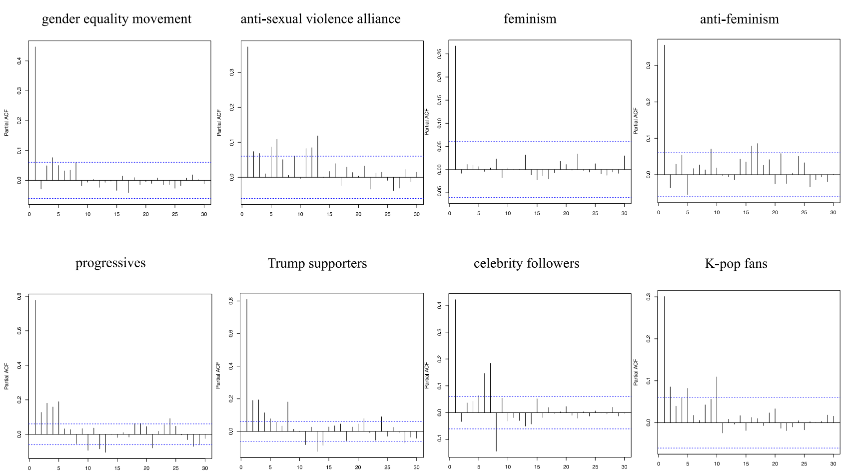


Figure 10. Partial auto-correlation functions (PACFs) of time series of the 8 retweeting flocks

Table 1. Selection of 9 flocks

flock label	flock description
national political journalist	Covering US national politics
progressive media	Appealing to progressive partisan audience, e.g., Jacobin and Splinter News
conservative media and pundits	Appealing to conservative partisan audience, e.g., Stephen Miller, Ben Shapiro, and National Review
#uniteblue	Promoting progressive causes and values
resistance	Opposed to the Trump presidency
Bernie Bros	Alleging support for Bernie Sanders
Christian constitutionalists	Showing firm conservative beliefs yet do not express solidarity with a specific political figure
the Trump train	Vowing clear and strong support for Donald Trump
white nationalists	Espousing beliefs in ethnocentrism and nationalism

Table 2 Correlations of time series of individual accounts within and between flocks

	the abortion law case		the Mueller investigation	
flock label	average within-flock correlation	average between-flock correlation	average within-flock correlation	average between-flock correlation
national political journalists	0.075	-0.006	0.234	-0.009
progressive media	0.132	-0.006	0.121	-0.006
conservative media/pundits	0.138	-0.009	0.221	-0.009
#uniteblue	0.160	-0.008	0.170	-0.011
the resistance	0.193	-0.008	0.250	-0.013
Bernie Bros	0.169	-0.007	0.115	-0.008
Christian constitutionalists	0.094	-0.010	0.142	-0.011
the Trump train	0.184	-0.012	0.233	-0.014
white nationalists	0.071	-0.007	0.089	-0.006

Table 3. Summary of feature accounts for all 15 flocks based on retweeting relationships

id	flock label	top feature accounts	most representative words in feature accounts profile descriptions	most frequent in feature accounts profile descriptions	total number of feature accounts	percent of verified feature accounts	median follower count	median friend count
2	gender equality movement	@HeforShe, @UN_Women, @WomenintheWorld, @GlblCtzn, @SayNO_UNiTE, @e_nyamayaro, @UNWomenUK, @UN, @phumzileunwomen, @iHeforShe	solidarity, march, gender, movement, equality, check, woman, #un, #genderequality, entity, empowerment, womens, executive, @unwomen, director, violence, sexual, assault, impact, share	love, woman, de, life, feminist, lover, social, student, view, world, writer, la, tweet, music, fan, human, live, book, gender, follow	144	53%	37932	1058
12	anti-sexual violence alliance	@PixelProject, @DavidLeanLeano, @yesallwomen, @MichaelGLFlood, @VictimRightsLaw, @EverydaySexism, @TrojanManifesto, @STVNews, @NSVRC, @ariel_henley9	century, 21st, violence, awareness, style, raise, stop, day, global, woman, time, sexual, nasa, viking, puppy, minnesota, survivor, disney, csa, twin	love, child, life, abuse, feminist, survivor, sexual, woman, violence, view, live, book, writer, fan, support, lover, music, tweet, endorsement, follow	81	26%	13534	1186
6	feminism	@WeNeedFeminlsm, @projectFem4All, @girlprobIem, @shadyemoji, @musicnews_shade, @MarinasDiamonds, @fatimalmao, @feminizza, @eemanabbasi, @EvrydayFeminism	womens, equal, support, follow, feminism, true, leftist, fem, download, sexuality, daily, #freepalestine, status, activism, womanist, struggle, black, gender, post, intersection	love, life, feminist, de, girl, follow, la, live, world, music, time, fuck, blacklivesmatter, ig, people, heart, sc, lover, day, art	144	18%	11134	612

8	feminism	@mehdihaddache, @EveForster, @unsmokabIe, @PEACHYBLACKG0RL, @irenicpoet, @afrodreamboy, @JaggedEdgeAF, @_reecelamaster, @antoniodelotero, @kennabbby	guy, jar, leftist, #freepalestine, queer, status, cognitive, neuroscientist, download, metal, generation, struggle, flaw, #allblacklivesmatter, whore, pan, whiskey, chance, amaze, black	love, life, fan, de, ig, account, time, live, sc, girl, la, fuck, world, music, student, feminist, instagram, snapchat, insta, people	47	13%	6155	483
11	feminism	@ansontm, @darrenhayes, @shutupgunther, @SoDamnTrue, @SarahSahim, @enews, @ItsAlexJackson, @joshgad, @sarahlynn72, @yngmojo	paint, stuff, gay, leftist, accord, slave, lily, cruelty, shaker, pan, filmmaker, rip, hulu, movie, babe, queer, authority, album, diaspora, status	love, life, follow, fan, ig, people, live, de, lover, music, tweet, account, sc, girl, time, twitter, la, social, writer, person	260	20%	14038	608
13	feminism	@ltsFeminism, @FeminismDaiIy, @feministculture, @verge, @danacfinley, @AndreaRussett, @LaurenJauregui, @implicitldemand, @1942bs, @HolySiaFurler	womens, equal, post, content, support, sexuality, feminism, activism, intersection, gender, true, race, leftist, status, download, struggle, found, fem, black, daily	love, life, de, girl, ig, feminist, live, follow, sc, blacklivesmatter, music, world, snapchat, time, fan, enthusiast, la, art, heart, instagram	115	15%	8899	625
7	anti-feminism	@MeninistTweet, @Ieansquad, @Sadieisonfire, @AnthonyLarme, @barstoolsports, @CauseWereGuys, @TooSexist, @The_HelenKeller, @FillWerrell, @halalyouth	sarcasm, parody, create, contact, instagram, feather, tall, sexist, priestess, machine, peer, drop, walk, @theonion, pimp, @nero, fabulous, evidence, unofficial, misandry	love, life, sc, live, snapchat, god, game, follow, ig, fan, people, day, music, fuck, tweet, time, world, football, en, sport	33	9%	16262	420
3	progressives	@funder, @thehill, @krassenstein, @Alyssa_Milano, @RVAwonk, @ProudResister, @robreiner, @EdKrassen, @joncoopertweets, @JuddLegum	#theresistance, #resist, #trumprussia, senator, editor, news, washington, #fbr, @thedemcoalition, critic, msnbc, #amjoy, chair, break, staff, resistance, @cnn, dem, michael, whiskey	love, life, lover, writer, resist, fan, mom, live, music, theresistance, proud, world, tweet, politic, feminist, time, trump, people, woman, liberal	4099	49%	28153	1200
14	progressives	@chriscaban_, @AriannaDantone, @swanktheog, @softsadsatan, @13rwclayhannah, @ryanyeetz, @lexi4prez, @ajplus, @zaralarsson, @LizStrand	flaw, shout, ocean, sense, humor, black, gay, download, lily, cruelty, leftist, status, rip, twin, shit, disney, app, album, potato, viking	love, life, ig, blacklivesmatter, sc, feminist, girl, time, live, black, music, god, de, fuck, fan, world, student, lover, follow, enthusiast	900	14%	7882	588
4	Trump supporters	@PrisonPlanet, @RealCandaceO, @Thomas1774Paine, @RealJamesWoods, @mitchellvii, @FoxNews, @Cernovich, @charliekirk11, @IngrahamAngle, @StefanMolyneux	#maga, conservative, 2a, #americafirst, america, news, #buildthewall, @tpusa, #nra, #trump2020, @dineshdsouza, #trump, 1a, #draintheswamp, host, radio, #tcot, #kag, @genflynn, political	maga, love, trump, conservative, god, proud, life, christian, american, country, patriot, family, pro, follow, america, supporter, 2a, fan, nra, president	2345	26%	25858	1589

9	celebrity followers	@EmmaWatson, @SadiqKhan, @JensenAckles, @quenblackwell, @slamup, @TSwiftNZ, @emmaggarland, @katyperry, @ProjectBuddy, @Lin_Manuel	goodwill, @unwomen, ambassador, global, actor, facebook, instagram, @theonion, disney, begin, #un, viking, nasa, pan, assault, @thedailyshow, wild, antisexual, sexuality, twin	love, life, de, fan, music, lover, girl, follow, la, live, world, time, writer, feminist, book, instagram, art, enthusiast, people, ig	82	44%	45781	450
15	K-pop fans	@allkpop, @soompi, @OH_mes, @KeshaRose, @Koreaboo, @allkpopBuzz, @that1mum, @netizenbuzz, @drunktaeyeon, @MADBLACKTHOT	kpop, gossip, celebrity, break, faves, gifs, fashion, choice, community, original, report, news, time, status, download, korean, korea, struggle, app, generation	love, life, fan, exo, follow, bts, account, live, girl, stan, music, de, kpop, world, got7, time, ig, army, lover, tweet	155	20%	24130	525
1	mixed	@RaulOrozco, @SoulsDefence, @TODAYshow, @Ian56789, @michaeldickson, @thepileus, @jbarro, @acupoker, @TheAnonJournal, @davidsheen	follow, numb, reply, cruelty, dislike, geopolitical, stock, curious, grave, ellen, americas, trader, eu, europe, morning, oifoef, homeland, sweetheart, lose, @thedemcoalition	animal, love, lover, life, fan, music, world, follow, cat, people, tweet, dog, live, news, resist, twitter, de, family, god, block	14	36%	45222	5482
5	mixed	@LoitersquadTV, @jessthesav, @NotABonerGarage, @ItsTheJokers, @Himosexual, @FeministBS, @JenniferAnWorld, @AliMaadelat, @CelebsInHS, @Trekles	promo, notification, dm, content, laugh, follow, squad, dick, join, clip, bring, affiliate, picture, regret, dumb, #blacklivesmatter, tv, absolutely, match, egg	love, follow, dm, post, life, ig, tweet, content, snapchat, account, sc, notification, girl, god, live, gmail.com, music, time, de, world	58	5%	22938	796
10	mixed	@cprandoni_, @TomiLaffly, @DomPerinyon, @kellyblaus, @christielock, @0point5twins, @jaypugz, @numbfeelingx, @NoToFeminism, @ConnorFranta	summer, shit, black, leftist, alpha, electrical, fashion, @vulture, status, @variety, shaker, wizard, fem, crystal, jihad, struggle, @bitchmedia, @theintercept, #allblacklivesmatter, @theyoungturks	love, life, fan, time, writer, ig, girl, lover, de, live, feminist, music, student, world, enthusiast, account, sc, tweet, art, instagram	92	29%	11924	692

Table 4. The most frequent bigrams in unique retweeted tweets by the 8 flocks

flock label	most frequent bigrams (frequencies) in unique retweeted tweets
gender equality movement	gender equality (155), heforshe artsweek (76), child sexual (71), heforshe heforshe (60), heforshe impact (46), impact champion (43), heforshe whatweshare (41), gender stereotype (40), assault survivor (38), experience sexual (37), gender inequality (34), shiftyourperspective heforshe (32), heforshe turnstwo (30), gender base (29), report sexual (29), heforshe commitment (28), domestic violence (27), heforshe champion (25), equality heforshe (24), heforshe join (23)
anti-sexual violence alliance	child sexual (404), childhood sexual (158), raise awareness (64), yesallwomen yesallwomen (52), abuse survivor (37), abuse child (36), assault survivor (24), abuse victim (20), domestic violence (19), respectyourself l6hjh (19), sexual exploitation (18), experience sexual (16), anti feminist (15), male sexual (15), male survivor (15), report sexual (15), abuse exploitation (14), assault awareness (14), assault victim (14), bbc news (14)

feminism	white feminism (168), white feminist (138), feminist icon (120), taylor swift (109), tw sexual (65), anti feminist (60), assault woman (60), intersectional feminist (49), trans woman (48), male feminist (47), assault survivor (45), white woman (45), black woman (43), assault victim (42), black feminist (41), donald trump (41), hillary clinton (40), rape culture (39), woman attempt (38), emma watson (37)
anti-feminism	campus police (12), twitter feminist (10), youtube video (10), male feminist (9), feminism feminism (7), anti feminist (6), campus campus (6), feminist icon (6), permit campus (6), feminist vegan (5), wave feminism (5), black people (4), feminist feminist (4), feminist woman (4), fun laugh (4), intersectional feminist (4), lena dunham (4), radical feminism (4), sensitive people (4), vegan sensitive (4)
progressives	donald trump (1880), assault woman (1483), assault survivor (1391), misconduct allegation (1347), harassment allegation (1329), fox news (1260), brett kavanaugh (1232), assault victim (1223), child sexual (1181), white feminism (1121), allege sexual (1083), sexual harasser (1016), harvey weinstein (978), roy moore (956), sexual assaulter (921), bill cosby (826), woman accuse (819), sexual abuser (795), black woman (775), harassment claim (774)
Trump supporters	bill clinton (959), harvey weinstein (721), male feminist (638), child sexual (623), misconduct allegation (608), harassment allegation (603), assault victim (569), harassment claim (547), hillary clinton (540), allege sexual (536), woman accuse (451), assault woman (360), sexual harasser (343), brett kavanaugh (339), modern feminism (323), amid sexual (321), linda sarsour (306), al franken (305), john conyers (303), sexual abuser (287)
celebrity followers	kcafavmusicvideo metoo (504), metoo kcafavmusicvideo (115), metoo meghan_charts (45), megatronz unite (24), unite kcafavmusicvideo (23), metoo meghan_trainor (20), lucas_megatron meghan_trainor (17), vote kcafavmusicvideo (17), emma watson (16), metoo lucas_megatron (15), metoo metooindia (15), spotify kcafavmusicvideo (15), metoo itunes (13), proud feminist (13), assault survivor (12), metoo metoo (12), mj akbar (12), cinco kcafavmusicvideo (11), meghan_charts kcafavmusicvideo (11), nove kcafavmusicvideo (11)
K-pop fans	feminist issue (29), issue susie (29), social disease (29), susie orbach (29), feminist healthfood (27), park yoochun (26), mgwv metoo (22), organic healthy (22), trapadrive mgwv (22), healthfood organic (19), allege sexual (18), woman attempt (18), allegedly sexually (17), assault charge (17), workplace sexual (16), min ki (15), bill cosby (14), blog post (14), assault victim (13), feminist icon (13)

Note: The most frequent 10 bigrams were removed: "sexual assault", "sexual harassment", "sexually assault", "sexual abuse", "sexual misconduct", "sexually harass", "sexual violence", "sexually abuse", "metoo movement", "assault allegation"

Appendix I

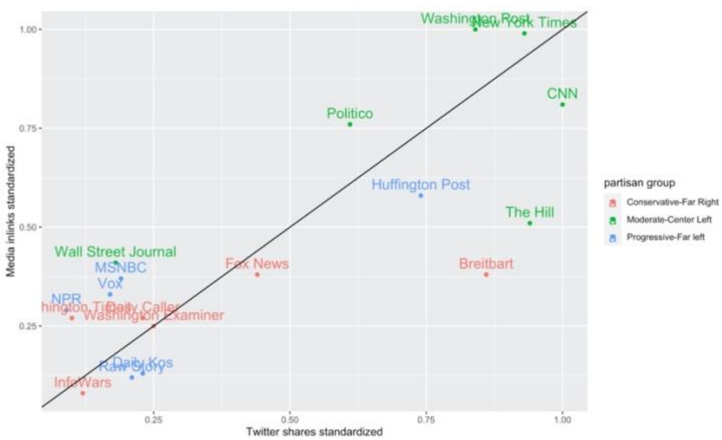
The PPR sampling evaluates nodes in the network with an approximate PPR vector and samples those nodes with the highest scores. The PPR vector is defined as the stationary probability distribution of which we call a personalized random walk. At each step of the random walk, the walker returns to the seed node with probability α, and, with probability 1 - α the random walker goes to an adjacent node chosen uniformly at random. We chose 59 Twitter accounts as seed nodes, including activists, pundits, journalists and media outlets spanning the whole political spectrum in the United States, and implemented the method to collect following network data. This approach produced a total of 267,117 Twitter accounts, with a total of 10,174,291 friends that they followed. Given that an account who follows or is followed by few accounts is difficult to classify, we removed any accounts who follow fewer than 2 friends and those followed by fewer than 5 accounts. This filtering resulted in a reduced sample.

In terms of the two selected cases, the first one was driven by governors in conservative states, whereas the second one by Democrats in Congress. To collect tweets about abortion in general and the passing of abortion-related laws specifically, I chose general search terms that can capture discussion from both liberals and conservatives, including "abortion", "pro-life", "pro-choice", "pro life", "pro choice", "prolife", "prochoice", "planned parenthood", "reproductive right", "roe v. wade", "roe v wade" and "infanticide;" specific terms to abortion bans passed by several states were also included: "heartbeat bill" and "fetal heartbeat." For the term “prolife,” I only included tweets where non-characters preceded and followed the term, so as to exclude noise introduced by terms like “proliferate.” Between January 1, 2019 and June 30, 2019, 748,448 tweets were collected. For the Mueller investigation, search terms were drawn based on the following categories: 1) terms for the investigation ("mueller", "russia probe", "russia inquiry", "russia investigation", "special counsel" and "russia hoax"), those prosecuted by the special counsel ("flynn", "roger stone", "michael cohen", "manafort", "jerome corsi", "kilimnik", "papadopoulos", "sam patten", "richard pinedo", "rick gates", "zwaan", "veselnitskaya"), personnel from FBI involved ("lisa page", "strzok", "rod rosenstein", "whitaker", "barr", "sessions", "john brennan", "james clapper", "comey" and "andrew mccabe") and those involved in Trump’s Russia affair ("carter page", "steele dossier"). Similar to the treatment of “prolife,” tweets containing "barr" and "sessions" were included only when non-characters preceded and followed the terms, in order to reduce noise. From November 1, 2018 to July 31, 2019, 3,354,903 tweets were collected from the archive.

Appendix II

Faris et al. (2017) took an audience network approach to estimate the partisanship of media outlets based on how Twitter accounts mentioning Clinton and Trump embedded media outlets in their tweets. They tracked Twitter shares of each media outlet, which demonstrates virality on social media, and the linking patterns among media outlets, which estimates the centrality of each media outlet. I created a measure called Twitter/media ratio by dividing the standardized Twitter shares score by the standardized media inlinks score. If the ratio of a media outlet exceeds one, it suggests that among all the media outlets this media outlet tended to be more prominent on Twitter than within news media. My selection of media outlets was balanced on partisan score and Twitter/media ratio.

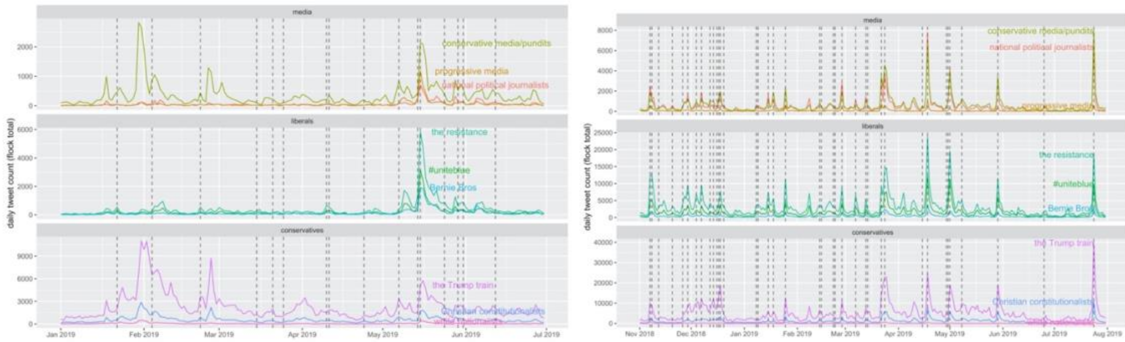
The progressive and far-left news media network is represented by Huffington Post, Daily Kos, Raw Story, MSNBC, NPR, and Vox, where the first three outlets skew toward Twitter shares and the last three toward media inlinks. The conservative and far-right news media network includes Breitbart, Fox News, InfoWars, Washington Times, Daily Caller and Washington Examiner, again with the first three more viral on Twitter and the last three more central within news media. The moderate and center-left news media network consists of CNN, The Hill, Washington Post, New York Times, Politico and Wall Street Journal, where only CNN and the Hill have a Twitter/media ratio over 1.



Selection of 18 media outlets from mediacloud.

Appendix III

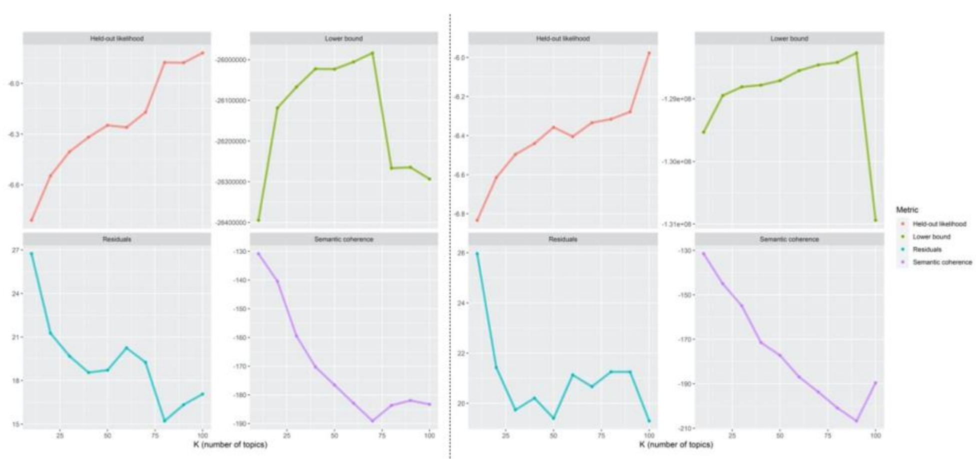
Since there might be significant variation in both the number of active accounts in the flocks and the tweets they posted on a given day, which might cause the total number of tweets per flock to be a biased measure of flock attention, I calculated the daily average number of tweets by each account per flock. This measure is highly correlated with the daily total number of tweets per flock at 0.96 and 0.95 for abortion laws and the Mueller investigation respectively. Therefore, the daily total number of tweets per flock is a proper estimate of the level of attention of each flock.



Daily total number of tweets by flock for the abortion case (left) and the Mueller case (right). Each vertical line represents a related event

Appendix IV

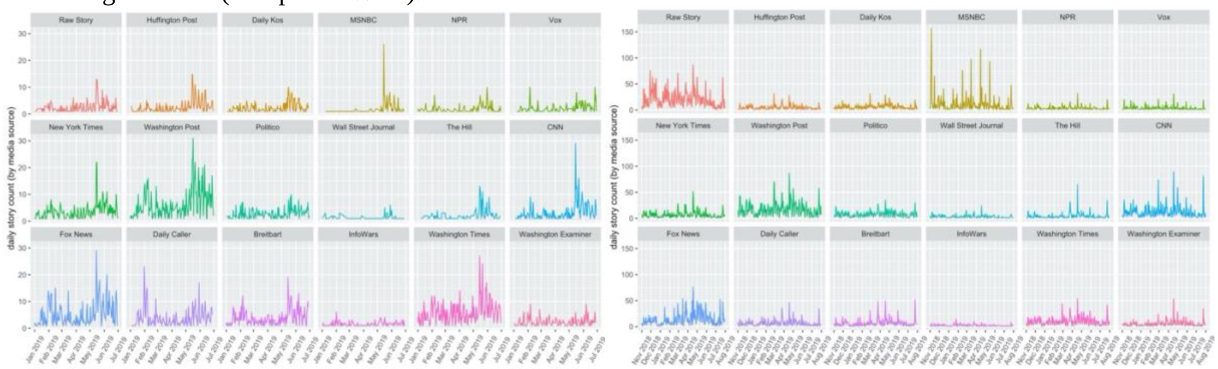
Due to the preponderance of duplicate tweets (as retweets), I took the unique tweets (n = 214,754 for the abortion laws; n = 1,085,505 for the Mueller investigation) for topic modeling. As a first step, preprocessing includes 1) removing URLs, Twitter handles, non-ASCII characters, numbers and symbols, 2) tokenizing and lemmatizing words, and 3) removing stopwords. Second, a document-term matrix was created, where each document represents a tweet and each term is a token (i.e., word or unigram) that appears in the documents. Given that both infrequent terms and frequent terms bring noise and reduce model accuracy, I removed infrequent terms, which appeared in less than 0.005% of the documents, and frequent terms, which appeared in over 90% of the documents. Through this filtering, the total number of tokens in the topic models was around 10,000. Third, to find the statistically optimal number of topics, i.e., K, I relied on five metrics to evaluate the models where K ranges from 10 to 100 with an interval of 10. Lower bound is an approximation to the lower bound on the marginal likelihood and thus can be thought of as a model's internal measure of fit. Held-out likelihood is the probability of held-out documents given a trained model. Residuals are the unexplained variance of model. All three metrics are measures of goodness-of-fit of the model. Semantic coherence evaluates the likelihood of highly probable words under a topic co-occurring within the same document, whereas exclusivity offers a counterpoint because if K is small enough semantic coherence can be easily achieved. Based on the diagnostics (Figure 5.4), the optimal K is 70 (low residuals and high held-out likelihood and lower bound) for the abortion laws corpus and 50 for the Mueller investigation corpus.
Topic modeling generates two main results: each token has a probability distribution into each topic, and each document has a probability distribution into each topic. I interpreted each topic by examining the top 20 tokens as well as the top 200 documents (i.e., tweets). Then I grouped the topics into themes.



Model diagnostics for the optimal number of topics (K). Results for (unique tweets from) the abortion law corpus on the left and the Mueller investigation corpus on the right.

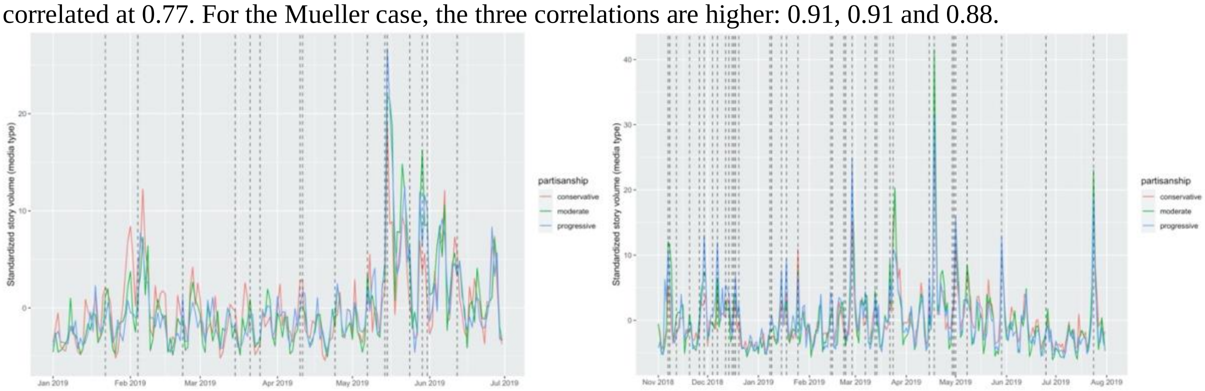
Appendix V

The daily volume of stories of each media outlet varies, which presents a challenge for aggregating the raw counts of stories together by news media network. This means that if the raw story counts are aggregated, variance in the outlets with fewer numbers of stories will be overridden by outlets with greater numbers of stories. Furthermore, there is some variation in the attention patterns of media outlets even within a news media network. The time series of stories per day of media outlets within a news media network do not necessarily correlate that well. For the abortion case, correlations range from 0.3 to 0.6 for the progressive and far-left outlets, 0.2 to 0.8 for moderate and center-left outlets, and 0.3 to 0.7 for the conservative and far-right outlets. The time series of media story counts for the Mueller case hang together better within each media type, with 0.6 to 0.8 correlations for the progressive and far-left outlets (except MSNBC), 0.7 to 0.8 for moderate and center-left outlets, and 0.7 to 0.8 for the conservative and far-right outlets (except InfoWars).



Daily total number of stories by each media outlet for the abortion case (left) and the Mueller case (right)

The standardized measure of attention of all three news media networks turns out to be highly correlated, suggesting that news attention might be heavily driven by external events. Specifically, for the abortion case, attention of the moderate and center-left news media networks is correlated with attention of the progressive and far-left networks at 0.89 and with that of the conservative and far-right networks at 0.81, whereas attention between the left and right is correlated at 0.77. For the Mueller case, the three correlations are higher: 0.91, 0.91 and 0.88.



Attention of media by news media network for the abortion case (left) and the Mueller case (right)

Appendix VI

Top bigrams and keywords in the headlines of news stories about abortion laws.

media_type	top_bigrams	keywords
Progressive-Far left	abortion ban (81), abortion law (62), supreme court (51), joe biden (36), abortion bill (29), abortion clinic (25), donald trump (25), plan parenthood (24), hyde amendment (20), alabama abortion (18), susan collins (18), trump administration (18), fetal heartbeat (17), fox news (17), heartbeat abortion	thread, explain, woman, republican, minireport, owl, sentence, jeer, cheer, midday, susan, radio, rightwing, collins, gop,

	(17), heartbeat bill (17), pete buttigieg (17), ban abortion (16), antiabortion law (14), sen harris (14), elizabeth warren (13), federal judge (13), gag rule (13), governor sign (13), night owl (13), abortion restriction (12), antiabortion bill (12), brett kavanaugh (12), kirsten gillibrand (12), louisiana abortion (12), kamala harris (11), meghan mccain (11), ralph northam (11), health care (10), abortion debate (9), alabama lawmaker (9), joe bidens (9), pass bill (9), abortion access (8), abortion provider (8), bill ban (8), democratic debate (8), family plan (8), gov ralph (8), overturn roe (8), past abortion (8), senate pass (8), sexual assault (8), stacey abrams (8), strict abortion (8)	lifetime, edition, story, antiabortion, gabbard, progressive, view, evangelical, huffpost, brett, rant, texas, christian, ban, marriage, neartotal, alabama, wing, fundraising, cartoon, pramila, people, tulsi, scotus, night, roe, dangerous, news, internet, handmaid, meghan, assault, rape, idea, finally
Moderate-Center Left	abortion law (112), supreme court (93), abortion ban (76), abortion bill (66), joe biden (65), trump administration (47), plan parenthood (44), alabama abortion (40), abortion clinic (35), donald trump (32), heartbeat abortion (32), ban abortion (31), governor sign (27), hyde amendment (27), fox news (26), health care (26), white house (25), heartbeat bill (23), federal judge (21), antiabortion law (19), democratic debate (18), elizabeth warren (18), house democrat (18), abortion restriction (17), town hall (16), gag rule (15), lateterm abortion (15), playbook pm (15), abortion debate (14), family plan (14), fetal heartbeat (14), louisiana abortion (14), president trump (14), ralph northam (14), antiabortion bill (13), kirsten gillibrand (13), stacey abrams (13), abortion access (12), appeal court (12), federal fund (12), pass bill (12), bernie sander (11), bill pass (11), democratic candidate (11), democratic presidential (11), drug price (11), mueller report (11), protect abortion (11), union address (11), va gov (11)	daily, playbook, health, trailer, analysis, fortune, pm, price, opinion, impossible, politic, brexit, trump, transcript, divide, power, debt, dealbook, hiv, voice, protection, motivate, hurricane, witness, bit, devos, chronicle, hag, comatose, torch, loan, gamble, correction, lerer, onstage, italy, medicareforall, canada, perspective, biden, meet, presidential, race, roberts, player, shape, trudeau, iran, drug, corporation
Conservative-Far Right	plan parenthood (167), abortion law (153), abortion ban (126), abortion bill (113), supreme court (80), heartbeat abortion (61), lateterm abortion (61), abortion clinic (58), hyde amendment (50), joe biden (49), donald trump (44), heartbeat bill (40), ralph northam (40), trump administration (39), fetal heartbeat (36), abortion debate (33), alabama abortion (33), alyssa milano (29), governor sign (29), kamala harris (29), abortion comment (28), bear alive (28), ban abortion (26), pete buttigieg (24), north carolina (23), union address (21), virginia governor (21), democratic party (19), tucker carlson (19), abortion survivor (18), brian sims (18), protect abortion (18), sign heartbeat (18), abortion restriction (17), bill ban (17), doug jones (17), kirsten gillibrand (17), louisiana abortion (17), abortion rule (16), coronavirus fuel (16), fuel abortion (16), health care (16), restrict access (16), super bowl (16), antiabortion law (15), heartbeat law (15), house democrat (15), judge block (15), prolife activist (15), senate pass (15)	prolife, parenthood, editorial, proabortion, sims, infanticide, nolte, gov, prolifers, bill, lateterm, dem, ted, brian, medium, evers, haskins, sasse, plan, session, editor, bear, youtube, fuel, dems, exclusive, northam, late, andrew, flipflopflip, abort, virginia, unborn, doug, unplanned, baby, ocasiocortez, propaganda, oks, beltway, clemsons, dabo, swinney, ticket, truth, till, feds, byrne, cling

Top bigrams and keywords in the headlines of news stories about the Mueller investigation.

media_type	top_bigrams	keywords
Progressive-Far left	mueller report (947), michael cohen (513), robert mueller (402), roger stone (379), donald trump (376), white house (368), bill barr (261), fox news (254), mueller probe (212), william barr (190), press conference (159), paul manafort	explain, trump, msnbc, cnn, firsthand, analyst, radio, independence, jeer, minireport, hakeem, news,

	(153), special counsel (147), mueller investigation (141), rudy giuliani (125), ag barr (123), report trump (123), russia probe (120), trump announce (115), house democrat (114), trump jr (114), barr press (113), announce barr (109), conference question (109), doj independence (109), russia investigation (103), legal analyst (102), michael flynn (98), president trump (98), house judiciary (96), trump campaign (93), hakeem jeffries (88), mueller firsthand (88), sarah sander (88), democratic call (87), jeffries respond (87), rep hakeem (87), justice department (81), trump tower (81), federal prosecutor (80), james comey (80), red line (77), judiciary committee (76), lindsey graham (75), democrat ready (73), conspiracy theory (72), kellyanne conway (72), trump red (72), act ag (70), jeff session (68)	fox, jeffries, bill, conference, expert, lie, watch, cheer, midday, conservative, rant, exprosecutor, thread, maddow, reveal, respond, red, columnist, nicolle, psychiatrist, legal, hard, yahoo, announce, ag, vf, fmr, mueller, secret, bust, kremlin, press, internet, hilariously, huffpost, rudy, tableread, wallace
Moderate-Center Left	mueller report (1048), michael cohen (412), white house (372), donald trump (365), roger stone (289), william barr (246), mueller probe (215), house democrat (177), robert mueller (154), russia probe (123), special counsel (120), trump jr (115), paul manafort (114), president trump (113), fox news (112), mueller investigation (104), russia investigation (96), trump administration (93), justice department (90), playbook pm (89), report trump (86), trump campaign (84), michael flynn (79), impeach trump (76), justice dept (76), house panel (68), supreme court (68), hope hick (65), mueller testimony (63), sarah sander (62), house judiciary (59), trump call (59), mueller finding (57), grand jury (56), hillary clinton (56), morning bit (56), kellyanne conway (55), nancy pelosi (55), investigate trump (52), matthew whitaker (52), ivanka trump (51), trump tower (50), act attorney (47), federal prosecutor (47), rudy giuliani (45), capitol report (44), james comey (44), justin amash (44), kamala harris (42), trump claim (42)	playbook, analysis, opinion, politic, fortune, daily, pm, cybersecurity, bit, dealbook, power, dept, annotate, stock, newswatch, guide, aftermath, factchecking, transcript, takeaway, invitational, brexit, trailer, plainspoken, moonshot, inquiry, huawei, week, lpga, hurtful, market, muellerrelated, kickoff, unfit, latenight, include, rein, china, style, nightmare, usmca, washington, divide, india, lerer, quotation, lean, inequity, fiftytwo, fighter
Conservative-Far Right	mueller report (834), donald trump (408), michael cohen (404), robert mueller (377), roger stone (352), russia probe (265), william barr (240), mueller probe (228), white house (214), adam schiff (173), hillary clinton (165), special counsel (164), house democrat (124), james comey (124), president trump (123), house dems (118), trump campaign (111), impeach trump (108), kellyanne conway (106), ag barr (105), russia investigation (105), trump impeachment (105), lindsey graham (100), steele dossier (99), trump jr (97), justice department (86), house judiciary (80), michael flynn (77), paul manafort (74), mueller testimony (71), judiciary committee (69), nancy pelosi (69), cohen hear (67), devin nunes (67), andrew mccabe (62), mueller investigation (62), rod rosenstein (60), tucker carlson (60), christopher steele (57), personal email (57), trump administration (57), matthew whitaker (56), conspiracy theory (55), supreme court (55), jeff session (54), steve bannon (54), russia collusion (53), grand jury (50), mueller hear (50), alec baldwin (49)	dems, collusion, nolte, hillary, schiff, medium, adam, clinton, blackberry, dossier, ap, fbi, nadler, trey, obama, gowdy, fisa, smollett, steele, bossie, mark, beltway, christopher, comey, steve, bible, fusion, abuse, antitrump, gp, tucker, david, exclusive, jordan, rating, baldwin, avenatti, medal, mccarthy, rep, levin, alec, andrew, painting, liberal, probe, peter, dem, mirror, sen

Appendix VII

The keywords used for the data retrieval include: "#metoo", "#timesup", "sexual assault", "sexually assault", "sexual harass", "sexually harass", "sexual molest", "sexually molest", "sexual misconduct", "feminism", "feminist", "sexual abuse", "sexually abus", "sexual violence", "#everydaysexism", "#yesallwomen", "#heforshe", "#believewomen", "#believesurvivors", "#whyididntreport", "#nastywoman." These keywords were intended to cover not only discussions about sexual violence, but also broader discussions surrounding feminism and women's empowerment that preceded and accompanied the rise of the #Metoo movement. 1,121,013 tweets

Then I applied two language detection algorithms, cld2 and cld3 developed by Google Chrome, to identify non-English tweets. If either algorithm detects a tweet to be English, the tweet would be included. Figure 6.1 displays the daily counts of English tweets over the three-year period.

Appendix VIII

The retweeting relationship produces a 540,267 (users: accounts that retweeted other accounts' tweets and compose the retweeting flocks) X 123,899 (features: accounts whose tweets were retweeted) matrix. Given that features followed by too few accounts can bring much noise, I applied a threshold to filter out features retweeted by less than 10 users. This trims the original matrix down to 411,429 X 8569 in dimensions. Using the spectral method used in Chapter 4, I found that the optimal number of K was around 15. The scree plot shown in Figure 6.2 displays the eigenvalues on the y-axis and the number of K on the x-axis and suggests that the margin of error levels off when K equals 15

Appendix IX

The interpretation of the retweeting flocks based on the feature accounts that they retweeted can be validated by the most representative words and the most frequent words in the profile descriptions of all accounts that compose the flocks. The representative words in the profile descriptions of accounts in the gender equality movement flock are @heforshe, woman, gender, equality, @heforshe, and @emwaston (the UN Women Global Goodwill Ambassador), which agree with the most representative words in the profile descriptions of the corresponding feature accounts. The word "feminist" was among the most frequent word in the profile descriptions of the gender equality movement flock, the anti-sexual violence flock, all the feminist flocks, the progressive flocks, and the celebrity followers flock, suggesting the relevance of feminism to these flocks. Words like "game" "sport" and "#meninist" (a parody hashtag of #feminist) are associated with the profile descriptions of accounts in the anti-feminism flock. In addition, words that indicative of progressive values and identities like "#theresistance, #resist, #resistance, #notmypresident, #impeachtrump, progressive, #bluewave, democrat" are associated with profile descriptions of accounts in the progressive flocks, whereas words like "maga, trump, conservative, god, proud, christian, american, country, patriot, family" with the Trump supporters flock. All these suggest that the flocks are meaningful homogeneous groups. These accounts that composed each flock tended to be ordinary users who were not verified: only around 1% of accounts within each retweeting flock were verified. They also had only a few hundred followers and friends. Out of privacy concerns, I chose not to display the representative accounts that make up the retweeting flocks.

Summary of member accounts for all 15 flocks based on retweeting relationships

id	flock label	most representative words in user accounts profile descriptions	most frequent words in user accounts profile descriptions	total number of user accounts	percentage of all user accounts	median follower count	median friend count
2	gender equality movement	#heforshe, de, la, woman, gender, en, vamp, equality, global, feminist, @heforshe, @emwatson, heforshe, mujeres, nero, student, potterhead, emma, network, #genderequality	love, woman, de, life, feminist, lover, social, student, view, world, writer, la, tweet, music, fan, human, live, book, gender, follow	6165	1.5%	298	373

12	anti-sexual violence alliance	abuse, fanmember, hayley, bush, transgender, lesbian, independannservative, cube, asperger, aka, lutheran, female, syndrome, employee, army, anti, sexual, outlander, violence, constitution	love, child, life, abuse, feminist, survivor, sexual, woman, violence, view, live, book, writer, fan, support, lover, music, tweet, endorsement, follow	1925	0.5%	362	434
6	feminism	snapchat, de, snap, la, sc, trash, ig, intersectional, emo, stan, mi, 5sos, es, harry, feminist, insta, #blacklivesmatter, en, fangirl, el	love, life, feminist, de, girl, follow, la, live, world, music, time, fuck, blacklivesmatter, ig, people, heart, sc, lover, day, art	10882	2.6%	400	325
8	feminism	de, account, ig, insta, yo, sc, @btstwt, stan, en, lo, bitch, bts, quem, se, por, sheher, multifandom, amor, meu, trash	love, life, fan, de, ig, account, time, live, sc, girl, la, fuck, world, music, student, feminist, instagram, snapchat, insta, people	4140	1%	367	332
11	feminism	sc, ig, de, bitch, la, insta, fuck, tu, jour, snapchat, mon, une, por, bien, yo, mais, rip, je, amos, le	love, life, follow, fan, ig, people, live, de, lover, music, tweet, account, sc, girl, time, twitter, la, social, writer, person	10691	2.6%	314	319
13	feminism	insta, sc, #blacklivesmatter, snapchat, ig, feminist, trash, intersectional, 5sos, makeup, queen, theythem, hufflepuff, snap, content, vie, feel, fuck, gavin, pour	love, life, de, girl, ig, feminist, live, follow, sc, blacklivesmatter, music, world, snapchat, time, fan, enthusiast, la, art, heart, instagram	8636	2.1%	415	338
7	anti-feminism	snapchat, sc, game, gt, baseball, champ, sponsor, varsity, hoe, nigga, play, rip, ti, #meninist, snap, youtuber, girlfriend, wrestle, class, bmx	love, life, sc, live, snapchat, god, game, follow, ig, fan, people, day, music, fuck, tweet, time, world, football, en, sport	2709	0.7%	294	286
3	progressives	#theresistance, #resist, #resistance, #fbr, #notmypresident, #impeachtrump, writer, progressive, #bluewave, democrat, resist, #trumprussia, lover, #stillwithher, #bluewave2018, resistance, feminist, liberal, #uniteblue, politic	love, life, lover, writer, resist, fan, mom, live, music, theresistance, proud, world, tweet, politic, feminist, time, trump, people, woman, liberal	195963	47.6%	321	466
14	progressives	ig, sc, #blacklivesmatter, bitch, snapchat, rip, insta, fuck, sheher, instagram, snap, intersectional, stan, black, hoe, makeup, moon, university, theythem, #allblacklivesmatter	love, life, ig, blacklivesmatter, sc, feminist, girl, time, live, black, music, god, de, fuck, fan, world, student, lover, follow, enthusiast	62284	15.1%	412	346
4	Trump supporters	#maga, conservative, trump, 2a, god, christian, maga, country, patriot, american, supporter, america, #nra, president, #kag, #trump2020, #trump, #trumptrain, #americafirst, #draintheswamp	maga, love, trump, conservative, god, proud, life, christian, american, country, patriot, family, pro, follow, america, supporter, 2a, fan, nra, president	88439	21.5%	382	505
9	celebrity followers	de, harry, watson, potter, emma, potterhead, la, ser, hogwarts, je, mi, instagram, mais, @emwatson, #potterhead, fangirl, slytherin, arquitectura, stan, @emmawatson	love, life, de, fan, music, lover, girl, follow, la, live, world, time, writer, feminist, book, instagram, art, enthusiast, people, ig	3517	0.9%	270	318
15	K-pop fans	kpop, got7, bts, exo, stan, multifandom, kim, exol, @btstwt, nuest, elf, 2pm, shinee, infinite, nct, jyj, lee, bap, b1a4, shipper	love, life, fan, exo, follow, bts, account, live, girl, stan, music, de, kpop, world, got7, time, ig, army, lover, tweet	6216	1.5%	234	276
1	mixed	animal, adopt, de, cruelty, lover, son, droit, perritos, hijos, amante, mi, adepte, whippet, toute, vida, greyhound, los, como, vie, jai	animal, love, lover, life, fan, music, world, follow, cat, people, tweet, dog, live, news, resist, twitter, de, family, god, block	610	0.1%	484	642

5	mixed	dm, content, post, notification, parody, promo, gavin, page, @viralsocialco, @vantablvck, neck, follow, account, viral, drake, submission, |we, send, affiliate, snapchat	love, follow, dm, post, life, ig, tweet, content, snapchat, account, sc, notification, girl, god, live, gmail.com, music, time, de, world	3047	0.7%	778	470
10	mixed	ig, sc, insta, sheher, stan, #blacklivesmatter, snapchat, spooky, theythem, hehim, feel, scorpio, instagram, bi, venmo, fuck, bitch, gay, shit, de	love, life, fan, time, writer, ig, girl, lover, de, live, feminist, music, student, world, enthusiast, account, sc, tweet, art, instagram	6205	1.5%	293	317