



Homophily and polarization on political twitter during the 2017 Norwegian election

Bernard Enjolras¹ · Andrew Salway²

Received: 25 August 2022 / Revised: 11 December 2022 / Accepted: 13 December 2022
© The Author(s) 2022

Abstract

Ideological homophily on social media has been receiving increased scholarly interest, as it is associated with the formation of filter bubbles, echo chambers, and increased ideological polarization. And yet, no linkage necessarily exists between ideological homophily, echo chambers, and polarization. Despite political interactions on social media taking place to a large extent between like-minded individuals, cross-cutting interactions are also frequent. Using Twitter data, we investigated the extent to which ideological homophily, echo chambers, and polarization occur together and characterize the network of political Twitter users during the 2017 election in Norway. Despite the presence of some degree of ideological homophily, we did not find evidence of echo chambers in the Norwegian political Twittersphere during the 2017 election. And yet, the retweet network is characterized by a significant degree of polarization across ideological blocs. Our findings support the thesis according to which polarization on social media may have drivers other than the technological deterministic effect of social media affordances enhancing the formation of online echo chambers.

Keywords Homophily · Polarization · Social media · Echo chamber · Twitter · Election · Campaign

1 Introduction

Social media's increasing significance as an arena for political information and engagement is accompanied by increasing worries about their impact on the public sphere and opinion formation. A recurring theme in the literature on the Internet and politics is whether social media make a favorable or detrimental impact on the public political sphere (Colleoni et al. 2014). A particular domain of scholarly research that has received much attention concerns the effects of the ability, conferred by social media platforms to their users, to choose selectively, on an ideological basis, both the information and social connections with which one engages. This selective exposure ability is viewed as the main mechanism behind the formation of echo chambers that are viewed as provoking increased political polarization.

Two main perspectives emphasize different dynamics on this issue. The first perspective asserts that social media exerts a detrimental effect on the political public sphere, in that social media facilitate selective exposure, consequently reducing exposure to political differences and increasing ideological homophily. In so doing, echo chambers that favor political polarization are created (Galston 2002; Sunstein 2001).

The echo chamber (Sunstein 2001, 2018) and online filter bubble (Pariser 2011) metaphors refer to social media users selectively engaging with like-minded users and ideological content congruent with their ideological orientations. Through this process, social media users, as a result of selective exposure and ideological homophily, rarely are exposed to conflicting opinions and form ideologically homogenous clusters (Terren and Borge 2021) “in which pre-existing beliefs are repeated and reinforced—like reverberations in an acoustic echo chamber. (...) The notion of the echo chamber usually refers to a situation in which users mostly communicate with—and are exposed to content from—like-minded others” (pp. 100–101).

From this perspective, polarization is viewed as the result of social media enhancing ideological homophily, i.e., politically like-minded individuals enabled by social media to find

✉ Bernard Enjolras
bernard.enjolras@samfunnsforskning.no

¹ Center for Research on Civil Society, Institute for Social Research, Oslo, Norway

² Falmer, University of Sussex, Brighton, UK

one another, leading to the formation of echo chambers in which citizens are exposed only to information that corresponds with their political views (Sunstein 2001). The concept of homophily entails that similar people tend to connect with each other in social networks more often than dissimilar people. In the political domain, the most common mechanism for political homophily is probably the mechanism of selective affiliation, according to which people tend to select their communication partners among people who share their political beliefs (Bond and Sweitzer 2018). Selective affiliation may be based on a variety of both relevant and seemingly irrelevant similar characteristics (Centola and van de Rijt 2015). Evidence indicates that social networks' structure affects a wide range of opinions and behaviors, including political ones (Bond et al. 2012; Centola 2010; Christakis Fowler 2007, 2008; Fowler and Christakis 2008). In the political realm, homophily may lead to increased attitude homogeneity that can evolve toward political polarization inasmuch as network homophily affects the information that people receive and the attitudes they form (McPherson et al. 2001). In the political domain, individuals may cluster based on political identities (political party or ideological disposition) based on political issue positions (policy issues) or on their levels of political engagement (Huber 2013). Echo chamber formation may be thought of as the direct effect of homophilic tendencies and might be correlated with political polarization (Stroud 2010). However, network diversity and ideological heterogeneity have been demonstrated to be associated with higher levels of political tolerance (Mutz 2002). To sum up, this perspective posits a causal relationship between homophilic tendencies, echo chamber formation, and increased polarization: If social media users tend to follow and interact with people of the same ideology (i.e., clustering based on political identities), it should be reflected in the network structure, as people will cluster in ideologically homogenous echo chambers and tend to interact mostly with like-minded individuals, leading to a polarized network structure with few cross-cutting links.

Several studies, mostly based on US data, from a variety of online media contexts have found evidence of the existence of homophily and echo chambers—i.e., the clustering of online communication into like-minded subgroups with little linkage between each other (Adamic and Glance 2005; Aragón et al. 2013; Barbera 2015; Colleoni et al. 2014; Conover et al. 2011, 2012; Feller et al. 2021; Gaines and Mondak 2009; Garcia et al. 2015; Gruzd and Roy 2014; Halberstam and Knight 2014; Hargittai et al. 2008; Himelboim et al. 2013; Lawrence et al. 2010; Quattrociocchi et al. 2016; Yardi and Boyd 2010).

However, the second perspective asserts that social media make a positive contribution to the public political sphere. Considering that digital networks are cutting across social and geographical boundaries, they help increase exposure

to diverse opinions (Brundidge 2010). Exposure to a diversity of opinions is viewed as crucial for developing well-informed citizens (Gentzkow and Shapiro 2010) who are also tolerant of others' ideas (Nunn et al. 1978), whereas exposure to only like-minded opinions may lead to polarization toward ideological extremes (Brundidge 2010; Sunstein 2001). Brundidge (2010)—in line with (Wojcieszak and Mutz 2009) findings, according to which exposure to heterogeneous networks and political views online often happens accidentally—found evidence that social media use increases political discussion networks' heterogeneity. (Dubois and Blank 2018), focusing on individuals' media consumption in a high-choice multiple media environment in the UK—as opposed to single-media studies—found that individuals who are interested in politics and those with diverse media diets tend to avoid echo chambers, concluding that the echo chamber thesis is overstated. Vaccari et al. (2016), based on online surveys of representative samples of Italian and German individuals who posted at least one Twitter message about the 2013 elections, found that the degree of exposure to similar or dissimilar political views on social media varied substantially. The structure of individuals' offline social networks, as well as political discussions' intensity, appeared to be a determinant of the type of exposure they experienced on social media, despite a tendency toward homophily.

An apparent paradox exists between macro- and micro-level patterns (Barberà 2020) insofar as social and ideological homophily in social media does not necessarily entail exposure to ideologically homogenous content and information because social media enable greater exposure and contact with weak ties than in offline interactions—weak ties that are central to information spread and diversity. Thus, the link between ideological homophily and echo chambers on one hand, and polarization on the other, is questioned increasingly, and despite the significance of political interactions on social media between like-minded individuals, cross-cutting interactions are also frequent (Barberà 2020). Thus, the linkage between social media networks' structural characteristics (e.g., echo chambers) and political polarization needs to be nuanced (Barberà 2020), as polarization may be driven by social mechanisms other than homophily and echo chambers.

The research reported here investigates whether polarization in retweet networks corresponds with ideological homophily in friend-follower networks or whether we found indications that polarization might be driven, in the presence of cross-cutting interactions, by other mechanisms. Indeed, the echo chamber perspective rests on the premise that selective exposure and selective avoidance (Stroud 2017), which occur when people purposefully select information on the basis of their preferences or attitudes, might entail a dilution of political information effects (by limiting

political communication's impact on social media) or foster source selection and ideological self-segregation (Pariser 2011; Sunstein 2001). The result of selective exposure is a reinforcement of individuals' own beliefs, with opinions formed in such environments becoming polarized and extreme. However, selectivity, while resulting in increased exposure to consonant content, does not necessarily lead to avoidance of dissonant content (Garrett 2009a, b) and may increase exposure to political disagreement (Vaccari et al. 2016). Furthermore, the literature on motivated reasoning has indicated that prior attitudes strongly bias how people process arguments, and that this bias is reinforced through selective exposure (Taber et al. 2009). When people are presented with arguments opposing their initial beliefs in online debates, these arguments may lead to a stronger belief in already-held opinions—a phenomenon referred to as disconfirmation bias (Taber et al. 2009)—which may foster a logic of trench warfare in which cross-cutting interactions between ideologically opposed individuals tend to reinforce opposing opinions (Karlsen 2017). Such a mechanism, in which exposure to divergent information reinforces already-held opinions or positions, may explain why, despite the presence of cross-cutting friend-follower networks, the retweet network is polarized and driven by political homophily.

Thus, two alternative theoretical perspectives and afferent hypotheses link homophily in digital networks and network polarization, which this contribution aims to test:

H1: Polarization in retweet networks results from homophilic segregation into online echo chambers (Sunstein 2018), reflected in friend-follower networks.

H2: Polarization and homophilic structure characterize retweet networks despite cross-cutting links in friend-follower networks.

To test these alternative hypotheses, we analyzed Twitter data to investigate whether (a) online political friend-follower networks in the Norwegian Twittersphere indicate evidence of homophilic segregation (echo chambers), or (b) polarization may characterize interactions in the Norwegian Twittersphere in the absence of significant homophilic segregation, indicating the possible presence of polarizing mechanisms other than homophily and echo chambers, involving selective engagement (through interactions and sharing) with ideologically like-minded content and users.

Our empirical analysis was based on Norwegian Twitter data. Considering that, as emphasized by (Barberà 2020), “most of what we know about cyberbalkanization is based on data from the United States only” (p. 49), we expect the Norwegian context to provide a contrasting perspective to most of the research conducted in the US Twittersphere.

Indeed, in *Patterns of democracy*, Lijphart (1999) makes a distinction between two basic types of democracy:

majoritarian and consensus. The majoritarian model of democracy is characterized by a concentration of executive power in one-party government, dominance by the executive branch, a two-party system, majoritarian and disproportional representation, and interest group pluralism. However, the consensus model of democracy is characterized by executive power-sharing in broad coalition cabinets, a balance of power between executive and legislative branches of government, a multiparty system, proportional representation, and interest group corporatism. The differences characterizing these two types of democratic institutions reasonably can be expected to be reflected in the dynamics of political life, political culture, and the political public sphere.

Unlike the USA, which uses the majoritarian model, Norway, like many European countries, employs the consensus model. Norwegian democracy is characterized by a multiparty system, coalition governments, proportional representation, a political culture of consensus, and national media operating across ideological divisions. By analyzing the degree to which political communication on Twitter during the 2017 election in Norway was characterized by ideological homophily and polarization, we aimed to provide additional empirical evidence outside of the US context that might confirm or disprove the observed tendency toward the formation of echo chambers on Twitter in the US context.

Furthermore, we made methodological contributions to the computational analysis of Twitter data—first, by considering the complete universe of political tweets (not a selection based on users or hashtags) during an election campaign, and second, by comparing two methods—Barberà (2015) and Halberstam and Knight (2014)—to infer Twitter users' ideology.

2 Data and methods

To investigate degrees of ideological segregation and polarization levels on Twitter empirically, we required data on the relationships between Twitter users who are engaged with Norwegian politics on Twitter. While most Twitter studies collect data by querying the Twitter search API via keywords, we adopted another data collection strategy aimed at obtaining the entire universe of political tweets during the election campaign period. Below, we summarize the main steps taken to collect the data and create two networks—one representing friend/follower relationships and the other representing mentions and interactions.

2.1 Data

Considering that we were interested in mapping the political communication network on Twitter related to the national election, we selected, as a starting point, election candidates

who had a Twitter account, assuming that politically engaged Twitter users would follow at least one of these candidates. Thus, we made a list (P) of 1845 Norwegian political actors with Twitter accounts, comprising all the candidates in the 2017 Norwegian general election who had a Twitter account. By querying the open Twitter API, we made a list (U) of all 833,931 Twitter users who followed one or more of the accounts in P and counted how many of the accounts in P they followed. Considering that estimates of ideology would be unreliable for users following less than three politicians, we selected users to be retained in the analysis based on the following steps: First, we acquired a dump of 4.2 million tweets from the Twitter Historical PowerTrack API, comprising all tweets that: (i) were coded as Norwegian language by Twitter; (ii) were posted during the seven months leading up to and including the Norwegian general election in 2017 (March–September 2017); and (iii) were posted by one of the 264,853 accounts in U that followed more than one account in P.

Second, based on this dump and further data about accounts' followers and friends, we selected a sample of accounts that would be the focus of our investigation. We removed accounts that followed less than three of the accounts in P so that we could automate ideological coding of the selected accounts reliably, as explained below.¹ This gave us a set of 179,377 users whom we viewed as having been engaged actively with Norwegian politics on Twitter during the March–September 2017 period.

Considering that we were interested in political communication between the selected users, we needed to be able to classify tweets as political/nonpolitical, in which we adopt a broad definition of “political,” much like “political communication,” but not necessarily containing political content. From this perspective, communication with political actors would be viewed as “political” even if the content was not. A tweet was classified as “political” if: (i) it contained a word, phrase, or hashtag from a pre-compiled list based on Keynes analysis; or (ii) it mentioned, was sent by, or

interacted with the account of a political actor (interactions comprised replies, retweets, and quoted tweets).

Keyness (Edmundson and Wyllys 1961) is a statistic used in computational linguistics that highlights words that are unusually frequent in one set of texts (or corpus) compared with another set of texts (corpus). Here, the comparison was between tweets viewed as containing a term from the initial list of terms or interacting with an account from the initial list of actors, and the set of remaining tweets. Thus, the list of generated keywords was expected to include good candidates for expanding the initial lists. We used the list of comparatively frequent keywords to select the set of political tweets. Compared with the most prevalent way of collecting tweets (using the Twitter search API, which returns tweets containing a keyword or set of keywords), our method allowed us to collect a richer collection of political tweets based on an exhaustive list of keywords.

The lists of political terms and actors were compiled in two steps. First, one of the authors familiar with Norwegian political communication in social media manually compiled a list of 28 words, phrases, and hashtags that defined political topics. Initially, the list of political actors was taken to comprise the 1,845 accounts from List P above. These lists then were expanded in a semi-automated process, similar to Conover et al. (2011a), using the idea of Keynes analysis (Edmundson and Wyllys 1961).

By scanning the automatically generated list of the most frequent keywords and examining instances of tweets containing the suggested words, phrases, hashtags, and account names, one of the authors added 677 words, phrases, and hashtags to the list of political terms, as well as 249 more accounts viewed as “opinion leaders” to the list of political actors. Using the expanded lists, we filtered our initial set of 4.2 million tweets based on the presence of a political term or interaction with a political actor's account, resulting in a set of around 1.5 million “political” tweets. The frequency-based nature of the query expansion process means that we are confident that most political tweets were identified, and the use of Keynes analysis helped mitigate researcher bias in the selection of terms and accounts. Finally, we matched the list of political tweets with the list of users following at least three political actors on List P.

2.2 Measuring and identifying political homophily

Among the methodological approaches available to investigate the extent to which ideological homophily characterizes political communication networks, we used a combination of clustering algorithms and their visualizations, as well as link analysis.

When visualizing a network, how the nodes are laid out is significant as to what insights can be gained. We used the ForceAtlas2 layout algorithm (Jacomy et al. 2014) in

¹ Of the 833,931 accounts that followed at least one of the political actors in P: 264,853 followed > 1; 43,659 followed > 10; and 1,238 followed > 100. The actual dump that we received from the Twitter Historical PowerTrack API contained c. 25 million tweets. We then filtered these to get the 4.2 million tweets that Twitter coded as “Norwegian language.” After skimming the list of accounts that were removed for being “bot-like,” it appears that most of these were removed based on the criterion of having posted < 10 tweets during the seven-month period, but some accounts elicited thousands of tweets and very few friends and followers. We tested and validated the estimation of ideology following the Halberstam and Knight (2014) method for different thresholds of followed political actors (ranging from 1 to 10) and concluded that following at least three political actors is the threshold for providing valid ideological coding.

the Gephi visualization tool, which is a force-directed layout algorithm, i.e., it simulates repulsion forces between all nodes and attraction forces between nodes that share a link, such that the attraction's strength relates to the link's weight. It is intended to "turn structural proximities into visual proximities," i.e., the nodes are positioned in 2D space in such a way that they tend to be closer to nodes with which they share links. The nodes then can be colored—e.g., in our case, based on the user's majority party—to determine whether the network structure suggests homophily regarding whatever feature was colored. While such visualizations are a useful starting point in examining network data, we noted that they should not be the basis for strong claims about the network because some arbitrary choices are made in the visualization process, which can lead to quite different results, e.g., the layout algorithm's parameters, choice of color scheme, and, in the case of ForceAtlas2, deciding when to stop running the algorithm because it does not terminate itself. Notably, the layout is not a Cartesian projection, i.e., the 2D coordinates do not relate to any variables.

Thus, we added to our approach through the use of a community detection algorithm and homophily metrics. The objective was to identify and measure the extent to which network nodes have links with others that share a certain characteristic (e.g., majority party) vs. having links with nodes that do not have the same characteristic. Thus, the members of a community will have more relationships within the group than with nodes outside their group. Some community detection algorithms aim to partition a network into sets of nodes such that modularity is maximized (for an overview, see (Yang et al. 2016). Modularity is a network-wide measure of the fraction of within-community edges considering what would be expected in a randomized network (Clauset et al. 2004). Gephi implements the Louvain algorithm to derive a set of "modularity classes" (communities) based on maximizing modularity. We then can color the nodes (already laid out by ForceAtlas2) based on their modularity class to determine whether the Louvain algorithm supports our initial observations about homophily based on the ForceAtlas2 algorithm.

A more analytical approach is to compute measurements of homophily, also referred to as "assortativity," in political communication (Colleoni et al. 2014; Newman 2002, 2003). In simple terms, a homophily coefficient is computed as a ratio of the number of outbound ties directed to users who share the same political orientation and the total number of outbound ties. More formally, assortative mixing, i.e., "assortativity," is characterized (Newman 2003) by the quantity e_{ij} , which is defined as the fraction of edges in a network that connect a vertex of type i to one of type j . Thus, the "assortativity" coefficient for the whole network is $= \frac{\sum e_{ij} - \sum a_i b_i}{1 - \sum a_i b_i}$, in which a_i and b_i are the fractions of each type

of end of an edge that is attached to vertices of type i . On undirected graphs, in which the ends of edges are all of the same type, $a_i = b_i$. In this formula, $r=0$ when no assortative mixing is present (all nodes link to others of a different type), and $r=1$ when perfect assortative mixing is present (all nodes link to others of the same type).

2.3 Estimation of ideology

Several methods are available for estimating Twitter users' ideology. Social media users' ideology can be coded automatically based on communication content, e.g., supervised text classification of tweets and Facebook posts (Colleoni et al. 2014; Conover et al. 2011, 2012; Himelboim et al. 2013; Pennacchiotti and Popescu 2011, 2021). A second approach estimates ideology on the basis of endorsement, i.e., choices of who a user follows are taken to reflect their ideology such that ideology may be inferred (Barbera 2015; Barbera et al. 2015; Bond and Messing 2015). While Barbera (2015) has developed a Bayesian spatial model of Twitter users' following behavior, enabling estimation of ideal ideological points derived from the structure of the following links between Twitter users and political actors, Halberstam and Knight (2014) coded users' ideologies directly as a function of the known ideologies of the political actors they follow. Here, we proceed with the endorsement approach and estimate ideology using both Barbera (2015) and Halberstam and Knight's (2014) methods, enabling us to validate estimates on the set of political actors for whom we know the party to which they belong for the results with the first method. We assessed the two approaches' relative performance by comparing the ideology estimates' distributions on the left–right scale and by party. For the first method, we validated the ideology estimates using party affiliations of the 1,756 political accounts (candidates) through a non-empty follower list for whom we know party affiliations. For the second method, we used the entire set of Twitter users, including candidates, comprising 179,377 users.

The Norwegian parties represented in Parliament are designated by their English name, Norwegian name, and abbreviation in bold: Labor Party (*Arbeiderpartiet*, **A**); Conservative Party (*Høyre*, **H**); Progress Party (*Fremskrittspartiet*, **FRP**); Center Party (*Senterpartiet*, **SP**); Liberal Party (*Venstre*, **V**); Christian Democratic Party (*Kristelig Folkeparti*, **KRF**); Green Party (*Miljøpartiet de Grønne*, **MDG**); Socialist Left Party (**SV**); and Red Party (*Rødt*, **R**). The analysis included, in addition to these main parties, an array of minor parties not represented in Parliament, but rather field candidates in the 2017 election: the Christian Party (KRISTNE), a Christian right party; the Alliance (ALLI), a nationalist party; Democrats in Norway (DEMNO), a right-wing populist/nationalist party; Health Party (HELSE), a single-issue

Fig. 1 Twitter-based ideology estimates of candidates: the Barberá method

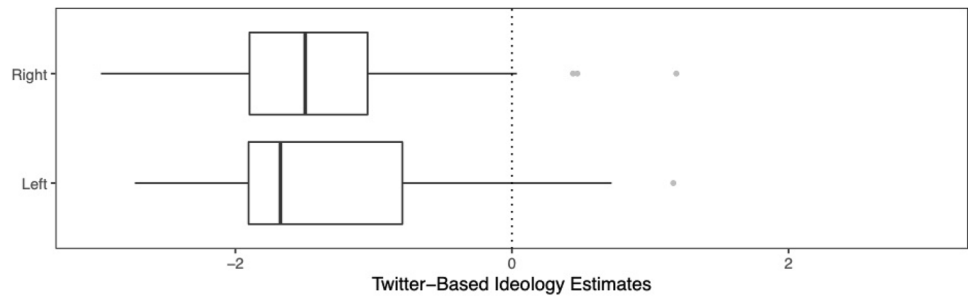
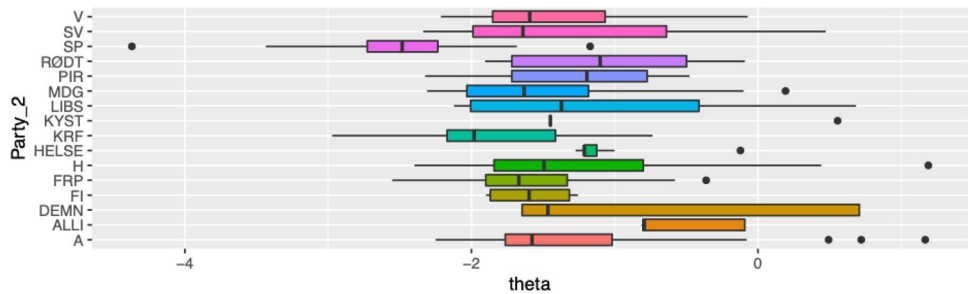


Fig. 2 Twitter-based ideology estimates of candidates by party: Barberá method



party; Coastal Party (KYST), a national conservative party; Pirate Party (PIR), promoting “pirate politics”; and the Capitalist Party (LIBS), a libertarian party.

2.3.1 Ideology estimation: the Barberá (2015) method

Following Barberá’s (2015) method, we identified the ideological latent space and estimated ideological ideal points for 179,377 political Twitter users—including 1,756 political accounts (candidates) for which we have collected followers. Figure 1 displays the distribution of Twitter-based ideology estimates of candidates on the ideological spectrum based on their positions on the left–right political spectrum, computed on the basis of their party membership, while Fig. 2 displays this distribution based on their party affiliation. With this estimation method, the average ideal points for right-wing and left-wing candidates are relatively close to each other, and distribution based on party does not reflect the Norwegian parties’ positions on the left–right ideological spectrum, with, e.g., the Center Party (SP), a party situated at the center-left of Norwegian politics, being more leftist than the radical-left party Rødt. To sum up, this method does not function well with our data, possibly because, contrary to Barberá et al. (2015), we did not initially restrict our matrix of connections to a subset of accounts with high ideological discrimination, but rather estimated ideological ideal points based on the set comprising all candidates and their followers.

2.3.2 Ideology estimation—Halberstam and Knight (2014) method

Furthermore, following Halberstam and Knight’s (2014) method, we coded our selected users for party ideology, a discrete class (one of the parties presenting candidates to the Norwegian election), and for ideology left–right, a scalar value (between 0 and 10) normalized for the analysis. The party ideology variable is calculated as the most common party of the political actors (from List P above) that the user follows. The ideology left–right variable is computed as the mean average of the values for the parties of the political actors that the user follows. The values used to position the parties on the left–right spectrum are based on the averaged self-identification of the candidates for each party during the 2017 national parliamentary election based on a candidate survey realized by Hesstvedt (2017). As is the case with the estimates based on the Barberá (2015) method, the ideological points have been normalized. As noted previously, Fig. 3 provides the distribution of Twitter-based ideology estimates of candidates on the ideological spectrum based on their position on the left–right political spectrum computed on the basis of their party membership, while Fig. 4 displays this distribution based on their party membership. This estimation method provides average ideological points for candidates belonging to the right and left sides of the political spectrum, respectively, that are more distant from each other than with the ideal point estimation method. Furthermore, the distribution of ideological estimates, according to the parties, reflects, to a greater extent, party positions on the

Fig. 3 Twitter-based ideology estimates of candidates: Halberstam and Knight method

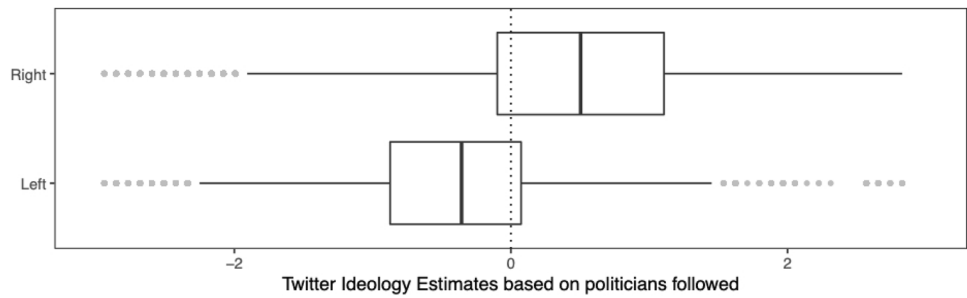
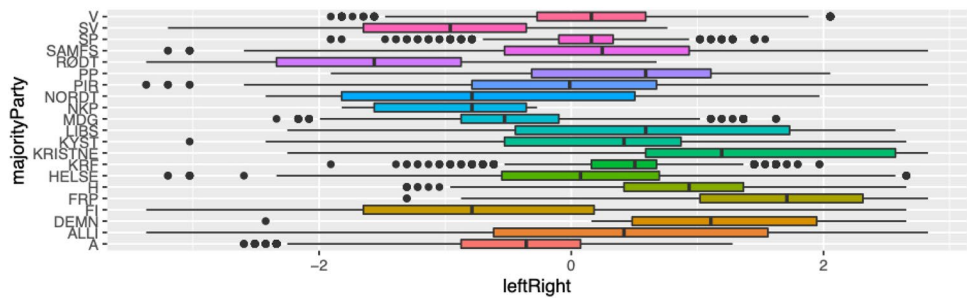


Fig. 4 Twitter-based ideology estimates of candidates by party: Halberstam and Knight method



left–right spectrum characterizing Norwegian politics, with the left-wing parties being positioned correctly on the left and the right-wing parties on the right.

Given these results, we will use ideology estimates based on Halberstam and Knight (2014) to analyze network homophily and polarization levels.

3 Homophily in follower networks

We now present the results from our comparative analysis of the follower network (112,000 nodes and 4.4 million edges). The main goal of the analysis was to assess the degree of homophily and ideological segregation characterizing the network. For this purpose, we used two of the methodological approaches outlined in the method section: network visualization and link analysis. In this analysis, we focused mainly on the Norwegian parties represented in Parliament.

Figure 5a depicts the follower network with the nodes laid out by the ForceAtlas2 algorithm, and colored based on each user’s majority party. While the users, coded as one or another of the two largest parties (A and H), are quite mixed throughout, it appears that the A nodes tend toward the bottom and H nodes toward the top. More pronounced is the separation between two of the medium-size parties’ MDG (clustering toward the top) and SV (clustering toward the bottom). A third medium-size party (V) appears to be spread quite evenly throughout.

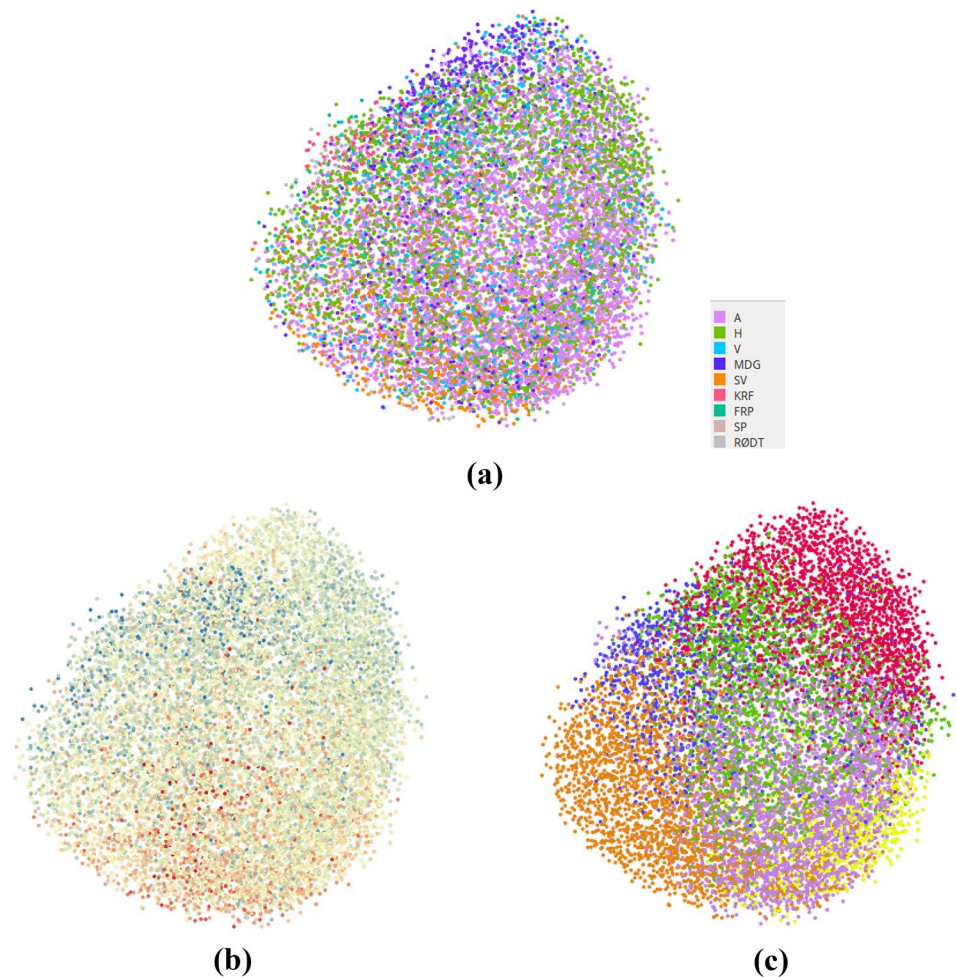
Figure 5b depicts the same layout of nodes colored based on the left–right ideological scale, in which strong blue is 0 (far right) and strong red is 10 (far left), with

cream being 5. This view of the network suggests quite some distance (i.e., loose connections) between the nodes representing more extreme ideological positions, but not to the extent that they are clustered tightly and cut off from other parts of the network. More pale red nodes are located toward the bottom (presumably mostly accounted for by the A party nodes, cf. Figure 5a) and more pale blue toward the top (where most H party nodes are located). A small area of very pale nodes is present toward the top that relates to an area comprising mostly MDG and V party nodes.

Running the Louvain algorithm for this network in Gephi (using its modularity function) resulted in a modularity score of 0.196, and identification of six communities, each comprising 6%–27% of the nodes. Figure 5c depicts the network now colored based on these six communities (the choice of colors is arbitrary and not related to Fig. 4a). Broadly speaking, the communities appear to have been quite well-clustered by the ForceAtlas2 layout algorithm, which increases our confidence in our observations about Fig. 5a, b.

Based on the visualizations of the friend-follower network, we did not find evidence of network segmentation, with the communities identified by the algorithm connected to each other, indicating the absence of echo chambers in which individuals are related only to like-minded individuals and exposed to like-minded ideologies. However, the visualizations indicate that homophily characterizes the network to some extent: Even if the communities that the algorithm identified are not congruent with the partitions by party or based on left–right orientation, individuals with the same political orientation or party affiliation tend to be more

Fig. 5 **a** Follower network, ForceAtlas2 layout, colored by majority party. **b** Follower network, ForceAtlas2 layout, colored by left–right scale (0 = blue = far right; 10 = red = far left). **c** Follower network, ForceAtlas2 layout, colored by modularity class (color figure online)



connected with each other and to form identifiable clusters, indicating a tendency toward forming homophilic ties.

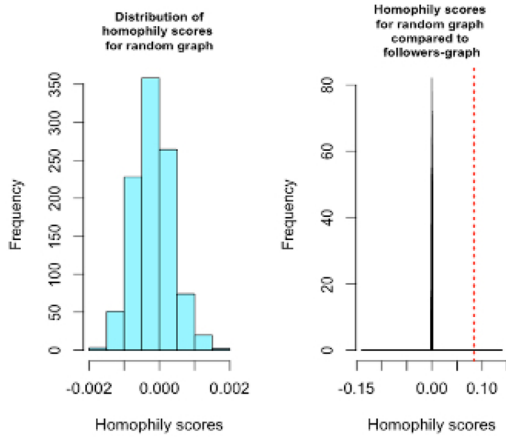
3.1 Coefficients of homophily (assortativity)

Figure 6A displays the assortative mixing coefficient (the fraction of edges in a network that connects a vertex of type i to one of type j) for the entire follower network and compares these indicators of homophily to what would appear if the network was entirely random. The assortative mixing coefficient r falls between $r=0$ when no assortative mixing is present (disassortative network) and $r=1$ when perfect assortative mixing is present, i.e., perfect homophily. The entire follower network's assortative mixing coefficient is 0.09. By comparison, equivalent random networks would have assortative mixing coefficients of 0.02 and 0.011, respectively, indicating that a higher degree of homophily (assortative mixing) is present in our network than would be the case if these networks' edges were drawn randomly. However, the assortative mixing coefficients vary across parties, as indicated in Fig. 6b.

Three parties—the Green Party (MDG), Christian Democratic Party (KRF), and Center Party (SP)—appear to have a higher assortative mixing coefficient than the overall network, whereas the Labor Party (AP) Conservative Party (H), Socialist Left Party (SV), Progress Party (FRP), and Liberal Party (V) have an assortative mixing coefficient less than the entire follower network. Overall, the network shows signs of assortative mixing (i.e., homophily), but the coefficients are closer to 0 than 1, indicating a moderate degree of homophily.

To sum up, the results from both network visualizations and assortative mixing analysis converge in indicating a relatively low level of homophily and network segregation for the entire network despite a tendency toward forming homophilic ties on the basis of party affiliation and ideological orientation. Overall, we did not find strong evidence of ideological segregation and echo chambers in the Norwegian Twittersphere based on the follower network analysis, but as already emphasized, this does not necessarily mean that politically motivated interactions on Twitter are not ideologically polarized.

(a) random graph compared with actual graph



(b) Assortative mixing coefficients by party²

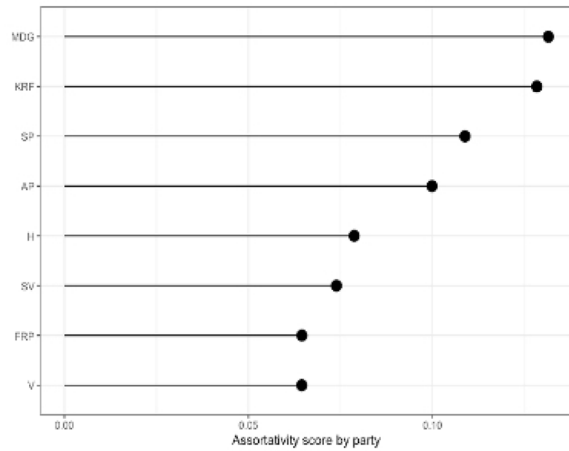


Fig. 6 Follower network distribution of homophily (assortative mixing coefficients)

3.2 Polarization in the Norwegian Twittersphere

While the estimate of the degree of homophily characterizing the Norwegian political Twittersphere has been made based on the networks of followers and on interactions (including all forms of interaction on Twitter, e.g., mentions, replies, quotes, and retweets), the analysis of polarization focuses on the most common form of interaction on Twitter, namely retweeting—an indicator of information diffusion. Here, we replicate some of the main steps in the analysis reported in Barberá et al. (2015). Using the same metrics allows us to compare our results to theirs directly and use the 2012 US election as a benchmark for our results. Following Barberà et al. (2015), we computed (i) the percentage of retweets that took place among individuals who were ideologically similar as an indicator of polarization, (ii) the degree of ideological homogeneity in the retweet network, and (iii) the rate of cross-ideological retweeting as an indicator of ideological asymmetry in polarization.

Figure 7 displays the proportion of retweets based on the ideology of the tweet and retweet’s authors. The intensity of each cell’s shading (size 0.25 SD×0.25 SD) represents the percentage of retweets published originally by users with a given estimated ideology and retweeted by users with a given estimated ideology. The highest polarization level would correspond to 100% of retweets falling along the 45° line. We found that most retweets occurred within ideological groups (along the 45° line in Fig. 7), i.e., left-oriented Twitter users tend to retweet tweets from left-oriented tweet authors and, conversely, on behalf of right-oriented Twitter

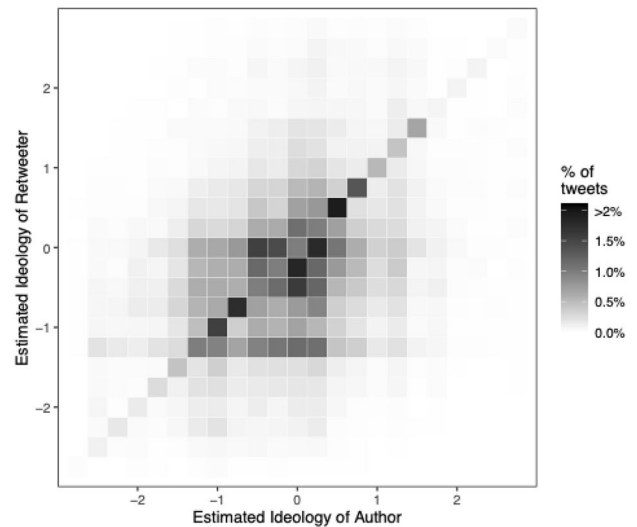


Fig. 7 Ideological polarization in retweets

users. To sum up, the figure reveals the existence of a significant polarization level in the retweet network.

Figure 8 provides a graph of the retweet networks from the 2017 election. Each node represents a Twitter user, and each edge represents a retweet. Nodes are colored based on the corresponding user’s ideology estimate, from right in blue to left in red. Edges are colored based on the ideology estimate of the user whose tweet was retweeted. The graph was designed using a force-directed layout algorithm enabling identification of ideologically homogeneous clusters. On such a graph representation, users who retweeted each

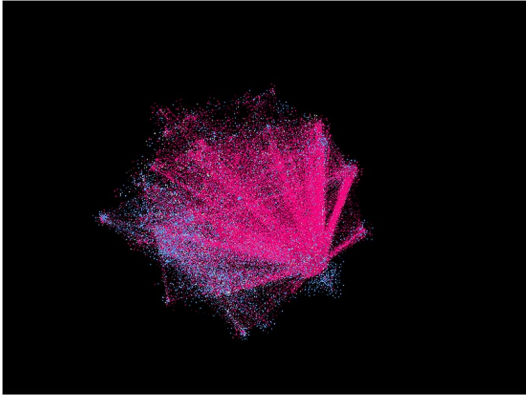


Fig. 8 Retweet network colored based on ideology

other's tweets often are near one another on the graph, while users who rarely or never retweeted each other are more distant. The network of retweets concerning the 2017 election is characterized, on one hand, by domination of left-oriented users, and on the other, by two distinct ideological clusters (left and right). While most of the left-oriented users tend to retweet from authors who are left-oriented, right-wing users appear to interact (retweet) left-oriented tweets. Thus, the graph in Fig. 8 provides further evidence of the coexistence of a relatively high polarization level in retweet networks and of the absence of an echo chamber. This evidence also is corroborated by the relatively high rate of cross-ideological retweeting from right-wing users retweeting left-wing users, as indicated in Fig. 9.

Figure 9 provides the estimated rate of cross-ideological retweeting for each ideological group after adjusting for each group's propensity to retweet and be retweeted. Indeed, if one group tweets more than another, the estimates based on a simple count of cross-ideological retweeting would be biased. To avoid this bias, we followed Barberá et al. (2015) and estimated the probability that one user would retweet

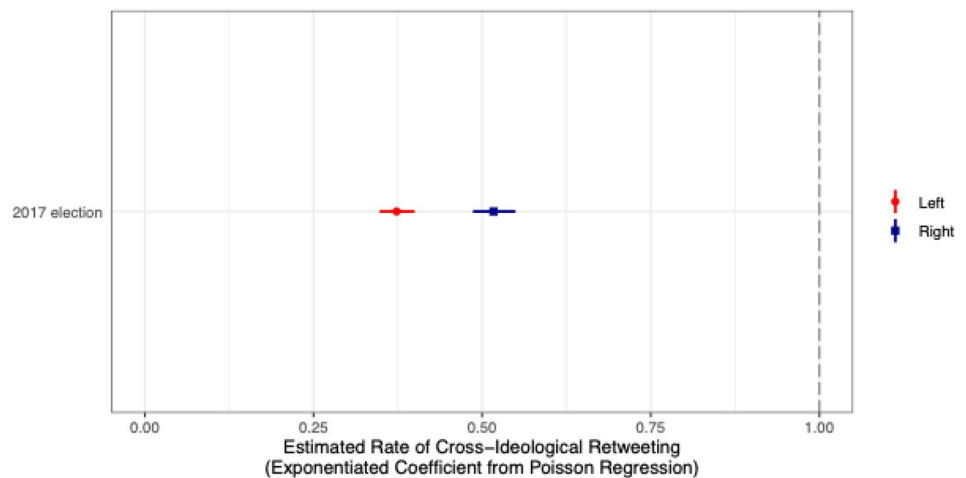
another user's post given the observed marginal rates of retweeting by left- and right-oriented Twitter users. Each point on Fig. 9 is the exponentiated coefficient of a Poisson regression for left-wing and right-wing Twitter users, respectively, with 99.9 percent confidence intervals. For each retweet between individuals of the same ideological orientation, 0.375 cases of left-wing users retweeting right-wing users were found, as well as 0.50 cases of right-wing users retweeting left-wing users.

4 Discussion and conclusion

With a backdrop of widespread concern about social media's effects on democracy, this study focused on one of these concerns and investigated the link between echo chambers and polarization in the Norwegian Twittersphere during the 2017 national election. While political Twitter networks in Norway are characterized by some level of ideological homophily, their structure did not indicate evidence of segmentation and echo chambers. The main structural clusters characterizing the friend-follower network cut across party affiliation and ideological blocs (left–right). However, some degree of ideological homophily exists in the Norwegian political Twittersphere, particularly among the main parties: the Labor Party and Conservative Party. However, despite higher degrees of homophily, particularly among the biggest parties, Twitter users do not operate within echo chambers, i.e., homogenous and isolated ideological clusters in the friend-follower network.

Simultaneously, the retweet network is polarized and driven by homophily, indicating that Twitter users tend to retweet content from users who share their ideological orientation (party affiliation). Compared with the results from Barberá et al. (2015), relative to the 2012 US election, the Norwegian retweet network, while revealing signs of polarization, is characterized by much more cross-ideological

Fig. 9 Cross-ideological retweeting



retweeting than is the case for the US network. In the same vein, while the aggregate ideological polarization (measured by average absolute distance, for all retweets, between the original author and the ideological center) has the same value (1.6), both in the Norwegian and US cases, cross-ideological retweeting rates are higher in Norway (0.375 for left-wing users and 0.5 for right-wing users) than in the USA (0.13 for Republicans and 0.26 for Democrats).

Thus, the Norwegian case is characterized by network polarization without echo chambers. These results support the idea, contrary to common wisdom, that polarization on social media may be driven by other social mechanisms, e.g., the existence of a trench warfare spiral in which cross-ideological interactions tend to reinforce existing ideological differences. In both the Norwegian and US contexts, the political Twittersphere during the elections was characterized by ideological asymmetry. However, the left dominates Norwegian political Twitter (in terms of number of users), and the direction of ideological asymmetry is the reverse of the US situation, with right-wing users displaying a higher rate of cross-ideological retweeting than left-wing users in Norway, while Democrats in the USA have higher rates of cross-ideological retweeting than Republicans. This finding may indicate that the propensity of cross-ideological interactions is not necessarily correlated to psychological traits associated with ideological positions on the left–right spectrum, but may be influenced by contextual factors, e.g., the respective numerical weights of different ideological groups in the Twittersphere.

The empirical findings shed light on the issue to determine whether social media help expand the public sphere in online networks (i.e., enable diversification of communicative actions and promote ideological diversity), or enhance echo chambers through formation of homogenous and segregated ideological groups that are conducive to increased ideological polarization. While several studies (Conover et al. 2011; Esteve Del Valle 2018; Williams et al. 2015) have established a connection between followers and retweet networks' tendency to exhibit more political homophily and the existence of ideologically congruent interactions, our results indicate that polarization may occur not necessarily as a consequence of homophilic tendencies, but may be an expression of ideological block confrontations, indicating that social media may contribute simultaneously to the extension of the public sphere and to network polarization.

Thus, this study confirms Hypothesis 2, i.e., that network heterogeneity on social media does not necessarily predict the absence of political polarization and that polarization in retweet networks is not a necessary consequence of friends-followers ideological network homogeneity or homophily. However, within the Norwegian national election's political and cultural context, social media, e.g., Twitter, are likely to facilitate heterogenous individual online networks, enabling

exposure to diversified information, and do not seem to lead to the formation of echo chambers of like-minded individuals. Nevertheless, Twitter friend-follower networks' relative heterogeneity does not necessarily mean that individuals become more united across the left–right ideological divide when it comes to the content that they support and help disseminate through their retweets. Network heterogeneity in the Norwegian political Twittersphere appears to be linked to polarization in the retweet network. Our data do not allow us to investigate and test the mechanisms that link network heterogeneity and political polarization that are in play, but previous studies have identified the frequency of political discussion (Lee et al. 2014; Strausset al. 2020; Vaccari et al. 2016) and exposure to ideologically heterogenous information (Karlsen 2017) as moderators of the relationship between network heterogeneity and political polarization. Our findings support the idea that the link between network structure and political polarization is mediated by other mechanisms and is not necessarily a result of echo chambers. A possible explanation for the existence of cross-cutting friend-follower ties may be related to the Norwegian political landscape, characterized by a proportional electoral system and a history of coalition governments that have helped develop a culture of cross-ideological cooperation that might be reflected in the Twittersphere in the form of cross-ideological ties in the friend-follower network.

These empirical results carry implications for political communication and democratic theory. First, political polarization, unlike what has become common wisdom, does not necessarily follow from network segregation in the form of echo chambers as a result of ideological homophily. The sociological tendency, prevalent in online networks, in which people tend to develop ties with people who are similar to them in terms of status and values is not necessarily incompatible with cross-ideological interactions and does not automatically lead to the formation of echo chambers. Second, our findings indicate that the existence of echo chambers on social media is not necessarily the result of technological determinism, but probably has social and political roots. Social media affordances are flexible enough to accommodate both types of dynamics, leading either to echo chambers or trench warfare spirals. In contexts in which echo chambers characterize political communication on social media, they likely are due to deepening mistrust between partisan groups, having originated in socioeconomic and identity conflicts, expressed not only in political disagreements, but also as mistrust between groups in the social structure and reflected online. Finally, from a normative perspective, our findings invite consideration of the negative valence associated with ideological polarization. It may be the case that outside of situations in which polarization is accompanied by echo chambers and reflects mistrust between opposing parties, it may be a sign

of democratic vitality, merely reflecting a democratic confrontation between diverging opinions in the public sphere.

However, these results contain several limitations. First, our study was based on Twitter data related to the 2017 Norwegian national election; thus, the functionalities of other social platforms and other political and institutional contexts may be more or less conducive to homophily and polarization. Our study's political context, focusing on the Norwegian case, also limits our findings' generalizability. Moreover, our study was based on digital traces, i.e., records of activities having taken place on Twitter that, despite their richness, provide limited information about individual attributes and do not allow for testing behavioral and communication mechanisms.

And yet, this research has shed new light on the relationship between homophily and ideological polarization, contributing to the still young and fragmented field of research on echo chambers and polarization, and their consequences for democracy. Future scholars, following Terren and Borge-Bravo (2021) advice, should mix trace data and self-reported data to test the mechanisms in play that link network structures to communication behavior and that might explain the observed ideological polarization patterns.

Author contributions Andrew Salway prepared the data, wrote parts of the methods section and prepared figure 5. BE did the remaining analyses and figures and wrote the rest of the manuscript.

Funding Funding was provided by Norges Forskningsråd, NFR: 281194, NFR: 281194.

Declarations

Competing interests The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Adamic LA, Glance N (2005) The political blogosphere and the 2004 U.S. election: divided they blog. In: Paper presented at the proceedings of the 3rd international workshop on link discovery, Chicago, Illinois <https://doi.org/10.1145/1134271.1134277>
- Aragón P, Kappler KE, Kaltenbrunner A, Laniado D, Volkovich Y (2013) Communication dynamics in twitter during political campaigns: the case of the 2011 Spanish national election. Policy Internet. <https://doi.org/10.1002/1944-2866.POI327>
- Barbera P (2015) Birds of the same feather tweet together: bayesian ideal point estimation using twitter data. *Polit Anal* 23(1):76–91. <https://doi.org/10.1093/pan/mpu011>
- Barberà P (2020) Social Media, echo chambers, and political polarization. In: Persily Tucker J (ed) *Social media and democracy: the state of the field, prospects for reform*. Cambridge University Press, Cambridge
- Barbera P, Jost JT, Nagler J, Tucker JA, Bonneau R (2015) Tweeting from left to right: Is online political communication more than an echo chamber? *Psychol Sci* 26(10):1531–1542. <https://doi.org/10.1177/0956797615594620>
- Bond R, Messing S (2015) Quantifying social media's political space: estimating ideology from publicly revealed preferences on facebook. *Am Polit Sci Rev* 109(1):62–78. <https://doi.org/10.1017/S0003055414000525>
- Bond RM, Fariss CJ, Jones JJ, Kramer ADI, Marlow C, Settle JE, Fowler JH (2012) A 61-million-person experiment in social influence and political mobilization. *Nature* 489(7415):295–298. <https://doi.org/10.1038/nature11421>
- Bond RM, Sweitzer MD (2018) Political homophily in a large-scale online communication network. *Commun Res*. <https://doi.org/10.1177/0093650218813655>
- Brundidge J (2010) Encountering “difference” in the contemporary public sphere: the contribution of the internet to the heterogeneity of political discussion networks. *J Commun* 60(4):680–700. <https://doi.org/10.1111/j.1460-2466.2010.01509.x>
- Centola D (2010) The spread of behavior in an online social network experiment. *Science* 329(5996):1194–1197. <https://doi.org/10.1126/science.1185231>
- Centola D, van de Rijt A (2015) Choosing your network: social preferences in an online health community. *Soc Sci Med* 125:19–31. <https://doi.org/10.1016/j.socscimed.2014.05.019>
- Christakis NA, Fowler JH (2007) The spread of obesity in a large social network over 32 years. *N Engl J Med* 357(4):370–379. <https://doi.org/10.1056/NEJMs066082>
- Christakis NA, Fowler JH (2008) The collective dynamics of smoking in a large social network. *N Engl J Med* 358(21):2249–2258. <https://doi.org/10.1056/NEJMs0706154>
- Clauset A, Newman MEJ, Moore C (2004) Finding community structure in very large networks. *Phys Rev E* 70(6):066111. <https://doi.org/10.1103/PhysRevE.70.066111>
- Colleoni E, Rozza A, Arvidsson A (2014) Echo chamber or public sphere? Predicting political orientation and measuring political homophily in twitter using big data. *J Commun* 64(2):317–332. <https://doi.org/10.1111/jcom.12084>
- Conover M, Ratkiewicz J, Francisco M, Gonçalves B, Menczer F, Flammini A (2011) Political polarization on twitter: In Proc 5th international AAAI conference on weblogs and social media (ICWSM), 2011. ICWSM test of time award 2021
- Conover MD, Gonçalves B, Flammini A, Menczer F (2012) Partisan asymmetries in online political activity. *EPJ Data Science* 1(1):6. <https://doi.org/10.1140/epjds6>
- Dubois E, Blank G (2018) The echo chamber is overstated: the moderating effect of political interest and diverse media. *Inf Commun Soc* 21(5):729–745. <https://doi.org/10.1080/1369118X.2018.1428656>
- Edmundson HP, Wyllys RE (1961) Automatic abstracting and indexing—survey and recommendations. *Commun ACM* 4(5):226–234. <https://doi.org/10.1145/366532.366545>
- Esteve Del Valle M, Borge Bravo R (2018) Echo chambers in parliamentary twitter networks: the catalan case. *Int J Commun* 12:21
- Feller A, Kuhnert M, Sprenger T, Welpel I (2021) Divided they tweet: the network structure of political microbloggers and discussion topics. Proceedings of the international AAAI conference on

- web and social media, vol 5(1). pp 474–477 Retrieved from <https://ojs.aaai.org/index.php/ICWSM/article/view/14150>
- Fowler JH, Christakis NA (2008) Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the framingham heart study. *BMJ* 337:a2338. <https://doi.org/10.1136/bmj.a2338>
- Gaines BJ, Mondak JJ (2009) Typing together? clustering of ideological types in online social networks. *J Inform Tech Polit* 6(3–4):216–231. <https://doi.org/10.1080/19331680903031531>
- Galston WA (2002) If political fragmentation is the problem, is the Internet the solution? In: Anderson DM, Cornfield M, Arterton FC (eds) *The civic web: Online politics and democratic values*. Rowman and Littlefield, Lanham, MD, pp 35–44
- Garcia D, Abisheva A, Schweighofer S, Serdült U, Schweitzer F (2015) Ideological and temporal components of network polarization in online political participatory media. *Policy Internet*. <https://doi.org/10.1002/poi.3.82>
- Garrett RK (2009a) Echo chambers online?: politically motivated selective exposure among internet news users I. *J Comput Mediat Commun* 14(2):265–285. <https://doi.org/10.1111/j.1083-6101.2009.01440.x>
- Garrett RK (2009b) Politically motivated reinforcement seeking: reframing the selective exposure debate. *J Commun* 59(4):676–699. <https://doi.org/10.1111/j.1460-2466.2009.01452.x>
- Genzkow M, Shapiro JM (2010) What drives media slant? Evidence from US daily newspapers. *Econometrica* 78(1):35–71
- Gruzd A, Roy J (2014) Investigating political polarization on twitter: a canadian perspective. *Policy Internet* 6(1):28–45. <https://doi.org/10.1002/1944-2866.POI354>
- Halberstam Y, Knight BG (2014) homophily, group size, and the diffusion of political information in social networks: evidence from twitter. NBER working paper series
- Hargittai E, Gallo J, Kane M (2008) Cross-ideological discussions among conservative and liberal bloggers. *Public Choice* 134(1):67–86. <https://doi.org/10.1007/s11127-007-9201-x>
- Hesstvedt S, Karlsen R (2017) Stortingskandidater. Rapport fra Stortingskandidaterundersøkelsen 2013. Retrieved from Oslo: <https://samfunnsforskning.brage.unit.no/samfunnsforskning-xmliui/handle/11250/2450099>
- Himmelboim I, McCreery S, Smith M (2013) Birds of a feather tweet together: integrating network and content analyses to examine cross-ideology exposure on twitter. *J Comput Mediat Commun* 18(2):40–60. <https://doi.org/10.1111/jcc4.12001>
- Huber G, Malhotra N (2013) Dimensions of political homophily: Isolating choice homophily along political characteristics. Paper presented at the American Political Science Association annual meeting, New Orleans, LA
- Jacomy M, Venturini T, Heymann S, Bastian M (2014) ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the gephi software. *PLoS ONE* 9(6):e98679. <https://doi.org/10.1371/journal.pone.0098679>
- Karlsen RS-J, Wollebæk K, Enjolras D, B. (2017) Echo chamber and trench warfare dynamics in online debates. *Eur J Commun* 32(3):257–273. <https://doi.org/10.1177/0267323117695734>
- Lawrence E, Sides J, Farrell H (2010) Self-segregation or deliberation? Blog readership, participation, and polarization in american politics. *Perspect Polit* 8(1):141–157. <https://doi.org/10.1017/S1537592709992714>
- Lee JK, Choi J, Kim C, Kim Y (2014) Social media, network heterogeneity, and opinion polarization. *J Commun* 64(4):702–722. <https://doi.org/10.1111/jcom.12077>
- Lijphart A (1999) *Patterns of democracy*. Government forms and performances in thirty-six countries. Yale University Press, New Haven
- McPherson M, Smith-Lovin L, Cook JM (2001) Birds of a feather: homophily in social networks. *Ann Rev Sociol* 27(1):415–444. <https://doi.org/10.1146/annurev.soc.27.1.415>
- Mutz DC (2002) The consequences of cross-cutting networks for political participation. *Am J Polit Sci* 46(4):838–855. <https://doi.org/10.2307/3088437>
- Newman MEJ (2002) Assortative mixing in networks. *Phys Rev Lett* 89(20):208701. <https://doi.org/10.1103/PhysRevLett.89.208701>
- Newman MEJ (2003) Mixing patterns in networks. *physical review. E Stat Nonlinear Soft Matter Phys* 67:026126. <https://doi.org/10.1103/PhysRevE.67.026126>
- Nunn CZ, Crockett AJ, Williams AJ (1978) *Tolerance for non-conformity*. Jossey-Bass Publishers
- Pariser E (2011) *The Filter Bubble*. Penguin Books
- Pennacchiotti M, Popescu A-M (2011) Democrats, republicans and starbucks aficionados: user classification in twitter. In: Paper presented at the Proceedings of the 17th ACM SIGKDD international conference on knowledge discovery and data mining, San Diego, California, USA <https://doi.org/10.1145/2020408.2020477>
- Pennacchiotti M, Popescu A-M (2021) A machine learning approach to twitter user classification. In: Proceedings of the international AAAI conference on web and social media vol 5(1). pp 281–288
- Quattrociochi W, Scala A, Sunstein CR (2016) echo chambers on facebook available at SSRN: <https://ssrn.com/abstract=2795110> or <https://doi.org/10.2139/ssrn.2795110>
- Strauss N, Alonso-Muñoz L, Gil de Zúñiga H (2020) Bursting the filter bubble: the mediating effect of discussion frequency on network heterogeneity. *Online Inform Rev Ahead Print*. <https://doi.org/10.1108/OIR-11-2019-0345>
- Stroud NJ (2010) Polarization and partisan selective exposure. *J Commun* 60(3):556–576. <https://doi.org/10.1111/j.1460-2466.2010.01497.x>
- Stroud NJ (2017) Selective Exposure Theories. In: Kenski K, Jamieson KH (Eds) *The Oxford Handbook of Political Communication* <https://doi.org/10.1093/oxfordhb/9780199793471.013.009>
- Sunstein C (2001) *Republic. com*. princeton. Princeton University Press, NJ
- Sunstein CR (2018) *Republic: divided democracy in the age of social media*. Princeton University Press
- Taber CS, Cann D, Kucsova S (2009) The motivated processing of political arguments. *Polit Behav* 31(2):137–155
- Terren L, Borge-Bravo R (2021) Echo chambers on social media: a systematic review of the literature. *Rev Commun Res* 9:99–118
- Vaccari C, Valeriani A, Barberá P, Jost JT, Nagler J, Tucker JA (2016) Of echo chambers and contrarian clubs: exposure to political disagreement among german and italian users of twitter. *Soc Media Soc* 2(3):2056305116664221. <https://doi.org/10.1177/2056305116664221>
- Williams HTP, McMurray JR, Kurz T, Lambert FH (2015) Network analysis reveals open forums and echo chambers in social media discussions of climate change. *Glob Environ Change Human Policy Dimens* 32:126–138. <https://doi.org/10.1016/j.gloenvcha.2015.03.006>
- Wojcieszak ME, Mutz DC (2009) Online groups and political discourse: Do online discussion spaces facilitate exposure to political disagreement? *J Commun* 59(1):40–56. <https://doi.org/10.1111/j.1460-2466.2008.01403.x>
- Yang Z, Algesheimer R, Tessone CJ (2016) A comparative analysis of community detection algorithms on artificial networks. *Sci Rep* 6(1):30750. <https://doi.org/10.1038/srep30750>
- Yardi S, Boyd D (2010) Dynamic debates: an analysis of group polarization over time on twitter. *Bull Sci Technol Soc* 30(5):316–327. <https://doi.org/10.1177/0270467610380011>