Ideological homophily and polarization in political Twitter during the 2017 Norwegian election

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Abstract

Ideological homophily on social media has received increased scholarly interest as it is associated to the formation of filter-bubbles, echo-chambers and increased ideological polarization. Yet, there is no necessary linkage between ideological homophily, echo chambers, and polarization. In spite of 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 investigate 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. We do not find that, in spite of the presence of some degree of ideological homophily, evidence of echo-chambers in the Norwegian political Twittersphere during the 2017 election. Yet, the retweets 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 other drivers than the technological deterministic effect of social media affordances enhancing the formation of online echo-chambers.

Introduction

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

Two main perspectives, emphasizing different dynamics, may be distinguished on that issue. The first perspective points to the detrimental effect of social media for the political public sphere: Because social media facilitate selective exposure, they consequently reduce exposure to political difference and increase ideological homophily and in so doing the formation of echo chambers that favor in turn political polarization (Galston, 2002; Sunstein, 2001). From this viewpoint, polarization is seen as the result of social media enhancing ideological homophily, i.e. the fact that politically likeminded individuals are enabled by social media to find one another, a fact leading to the formation of echo-chambers where citizens are only exposed to information that is congruent with their political views (Sunstein, 2001). The concept of homophily entails that similar people tend to connect 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 (R. M. Bond & Sweitzer, 2018). Selective affiliation may be based on a variety of both relevant and seemingly irrelevant similar characteristics (Centola & van de Rijt, 2015). There is evidence that social network structure affects a
wide range of opinions and behaviors, including political ones (R. M. Bond et al., 2012; Centola, 2010; Christakis & Fowler, 2007, 2008; Fowler & 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 people receive and the attitudes they form (McPherson et al., 2001). In the political domain, individuals may sort on political identities (political party or ideological disposition), according to political issue positions (policy issues), or on their levels of political engagement (Huber, 2013). The formation of echo chambers may be thought as the direct effect of homophilic tendencies and might be correlated with political polarization (Stroud, 2010). In contrast, network diversity and ideological heterogeneity has been shown to be associated with higher levels of political tolerance (Mutz, 2002). In sum, 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 sharing the same ideology (sorting 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 a polarized network structure with few cross-cutting links.

Several studies, mostly based on U.S. data, in 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 sub-groups with little linkage with each other (Adamic & Glance, 2005; Aragón et al., 2013; Barbera, 2015; Colleoni et al., 2014; M. Conover et al., 2011; M. D. Conover et al., 2012; Feller et al., 2021; Gaines & Mondak, 2009; Garcia et al., 2015; Gruzd & Roy, 2014; Halberstam & Knight, 2014; Hargittai et al., 2008; Himelboim et al., 2013; Lawrence et al., 2010; Quattrociocchi et al., 2016; Yardi & Boyd, 2010).

The second perspective, in contrast, points to the positive contribution of social media to the political public sphere: Since digital networks are cutting across social and geographical boundaries, they contribute to increasing exposure to diverse opinions (Brundidge, 2010). Exposure to a diversity of opinions is considered crucial for developing well informed citizens (Gentzkow & Shapiro, 2010) who are also tolerant of the ideas of others (Nunn et al., 1978), whereas exposure to only like-minded opinions may lead to polarization towards ideological extremes (Brundidge, 2010; Sunstein, 2001). Brundidge (2010)—in line with (Wojcieszak & Mutz, 2009)’s findings according to which exposure to heterogeneous networks and political views online often happens accidentally— have found evidence that social media use increases the heterogeneity of political discussion networks. Dubois and Dubois & 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, and conclude that the echo-chamber thesis is overstated. Vaccari et al., 2016, found, based on online surveys of representative samples of Italian and German individuals who posted at least one Twitter message about elections in 2013, 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 the intensity of political discussions appeared to be determinant of the type of exposure they experienced on social media, in spite of a tendency towards homophily.
There is an apparent paradox 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. The reason being that social media enable greater exposure and contact with weak ties than in offline interactions, weak ties that are central to the spread and diversity of information. Thus, the link between ideological homophily and echo chambers on the one hand, and polarization on the other hand, is increasingly questioned as, in spite of the importance of political interactions on social media between like-minded individuals, cross-cutting interactions are also frequent (Barberà, 2020). This means that the linkage between structural characteristics of social media networks (such as echo-chamber) and political polarization needs to be nuanced (Barberá, 2020) and that polarization may be driven by other social mechanisms than homophily and echo-chambers.

Indeed, there is evidence that polarization might be driven by increased exposure to ideologically heterogenous information: (Karlsen et al., 2017) find that the dynamics of online cross-cutting interactions could be more aptly described by the logic of ‘trench warfare’, in which opinions are reinforced through contradiction as well as confirmation. Survey experiments suggest that both confirming and contradicting arguments have similar effects on attitude reinforcement. This indicates that political attitudes are reinforced through both confirmation bias (people reinforce their opinion by encountering similar opinion) and disconfirmation bias (people use time and cognitive resources to degrade and counter argue attitudinally contrasting opinions) characterize online cross-cutting interactions.

Yet, existing research has not explicitly investigated the linkage between degree of ideological homophily and network polarization on social media. The research reported here fills this gap by investigating whether political polarization is the result of ideological homophily or whether we find indications that polarization might be driven, in the presence of cross-cutting interactions, by other mechanisms. Indeed, the echo chambers perspective rests on the premise of selective exposure i.e., that selective exposure and selective avoidance (Stroud 2017)—occurring when people purposefully select information on the basis of their preferences or attitudes—might entail a dilution of political information effects (by limiting the impact of political communication on social media) or foster sources selection and ideological self-segregation (Pariser, 2011; Sunstein, 2001). The result of selective exposure is a reinforcement of individuals’ own beliefs as opinions formed in such environments become polarized and extreme. However, selectivity, while resulting in increased exposure to consonant contents, does not necessarily lead to avoidance of dissonant ones (Garrett, 2009a, 2009b) and may increase exposure to political disagreement (Vaccari et al., 2016). Furthermore, the literature on motivated reasoning has shown that prior attitudes strongly bias how people process arguments, and 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 the already held opinions—a phenomenon referred to as disconfirmation bias (Taber et al., 2009)—that may foster a logic of trench warfare where cross-cutting interactions between ideologically opposed individuals tend to reinforce opposed opinions Karlsen et al., (2017).
We analyze Twitter data to investigate two research questions, namely, (a) the extent to which online political friends-followers’ and interaction networks on the Norwegian Twittersphere show evidence of homophily and of ideological segregation (echo-chambers), and (b) the degree to which polarization may characterize interactions on the Norwegian Twittersphere in the absence of significant ideological segregation (homophily), indicating the possible presence of other polarizing mechanisms than homophily and echo chambers and involving selective engagement (through interactions and sharing) with ideologically like-minded content and users. In addition to investigating these research questions, we make methodological contributions to the computational analysis of Twitter data by firstly, considering the complete universe of political tweets (and not a selection based on users or hashtags) during an election campaign and by comparing two methods—Barberá (2015) and Halberstam and Knight (2016)—for inferring Twitter users’ ideology.

Data And Methods

In order to investigate empirically degrees of ideological segregation and levels of polarization on Twitter, we require data about 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 by key-words, we adopted another data collection strategy aimed at obtaining the entire universe of political tweets during the election campaign period. Here we summarize the main steps taken to collect the data and create two networks, one representing friend/follower relationships and one representing mentions and interactions.

Data

We made a list (P) of 1845 Norwegian political actors with Twitter accounts: this comprised all the candidates standing 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. We then acquired a dump of 4.2 million tweets from the Twitter Historical PowerTrack API which comprised all tweets that: (i) were coded as Norwegian-language by Twitter; (ii) were posted in 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.

Based on this dump and further data about accounts’ followers and friends, we made a selection of accounts that would be the focus of our investigation. We removed accounts that followed less than 3 of the accounts in P, so that we could reliably automate ideological coding of the selected accounts, as explained next. This gave us a set of 179377 users that we consider to have been actively engaged with Norwegian politics on Twitter in the period March-September 2017.

Since we are interested in political communication between the selected users, we need to be able to classify tweets as political/non-political, where we adopt a broad definition of “political”, much like “political communication”, not necessarily political content. From this viewpoint communication with
political actors would be considered as “political” even if the content is not. A tweet was classified as “political” is: (i) it contained a word, phrase or hashtag from a pre-compiled list based on keyness analysis; OR (ii) it mentioned, was sent by, or interacted with the account of a political actor (interactions are replies, retweets and quoted tweets).

Keyness (Edmundson & 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 those tweets that were seen to contain a term from the initial list of terms or to interact with an account from the initial list of actors, and the set of remaining tweets. Thus, the list of keywords generated was expected to include good candidates for expanding the initial lists. We used the list of comparatively frequent key-words in order to select the set of political tweets. Compared to the most prevalent way of collecting tweets (using Twitter search API that returns tweets containing a key-word or set of key-words), our method allows us to collect a richer collection of political tweets based on an exhaustive list of key-words.

The lists of political terms and political actors were compiled in two steps. First, a list of 28 words, phrases and hashtags that defined political topics was manually compiled by one of the authors familiar with Norwegian political communication in social media. And, initially, the list of political actors was taken to comprise the 1845 accounts from list P above. Then, these lists were expanded in a semi-automated process, similar to Conover et al. (2011a), using the idea of keyness analysis (Edmundson & 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, and 249 further accounts considered to be “opinion leaders” to the list of political actors. Using the expanded lists we filtered our initial set of 4.2 million tweets according to the presence of a political term or interaction with an account of a political actor, resulting in a set of around 1.5 million “political” tweets. The frequency-led nature of the query expansion process means we are confident that most political tweets were identified, and the use of keyness analysis helps to 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 3 political actors in (P).

Measuring and identifying political homophily

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

When visualizing a network, the way in which the nodes are laid out is significant for what insights can be gained. We chose to use the ForceAtlas2 layout algorithm (Jacomy et al., 2014) in the Gephi visualization tool. It is a force-directed layout algorithm which means that it simulates repulsion forces between all nodes and attraction forces between nodes that share a link, such that the strength of the attraction
relates to the weight of the link. It is intended to “turn structural proximities into visual proximities”, i.e. the nodes are positioned in 2D space in such a way that nodes tend to be closer to nodes that they share links with. The nodes can then be colored, for example in our case according to the user's majority party, to see whether the network structure suggests homophily with regards to whatever feature was colored. Whilst such visualizations are a useful starting point in exploring network data, we note that they should not be the basis for strong claims about the network. This is because some arbitrary choices are made in the visualization process which can lead to quite different results, e.g. the parameters for the layout algorithm, the choice of color scheme, and, not least in the case of ForceAtlas2, the decision as to when to stop running the algorithm since it does not terminate itself. It is also important to note that the layout is not a Cartesian projection, i.e. the 2D coordinates do not relate to any variables.

We thus add to our approach with the use of a community detection algorithm and metrics for homophily. The objective is to identify and measure the extent to which network nodes have links with others that share a certain characteristic (e.g. majority party) versus having links with nodes that do not have the same characteristic. In other words, 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 can then color the nodes (already laid out by ForceAtlas2) according to their modularity class, to see 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 or “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 \( j \). The “assortativity” coefficient for the whole network is thus: \[
\sum e_{ij} - \sum a_i b_j \frac{1}{1 - \sum a_i b_j},
\] where \( a_i \) and \( b_i \) are the fraction of each type of end of an edge that is attached to vertices of type \( i \). On undirected graphs, where the ends of edges are all of the same type, \( a_i = b_i \). This formula gives \( r = 0 \) when there is no assortative mixing (all nodes link to others of a different type) and \( r = 1 \) when there is perfect assortative mixing (all nodes link to others of the same type).

**Estimation of ideology**

Several methods are available for estimating Twitter users’ ideology. The ideology of social media users can be automatically coded based on communication content, e.g. supervised text classification of tweets and Facebook posts (Colleoni et al., 2014; M. Conover et al., 2011; M. D. Conover et al., 2012;
A second approach consists in estimating ideology on the basis of endorsement, i.e. the choices of who a user follows are taken to reflect their ideology such that ideology may be inferred (Barbera, 2015; Barbera et al., 2015; R. Bond & Messing, 2015). While Barberà (2015) has developed a Bayesian spatial model of Twitter users’ following behavior enabling to estimate ideal ideological points derived from the structure of the following links between Twitter users and political actors, Halberstam and Knight (2016) have 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 Barberà (2015) and Halberstam and Knight (2016) methods. This enable us validate the 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 assess the relative performance of the two approaches by comparing the distributions of the ideology estimates on the Left-Right scale and by party. For the first method we validate the ideology estimates using the party affiliation of the 1756 political accounts (candidates) having a non-empty follower list for whom we know the party affiliation. For the second method, we use the entire set of Twitter users including the candidates and consisting 179377 users.

The Norwegian parties that are represented in the Parliament designed by their English name, Norwegian name and abbreviation in bold: Labor party (Arbeiderpartiet, A), Conservative Party (Høyre, H), Progress Party (Fremskritspartiet, 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 includes, in addition to these main parties, an array of minor parties which are not represented in the Parliament but presented candidates at the 2017 election. These are: The Christian Party (KRISTNE) a Christian right party, the Alliance (ALLI) a nationalist party, Democrats in Norway (DEMN) a right-wing populist/nationalist party, Health Party (HELSE) a single issue party, Coastal Party (KYST) a national conservatist party, Pirate Party (PIR) promoting “pirate politics”, and the Capitalist Party (LIBS) a liberalistic party.

**Ideology estimation – Barberá (2015) method**

Following the method developed by Barberá (2015), we identify the ideological latent space and estimate ideological ideal points for 179377 political Twitter users—including 1756 political accounts (candidates) for which we have collected the followers. Figure 1 displays the distribution of Twitter-based ideology estimates of candidates on the ideological space according to their position on the Left-Right political scale computed on the basis of their party-belonging, while Fig. 2 displays this distribution according to 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 the distribution according to party does not reflect the positions of the Norwegian parties on the Left-Right ideological scale, with for example Center Party (SP), a party situated at the center-left of Norwegian politics, being more leftist than the radical-left party Rødt. In sum, this method does not perform well with our data. This may be due to the fact that, contrarily to Barberá et al. (2015) we did not initially restricted our matrix of connections to a subset of accounts with
high ideological discrimination, but estimated ideological ideal points on the set constituted by all candidates and their followers.

**Ideology estimation - Halberstam and Knight (2016) method**

Further, following Halberstam and Knight (2016) method, we coded our selected users for “party ideology” which is a discrete class (one of the parties presenting candidates to the Norwegian election) and for “ideology left-right” which is a scalar value between (0–10) that has been 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 variable “ideology left-right” 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 scale are based on the averaged self-identification of the candidates for each party during the 2013 national parliamentary election based on a candidate survey realized by (Hesstvedt, 2017). As it is the case with the estimates based on Barberà (2015) method, the ideological points have been normalized. As previously, Fig. 3 displays the distribution of Twitter-based ideology estimates of candidates on the ideological space according to their position on the Left-Right political scale computed on the basis of their party-belonging, while Fig. 4 displays this distribution according to their party-belonging. This estimation method gives average ideological points for candidates belonging respectively to the right and left sides of the political spectrum that are more distant from each other than with the ideal point estimation method. Additionally, the distribution of ideological estimates according to parties reflect, to a greater extent, the party positions on the Left-Right scale characterizing Norwegian politics, with the Left-wing parties being correctly positioned on the left and the Right-wing parties on the Right.

Given these results, we will use ideology estimations based on Halberstam and Knight (2016) for analyzing network homophily and levels of polarization.

**Homophily in followers networks**

We present now the results of our comparative analysis of the *follower network* (112,000 nodes and 4,4 million edges). The main goal of the analysis is to assess the degree of homophily and ideological segregation characterizing the network. For this purpose, we use two of the methodological approaches outlined in the method section: network visualization and link analysis. In this analysis we focus mainly on the Norwegian parties that are represented in the Parliament.

Figure 5a shows the follower network with the nodes laid out by the ForceAtlas2 algorithm, and colored according to each user’s majority party. Whilst the users coded as one or other of the two largest parties (A and H) are quite mixed throughout, it does appear that A nodes are tending towards the bottom and H nodes towards the top. More pronounced is the separation between two of the medium size parties MDG (clustering towards the top) and SV (clustering towards the bottom). A third medium size party (V) appears to be spread quite evenly throughout.
Figure 5b shows the same layout of nodes colored according to the left-right ideological scale, where 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 tightly clustered and cut-off from other parts of the network. There are also more pale red nodes towards the bottom (presumably mostly accounted for by the A party nodes, cf. Figure 5a) and more pale blue towards the top (where most H party nodes are). There is a small area of very pale nodes towards the top which 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 the identification of 6 communities each comprising 6%-27% of the nodes. Figure 5c shows the network now colored according to these 6 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 Figs. 5a and 5b.

Based on the visualizations of friend-followers network we do not find evidence of network segmentation—the communities identified by the algorithm being connected to each other, indicating the absence of echo-chambers where individuals are only related to like-minded individuals and exposed to like-minded ideology. Yet, the visualizations display that homophily characterizes the network to some extent: even if the communities identified by the algorithm are not congruent with the partitions by party or according to Left-Right orientation, individuals with the same political orientation or party-affiliation tend to be more connected with each other and to form identifiable clusters, indicating a tendency to form homophilic ties.

**Coefficients of homophily (“assortativity”)**

Figures 6a displays the assortative mixing coefficient (the fraction of edges in a network that connect a vertex of type $i$ to one of type $j$) for the entire follower network and compare these indicators of homophily to what would append if the network was entirely random. The assortative mixing coefficient $r$ is comprised between $r = 0$ when there is no assortative mixing (disassortative network) and $r = 1$ when there is perfect assortative mixing i.e., perfect homophily). The assortative mixing coefficient of the entire follower network is of 0.09. In comparison, equivalent random networks would have an assortative mixing coefficient of respectively 0.02 and 0.011, indicating that there is a higher degree of homophily (assortative mixing) in our network than it would be the case if the edges of these networks were drawn randomly. However, the assortative mixing coefficients variate across parties, as shown in Fig. 6 (b). Three parties, Green Party (MDG), Christian democratic Party (KRF), Center Party (SP) appear to have a higher assortative mixing coefficient than the overall network, whereas the Labor Party (AP) the Conservative Party (H), Socialist Left Party (SV), Progress Party (FRP), and Liberal Party (V) have an assortative mixing coefficient lesser than the entire followers’ 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.

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

**Polarization in the Norwegian Twittersphere**

While the estimation of the degree of homophily characterizing the Norwegian political Twittersphere has been conducted on the networks of followers and of interactions (including all forms of interactions on Twitter—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, thus, to directly compare our results to theirs and to use the 20212 U.S. election as benchmark for our results. Following Barberà et al. (2015) we compute (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 indicator of ideological asymmetry in polarization.

Figure 7 displays the proportion of retweets according to respectively the ideology of the author of the tweet and of the retweeter. The intensity of the shading of each cell (of size $0.25 \times 0.25$) represents the percentage of retweets that were published originally by users with a given estimated ideology and retweeted by users with a given estimated ideology. The highest level of polarization would correspond to 100% of retweets falling along the 45° line. We find that most retweets occur within ideological groups (along the 45° line in figure 7) i.e., left-oriented twitter users tend to retweet tweets from left-oriented tweet authors and conversely on behalf of right-oriented twitter users. In sum the figures reveals the existence of a significant level of polarization in the retweets network.

Figure 8 depicts the graph of the retweet networks for the 2017 election. Each node represents a twitter user and each edge represents a retweet. Nodes are colored according to the ideology estimate of the corresponding user, from right in blue to left in red. Edges are colored according to the ideology estimate of the user whose tweet was retweeted. The graph was elaborated using a force-directed layout algorithm enabling to identify ideologically homogeneous clusters. On such a graph representation, users who retweeted each other’s tweets often are close to one another on the graph while users who rarely or never retweet each other are more distant. The network of retweets concerning the 2017 election is characterized by on the one hand, the domination of left-oriented users, and on the other hand, two distinct ideological clusters (Left and Right). While most of the Left-oriented users tend to retweet from authors that are Left-oriented, Right-wing users appear to interact (retweet) Left-oriented tweets. In other words, the graph in figure 8 provide further evidence of the coexistence of a relatively high level of
polarization in retweet networks and of the absence of echo-chamber. This evidence is also corroborated by the relatively high rate of cross-ideological retweeting from Right-wing users retweeting Left-wing users as shown on figure 9.

Figure 9 shows 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 a group tweet more than another, the estimates based on a simple count of cross-ideological retweeting would be biased. In order to avoid this bias, we follow Barberá et al. (2015) and estimate 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 figure 9 is the exponentiated coefficient of a Poisson regression for respectively Left-wing and Right-wing twitter users with 99.9 confidence intervals. For each retweet between individuals of the same ideological orientation there were 0.375 cases of Left-wing users retweeting Right-wing users, and 0.50 cases of Right-wing users retweeting Left-wing users.

### Summary And Conclusion

With the backdrop of a widespread concern about the effects of social media on democracy, the research reported here has focused on one of those concerns and investigated the linkage between echo chambers and polarization on 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 show evidence of segmentation and echo chambers. The main structural clusters characterizing the friends-followers network cut across party affiliation and ideological blocs (Left-Right). Yet, there exists some degree of ideological homophily on the Norwegian political Twittersphere, especially among the main parties: Labor Party and Conservative Party. However, in spite of higher degrees of homophily, especially among the biggest parties, Twitter users do not operate within echo-chambers.

At the same time, the retweets network is ideologically polarized, indicating that Twitter users tend to retweet content that is ideologically congruent with their ideological orientation. Compared to the results reported by Barberá et al. (2015) relative to the 2012 U.S. election, the Norwegian retweets network, while revealing signs of polarization, is characterized by much more cross-ideological retweeting than it is the case for the U.S. network. In the same vein, while the aggregate ideological polarization (measured by the 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 in the U.S. case, rates of cross-ideological retweeting are higher in Norway (0.375 for Left-wing users and 0.5 for Right wing users) than in the U.S. (0.13 for Conservatives and 0.26 for Liberals).

In other words, the Norwegian case is characterized by ideological polarization without echo-chambers. These results support the idea, contrary to the common wisdom, that ideological polarization on social media may be driven by other social mechanisms such as the existence of a trench warfare spiral where cross-ideological interactions tend to reinforce existing ideological differences. In both the Norwegian and U.S. cases, the political Twittersphere during the elections is characterized by ideological asymmetry.
However, the Norwegian political Twitter is dominated by Left (in terms of number of users) and the
direction of ideological asymmetry is the reverse of the U.S. situation, with Right-wing users displaying a
higher rate of cross-ideological retweeting than Left-wing users in Norway while Liberals in the U.S. have
higher rates of cross-ideological retweeting than Conservatives. 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 such as the respective numerical weights of different ideological groups in the Twittersphere.

These empirical results have Implications for political communication and democratic theory. First,
political polarization, in contrast to 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, according to which people tend to develop ties with people that
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 are not necessarily the result of
 technological determinism, but have probably social and political roots. Social media affordance are
flexible enough to accommodate both types of dynamics, leading either to echo-chambers or to trench
warfare spirals. In the cases where echo-chambers characterize political communication on social media,
they are most probably due to the deepening of mistrust between partisan groups having its origins in
socio-economic and identity conflicts, expressed not only in political disagreements but also mistrust
between groups, which take place in the social structure and are being reflected online. Finally, from a
normative viewpoint, our findings invite to reconsider the negative valence that is associated with
ideological polarization. It may be the case that outside the situations where polarization is accompanied
by echo-chambers and reflect mistrust between opposing parties, polarization may be a sign of
democratic vitality and just reflect the democratic confrontation of diverging opinions in the public
sphere.

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**Figures**

![Twitter-based ideology estimates of candidates-Barberá method](image)

**Figure 1**

*Twitter-based ideology estimates of candidates-Barberá method*
Figure 2

*Twitter-based ideology estimates of candidates by party- Barberá method*

Figure 3

*Twitter-based ideology estimates of candidates- Halberstam and Knight method*

Figure 4

*Twitter-based ideology estimates of candidates by party- Halberstam and Knight method*
Figure 5

a. Follower network, ForceAtlas 2 layout, coloured by majority party. b. Follower network, ForceAtlas 2 layout, coloured by left-right scale (0=blue=far right; 10=red=far left). c. Follower network, ForceAtlas 2 layout, coloured by modularity class.
Figure 6

*Follower Network distribution of homophily (assortative mixing coefficients) (a) random graph compared to actual graph (b) Assortative mixing coefficients by party*

Figure 7

*Ideological polarization in retweets*

Figure 8

*Retweet network colored according to ideology*
Figure 9

Cross-ideological retweeting