**The dynamics of message exposure in online political discussion forums:**

**Effects of motivation, homophily, and endogenous network processes**

**Expectations and hypotheses**

***Motivations and homophily***

From the perspective of the cognitive consistency principle, we expect that those with higher consistency motivation would be more selective than those with lower consistency motivation with regard to what they choose to expose themselves. All things being equal, individuals are more likely to choose to view the message that conforms their expectations (McPherson, Smith-Lovin, & Cook, 2001; Iyengar & Hahn, 2009). Yet at the same time, prior findings generally suggest that partisans with high consistency motivation are no more likely to “avoid” themselves from potentially attitudinally dissonant messages (Garrett, 2009; Garrett & Stroud, 2016). This leads us to expect that those with higher consistency motivation are equally likely to seek out (potentially dissonant) information presented by others irrespective of its congeniality with their prior attitudes. Yet at the same time, their messages are more likely to *be selected and viewed by others* within the context of online political discussion forum, presumably since they communicate clear, strong partisan messages (Ahn, Huckfeldt, & Ryan, 2014) than those with lower consistency motivation. These two expectations culminate to our first set of hypotheses:

**H1a**: Consistency motivation is associated with the higher propensity of one’s messages being selected by others in the online discussion forum.

**H1b**: Consistency motivation is associated with the higher propensity of selecting others’ messages in the online discussion forum.

The cognitive consistency principle further leads us to hypothesize a positive impact of partisan preference homophily in their message selection dynamics. Either based on an explicit application of political preferences or based on de facto preference homophily (based on other similar characteristics), research has repeatedly suggested that people can selectively construct their social environment around them (Kossinets & Watts, 2009; McPherson et al., 2001). Within the present context, this mean an ego (“focal respondent”) and alters (“potential discussion partner”) are more likely to select each other’s messages if they share same political preferences. Therefore, we posit that:

**H1c**: Same political preferences within a dyad increase the propensity of selecting each other’s messages in the online discussion forum.

From the perspective of the understanding principle, we expect those with higher understanding motivation to be more likely to seek out relevant information (i.e., more likely to select others’ messages) in general. Yet compared to those who have higher consistency motivation, those with understanding motivations are less likely to clearly communicate partisan messages, let alone they are presumably less expressive of their partisan viewpoints. This would lead them to be less likely to be selected by others compared to those with higher consistency motivation, resulting interesting asymmetries in their message selection patterns. Formally, we expect:

**H2a**: Understanding motivation is associated with the lower propensity of one’s messages being selected by others in the online discussion forum.

**H2b**: Understanding motivation is associated with the higher propensity of selecting others’ messages in the online discussion forum.

At dyadic level, we expect voters of similar candidate evaluation criteria (“evaluation criteria homophily”) would be more likely to select each other’s messages, irrespective of their congeniality towards their prior attitudes. This is based on the expectation that such information is of high utility to make relevant judgments regarding whom they should (or should not) support for. While prior literature generally agrees that voters actively glean relevant information from their social networks, they also appear to value political expertise more than shared preferences in selecting whom they interact with (Ahn, Huckfeldt, & Ryan, 2014). Hart et al.’s (2009) research, for instance, have found that disconfirmation bias (based on consistency motivation) is substantially reduced when individuals encounter messages with higher informational value. Since messages that are similar in terms of judgmental criteria (on which others make candidate evaluations) may contain highly relevant information and signal informational utilities, voters are more likely than otherwise to select such messages – especially when they are motivated to make accurate evaluations towards political candidate. Formally, we expect that:

**H2c**: Similarity in candidate evaluation criteria is positively associated with the propensity of selecting each other’s messages in the online discussion forum.

In addition to consistency and understanding motivations, hedonic motivation – or an idea that people seek to gain pleasure and enjoyment – is another important motivational underpinning of why people use media and interact with each other. That is, those who found using online discussion forum and interacting with others more pleasurable and enjoyable would be generally inclined to be remain active and more participatory than otherwise.

While it is expected that those who are high in hedonic motivations of using online discussion forums to be more active in general (i.e., more likely to view others’ messages and engage with others), it is not entirely clear whether and how such hedonic motivation is also related to the propensity of *being selected by others*. Therefore, we simply expect following:

**H3**: Hedonic motivation is positively associated with the propensity of selecting others’ messages in the online discussion forum.

***Endogenous influence of network structure***

*Reciprocity.* The notion of reciprocity, or the extent of which the relationships between actors in a social network are symmetric (Wasserman & Faust, 1994), represents one of the strongest and fundamental dynamic social processes in which how individuates create and maintain their social relationship (Snijders, 2011; Wasserman & Faust, 1994). Previous studies have generally emphasized the idea of mutual understanding, trust, and cooperation as the defining characteristics of reciprocity (Colman, 1990; Lubell & Scholz, 2001; Putman, 2000), and studies often find positive tendency towards reciprocity in many empirically observed social networks. Such positive tendency towards reciprocity is often found within an online discussion context as well (e.g., Hagemann, 2002; Graham & Wright, 2013).

Often in online discussion forums, users not only intentionally seek for certain information, but they also spontaneously exchange, respond, and react to others’ opinions and messages. This presumably may take a number of possible forms such as providing simple feedback cues (“likes” or “dislikes”), recommend such posts to others, and leaving a comment, etc. Yet the most simple and frequentist form of such “interaction” may manifest as continuous, interactive “discussion thread” – message exchange sequences – among a set of members. This also implies that such interaction patterns may have create a situation of which an actor *i* and actor *j* mutually choose to view each other’s messages, direct and return their attentions to each other – provided that leaving a reply or comments to an original message necessitate a responder to actually click and read that message at first place. Based on this expectation, we hypothesize that reciprocity would be one of the significant and positive predictor of presence of ties within an online discussion network:

**H4**: There would be more than expected by chance likelihood of reciprocity in message selection pattern within a dyad.

*Transitivity, cyclic closure, and local hierarchy.* Transitivity and cyclic closure in online social network represent another fundamental social process of which how individuals select which messages that they select to read, determining the message exposure patterns, and overall structure of an online discussion forum. The concept of transitivity, sometimes described as “triadic closure,” denotes situation when nodes *i* is more likely than chance to form a tie to another node *j* when they are connected to *k* other nodes (Holland & Leinhardt, 1975). In contrast, cyclic closure denotes similar situation for node *j* to form a tie to node *i* when they are connected to *k* other nodes (see Figure 1 below for the respective diagrams).

It is worth noting that transitive closure can signify several different underlying mechanisms of which one can select potential alters in social network; While the most common explanation for transitive closure is that it reflects a local spread of social relations (e.g., “friends of my friends are my friends”), such a pattern also reflects the closure of structural hole, in that node *i* circumvents brokerage role of other node *k* in reaching out another node *j*. Another, equally plausible possibility is that a positive tendency for transitivity reflects a hierarchical nature of a given network, such that node *i* would seek to create a tie towards a higher status individual *j* given the exiting relations with intermediate-status individual *k*. This expectation is especially true when the network exhibits negative tendency towards cyclic closure (e.g., *j* is less likely to form a tie to low status individual *i* despite the positive tendency of *i* to form a tie *j*). Since positive tendency of cyclic closure is interpreted as the indication of generalized exchange, the lack of such exchange, coupled with positive triadic closure, signals local status hierarchy in a given network.

It is important to nothing that, within the context of “message selection” dynamics in an online political discussion forum, one usually cannot perceive actual message selection relations that others possess. To simply put, the information of whether or not *k* has chosen to view *j*’s messages is not available to *i* when *i* choose to view *j*’s messages (unless such information is explicitly visible via some functionalities in the system). Therefore, it is somewhat less likely that transitivity would reflect local spreads of social relationship, which requires actors to be aware of others’ social relationship in choosing others to interact. Within the context of predicting micro-level configurations within a triad (i.e., predicting a *i → j* message selection given *i → k → j* selection patterns), it is therefore more plausible to assume that such transitivity patterns naturally arise from the hierarchical nature of underlying criteria in which people choose each other’s messages.

It is now well documented that people’s political expertise level is not evenly distributed among public (Converse, 1990; Delli Carpini & Keeter, 1996; Downs, 1957; Huckfeldt, 2001; Verba, Schlozman, & Brady, 1995), and people routinely rely on and seek guidance from those who are more politically attentive and knowledgeable (Huckfeldt, 2001; McClurg, 2006). Therefore, one possible source of such hierarchical organization of network structure is an individual’s need for having political experts around and choose to view messages of those local experts. Assuming the underlying tie-generative process is indeed driven by such substantive interests, it is conceivable that the uneven level of political expertise within a triad would be manifested via a hierarchically organized message selection dynamic (e.g., *i* seek recommendations from *k*, and *k* seek recommendations from *j*, and *i* also seek recommendations from *j*; yet *j* does not seek recommendations from *i*). Therefore:

**H5a**: There would be more than expected by chance likelihood of transitive closure in message selection pattern among set of three actors.

**H5b**: There would be less than expected by chance likelihood of cyclic closure in message selection pattern among set of three actors.

*Structural equivalence and profile similarity.* Another important local configuration that help us understand the nature of message selection dynamics in online forums is the concept of structural equivalence and profile similarity. In addition to the hierarchical nature of underlying criteria in which people choose each other’s messages, they choose to interact with each other because they both connected to the same way to other actors in the network. That is, similar to the notion of structural equivalence, they maintain similar pattern of connections to all other actors in the network, such that they choose to view messages from the many same alters (“activity closure”), or they are chosen by same many alters (“popularity closure”: see Figure 1 below for the respective diagram), which signals the common properties of a given dyads. This may be viewed as structural bases of homophily, whereby the formation or maintenance of ties are driven by similarity in choices with respect to other actors in the system (DiMaggio, 1986). Therefore, we expect following:

**H6a**: There would be more than expected by chance likelihood of activity closure in message selection pattern among set of three actors.

**H6b**: There would be more than expected by chance likelihood of popularity closure in message selection pattern among set of three actors.

*Preferential attachment.* Several studies indicate that a structure of large, online social network tends to follow power-law distribution. While the existence of skewed degree distribution is rather common in any kind of human-induced social network (Barabási & Albert, 1999; Snijders, 2011), it appears that such tendencies are more pronounced in online context. For instance, Fisher, Smith, and Welser (2006) found highly imbalanced distribution of message posting and attraction in Usenet newsgroup discussions. Likewise, Himelboim’s (2011) analysis suggests a sharp inequality in ability to draw attention and elicit further engagement with a given message from a large number of users in online discussion groups. This is at least partly explained by the principle of “preferential attachment,” the idea that well-connected nodes or actors draw more connections by virtue of their already exiting connections, such that new nodes prefer making an association to already well-connected nodes that already have large connections in the network. Within an online discussion forum, one often employs certain heuristic cues such as the number of “views” and “likes” in selecting which messages to click, which signals utility based on popularity of a message. Therefore, a message that has large number of engagement cues (such as views or likes) usually draw disproportionate reactions by its self-reinforcing dynamics, leading to highly imbalanced distribution of message selections among members. Therefore, we expect:

**H7**: There would be more than expected by chance likelihood of selecting messages when such messages are *already* selected by a large number of others.

***Temporal dynamics in message selection criteria***

As elections near, it is reasonable to believe that individuals are more mobilized by campaign communication (Cho, 2013; Holbrook & McClurg, 2005), hence are expected to pay close attention to political messages both in online and offline. Not only a heightened attention to politics in general more likely to make them to do so (Song & Boomggaarden, 2017; Zaller, 1992), but they also may need more information to reduce uncertainties or anxieties regarding their decisions as the election day approaches (Atkin, 1973; Downs, 1957). While literature generally suggests that strong partisans and interested voters arrive their decisions early in the election campaign cycle than late-campaign deciders (Lazarsfeld, Berelson, & Gaudet, 1944/1968; Fournier, Nadeau, Blais, Gidengil & Nevitte, 2004), the nature and extent of changes in campaign environment (e.g., campaign competitiveness) may prompt even strong partisans to seek out confirmatory information. Studies have demonstrated that increases in uncertainty regarding the ultimate consequences of election outcome may further propel political information seeking behavior (Carnahan, Garrett, & Lynch, 2016; Valentino, Banks, Hutchings, & Davis, 2009). For instance, it is expected that messages coming from parties that are anticipated to win would have more informational “utility” than that of losing parties (Knobloch-Westerwick & Kleinman, 2012; Garnahan et al., 2016). Therefore, when the perception of one’s in-party candidate being succeed in the election is high, then citizens are more likely to show conformational bias (i.e., preference homophily). Literature also suggests if there’s no reason to believe counterattitudinal information at hand is useful for reducing decision-related uncertainty and anxiety, then individuals are more expected to rely on confirmatory evidence (Valentino et al., 2009). To the extent that changes in campaign environment (e.g., campaign competitiveness) *over time* induce more anxiety and uncertainty regarding the election outcome (which is a reasonable assumption to make), then this further suggests that the effect of various forms of homophily may increase over time until the election day rather than being constant over the course of campaign. Therefore, we posit:

**H8**: The effect of preference homophily in message selection increases over time

**Data and Methods**

In order to test our predictions, we draw a unique set of whole network panel data matched with panel survey responses collected during the 2012 Korean presidential election. The data were collected from an online discussion forum hosted on research firm’s server where participants’ posting and viewing activities during 27 day-period until Election day (from November 23 to December 19, 2012) is unobtrusively logged. A South Korean market research firm Embrain invited 400 participants from a nationally representative panel (in terms of gender and age distribution), of which a total of 334 participants remained on the discussion forum and completed three waves of panel surveys. Surveys measured participants’ candidate evaluations and its criteria, policy preferences, motivations for using the online discussion forum, and key covariates such as their media use, political interest, offline discussion frequencies, and sociodemographic variables. Participants were instructed to freely post and read each other’s opinions regarding upcoming election as they normally would in other online forums in return for a monetary incentive of $100 provided upon the completion of the study. Participants’ electronic log data regarding their message viewing and posting activities were later retrieved from the research firm’s web server and matched with participants’ survey responses. At the start of the W1 survey, 22 participants (6.5%) out of all 334 participants did not initially identify their candidate preference nor had favored one of two major candidates based on relative thermometer ratings. Since we control for actors’ candidate choices and homophily as a key predictor in our model, we limit the analysis to those with known candidate choices across all three survey waves (N = 312), excluding 22 cases from further analysis.[[1]](#footnote-1)

**Construction of Networks and Analysis Strategy**

Based on electronically recoded participants’ message browsing behaviors, we derive a “message selection” network as an directed actor-actor binary matrix (312 x 312), such that the cell entry of network X*ij* is 1 ( = actor *i* selects actor *j*’s message) and zero for otherwise. Based on the dates of three waves of panel survey responses (W1 = Nov 27th to 29th, W2 = Dec 11th to 13th, W3 = after the election day, which was Dec 19th, 2012), we partition participants’ electronic log data in a way that it closely matches with survey dates in creating a longitudinal panel series of message selection-exposure networks (e.g., log data from Nov 27th to 29th were regarded as the 1st wave of the network panel), except for the last wave of the network panel. Since the 3rd wave of the panel survey was conducted *after* the election day whereas behavioral log data were collected *only until* the election day, we regard the last three days of behavioral log data (Dec 17th to 19th) as the last panel in network.[[2]](#footnote-2) In addition, since the log data were available from November 23rd, behavioral log data *before* the first wave of panel survey (Nov 27th) or *in-between* each survey waves were regarded as lagged observation of the respective network panel wave. Specifically, we treat log data from Nov 23rd to 26th as the lagged observations of the first network panel while data from Nov 27th to 29th constitute 1st wave of the network panel. Likewise, log data from Nov 30th to Dec 10th constitute lagged observation of the second network panel (Dec 11th to 13th) while log data from Dec 14th to 16th constitute lagged observation of the last network (Dec 17th to 19th).[[3]](#footnote-3)

**Measures**

**Motivations for using online discussion forum.** For consistency motivation (Cronbach’s α = .86, *M* = 4.36, *SD* = 1.03), respondents were asked six items (based on a 7-point scale from “Not at all” = 1 to “Very much” = 7) whether they visit online discussion forums (including discussion forums other than current study) primarily “to justify my opinion of the issue” or “to confirm that my opinion on the issue is correct.” Understanding motivations (α = .81, *M* = 5.26, *SD* = .82) and hedonic motivations (α = .75, *M* = 4.47, *SD* = 1.04) were assessed in a similar manner, respectively using four (e.g., “to make an accurate and objective assessment of the issue”) and three items (e.g., “it is interesting and fun”) tapping said motivations.

**Preference homophily**. In order for assess the extent and nature of the preference homophily, we define three different measures of political preference homophily based on (a) candidate choice, (b) ideological policy preference, and (c) candidate evaluative criteria. First, a candidate preference homophily was operationalized based on respondents’ self-reported candidate choice across three survey waves (“1” supporting Moon Jae-in vs. “0” supporting Park Geun-hye; W1: *M* = .60, *SD* = .49; W2: *M* = .66, *SD* = .47; W3: *M* = .61, *SD* = .48), such that a tie was identified as homophilous (coded as “1”) if a given dyad shares the same candidate preference. Next, ideological policy preference homophily (W1: *M* = .40, *SD* = .16; W2: *M* = .38, *SD* = .16; W3: *M* = .39, *SD* = .16, all range = 0 to 1) was operationalized based on respondents’ dyadic Euclidean distance, *d*, out of liberal vs. conservative oriented policy preferences towards economic and north-Korea issues. Policy preferences were measured three times across panel surveys, and respective Euclidean distances were later converted to similarity measures by taking 1 / (1 + *d*), where *d* is the Euclidean distance, in a way that a greater value of the similarity measure would represent higher degree of “homophily” between a given dyad. Lastly, we define candidate evaluative criteria homophily (*M* = .48. *SD* = .15, range = 0 to 1) in a similar manner, 1 / (1 + *d*), using a dyadic Euclidean distance *d* in terms of relative importance of competence/impression (e.g., policy, competence, or perceived personal characters such as integrity) and personal background dimensions (e.g., party affiliation, political career, place of origin, etc.) in making candidate evaluations. Since candidate evaluative criteria was measured only once at Wave 1 survey, we regard candidate evaluative criteria to be relatively stable and invariant across all waves.

**Network-endogenous measures.** Reciprocity of message selection relation was measured by whether a pair of actors had mutual “selection” ties with each other. For measures tapping a series of triadic configurations (transitive closure, cyclic closure, activity closure, and popularity closure: see Figure 1 for details), we rely on *directed* version of the geometrically weighted edgewise shared partner (directed GWESP) statistics following the model specifications proposed by Snijders et al. (2006) and Robins et al. (2007). The GWESP term models a linear combination of an entire distribution of directed triangles (*i, h, j*) for a given connected dyad (*i, j*) in the network, and this effect of the triangle distribution is *weighted to produce a decreasing return* following a decay parameter (for a detailed discussion of this measure, see Hunter, 2007 and Hunter & Handcock, 2006). As described above, our theory suggests that a series of triadic closure patterns would have a substantial effect on message selection dynamics. Similarly, for measuring activity spread and popularity spread, geometrically weighted out-degree and in-degree distribution (GWD-out and GWD-in) terms were used where the parameter estimates for GWD terms represent “evenness” of in- and out-degree based on message selection activities across the network (for details see Hunter, 2007). We expect these terms to be significantly and highly negative, which signify differential message selection activities across the network.

**Control variables.** In addition to focal predictor variables, we control for a host of variables that are known to be related to the extent of political discussion in order to establish a plausible baseline in our analysis. First, we control for participants’ sociodemographic factors, including *gender* (1 *being* “female,” 48.39%), *age* (in 10-year increment, *M* = 3.55, *SD* = .98), *education* (from “not finished elementary school” = 1 to “currently in post-graduate education or more” = 9, *M* = 7.71, *SD* = .97) and *region of origin* (1 being “Seoul” vs. 0 being “other regions”, 40.38% from Seoul). In our analysis, we also control for two demographic homophily variables, one based on their gender and the other based on their regional origin (all coded as 1 if a dyad share same gender or same regional origin) since demographic homophily may be confounded with respondents’ candidate preference homophily (McPherson et al., 2000). We also control for respondents’ offline discussion frequency (from “Never” = 1 to “Always” = 7, W1: *M* = 4.50, *SD* = 1.04; W2: *M* = 4.62, *SD* = 1.18; W3: *M* = 4.82, *SD* = 1.17), media use frequency (measured in hours, W1: *M* = .76, *SD* = .42; W2: *M* = 1.56, *SD* = 1.66; W3: *M* = 1.65, *SD* = 2.32), and internal discussion efficacy (from “Not at all agree” = 1 to “Strongly agree” = 7, *M* = 4.72, *SD* = .98). Media use frequency was defined as the average hour of exposure to internet news, newspaper and television news exposure regarding the upcoming election, and internal discussion efficacy were gauged using a four-item composite measure tapping how competent and efficacious an individual is in typical political discussion settings.[[4]](#footnote-4)

**Analysis Strategy**

Since we aim to properly capture and explain substantive interdependencies among set of actors in their message selection behaviors over time, we modeled longitudinally observed message selection networks using a Temporal Exponential Random Graph Model (TERGM), a time-series extension of the ERGM framework with bootstrapping resampling technique as described in Desmarais and Cranmer (2012). The integral part of this approach is to regard the ties in a given network to be a random variable (1 for existence of ties, and zero for otherwise) to be explained simultaneously by a collection of actor covariates and network-endogenous dependencies (Robins et al., 2007; Snijders et al., 2006). The ERGM method is now regarded as the most versatile yet highly flexible framework for statistically evaluating underlying generative properties of a given network, as exemplified in recent applications of ERGM to various substantive problems such as policy collaboration (Cranmer et al., 2017; Lai, She, & Ye, 2015; Shumate, Fulk, & Monge, 2005), diffusion of online news (Kim, Baek, & Kim, 2015), mediated campaigning (Song et al., 2017), friendship formation (Goodreau et al., 2009; Lewis et al., 2008), and offline political discussion (Song, 2015).

Since our analytical strategy requires all cell entries are defined as binary, we opted for dichotomizing multiple number of selection instances within a same dyad by employing mean number of message selection instances across all dyadic pairs as a threshold. Therefore, our model only speaks to relatively routine, repeated message selection dynamics in a given network panel rather than entire message selection dynamics including accidental, spontaneous selection behaviors. Also, in applying a longitudinal inferential network analysis technique, we also regard observation at a given time point is dependent only upon the previous state of the network (i.e. lagged observation). In capturing temporal dependencies, we include series of lagged endogenous network statistics which might be relevant in messages selection behaviors as additional control variables, along with few additional endogenous network statistics (such as *isolates* and *two-paths*) in order to control temporal or lower-order effects in estimating the effect of key parameters. Details on the applied models are provided in the appendix. Table 1 below summarize key model terms included in our analysis, with their graphical depiction and substantive interpretation of the effects.

[Table 1 About Here]

Once models were fitted, we assessed goodness-of-fit procedures to identify the model degeneracy and adequacy of our estimated models. We do so by simulating nine hundred new networks (three hundred new networks for each time point) and compare the network characteristics from the simulated networks with that of the observed network, as described in Hunter, Goodreau, and Handcock (2008). These results indicate that model specification is satisfactory to adequately recover underlying data generating process (gof results are presented in the Appendix). For the current application, we used maximum pseudolikelihood estimation with bootstrapped confidence intervals (Desmarais & Cranmer, 2012), as implemented in the *btergm* package in R (Leifeld, Cranmer, & Desmarais, 2017).

**Results**

Table 2 reports the key estimated parameters from the final TERGM specifications along with its 95% confidence intervals (using 1000 replications, with significant results being bolded). Full model results, including our model building procedures, are reported in the Appendix and graphically Figure 1 below. Relevant to our main research interest, the leftmost final model specification (“Final Model”) includes the motivation and homophily block while properly controlling for hypothesized network structural influence, while series of interaction models from 2nd to 4th columns of Table 2 additionally test the interaction effects between time trends and various homophily terms, capturing whether the effects of preference homophily increases over time. Across all models, coefficients can be interpreted as log odds of a tie conditional on the rest of the respective network and other model terms.

[ Table 2 and Figure 1 About Here]

Our first set of hypotheses posit that messages written by individuals with certain motivations are more likely to be selected by others (H1a, H2a & H3), as well as such individuals are more likely to select others’ messages (H1b & H2b). We found mixed support for these expectations, in that some of the hypothesized effects of motivations fell short of traditional level of significance. Specifically, for final model specification (the first column of Table 2), the effects of consistency motivations were not significant in predicting messages selection instances both for incoming ties (“one’s message being selected”: b = .034, 95% CIs = [-.021, .113]) and for outgoing ties (“select others’ messages”: b = .025, 95% CIs = [-.112, .077]). This was also true for understanding motivations predicting incoming ties (b = -.052, 95% CIs = [-.103, .022]). In contrast, understanding motivation was positively and significantly linked to the propensity for having out-going ties in message selection network (b = .028, 95% CIs = [.005, .087]), suggesting that those who pursue to understand the outside world better are more likely to select and read others’ messages in online discussion forums compared to those who are low in understanding motivations. Likewise, hedonic motivations are found to be significantly and positively related to the propensity for having more message selection instances in the network (b = .102, 95% CIs = [.087, .133]). Therefore only H2b and H3 are supported.

Among our dyadic-level homophily variables, neither candidate preference homophily (b = -.032, 95% CIs = [-.079, .047]) nor ideological policy preference homophily (b = -.108, 95% CIs = [-.212, .042]) found to be related to the message selection instances, fail to confirm H1c. Such null effects of two preference homophily terms indicate that consistency-driven dynamics (i.e., whether one shares same candidate preference or ideological policy preference) is not likely to be related to whether people choose to select and view each other’s messages. Instead, we have found consistent and quite strong effect of similarity in candidate evaluative criteria (i.e., candidate evaluative criteria similarity: H2c), such that the more similar a dyad in terms of their candidate evaluative criteria, the more they likely are to expose themselves to another’s messages, b = .407, 95% CIs = [.207, .415]. As can be seen in Figure 2,

Table 1.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Final Model** | **Interaction I** | **Interaction II** | **Interaction III** | |
| Edges (Intercept) | **-1.890** [-2.932; -.304]\* | **-1.819** [-2.815; -.304]\* | **-1.823** [-2.807; -.304]\* | **-1.936** [-2.937; -.304]\* | |
| ***Motivation and homophily*** |  |  |  |  | |
| Consistency motivation (in-ties) (H1a) | .034 [-.021; .113] | .037 [-.021; .113] | .037 [-.021; .113] | .037 [-.021; .113] | |
| Consistency motivation (out-ties) (H1b) | .025 [-.112; .077] | .019 [-.112; .071] | .019 [-.112; .071] | .019 [-.112; .071] | |
| Understanding motivation (in-ties) (H2a) | -.052 [-.103; .022]**†** | -.049 [-.103; .022] | -.049 [-.103; .022] | -.049 [-.103; .022] | |
| Understanding motivation (out-ties) (H2b) | **.028** [.005; .087]\* | **.036** [.012; .087]\* | **.035** [.011; .087]\* | **.035** [.011; .087]\* | |
| Hedonic motivation (in-ties) | -.012 [-.038; .001] | -.012 [-.038; .001] | -.013 [-.038; .001] | -.013 [-.038; .001] | |
| Hedonic motivation (out-ties) (H3) | **.102** [.087; .133]\* | **.102** [.094; .130]\* | **.102** [.094; .130]\* | **.102** [.094; .130]\* | |
| Same candidate preference (H1c) | -.032 [-.079; .047] | -.135 [-.211; .047] | -.033 [-.079; .047] | -.032 [-.079; .047] | |
| Similar policy preference (H1c) | -.108 [-.212; .042] | -.091 [-.225; .042] | -.090 [-.230; .042] | .094 [-.764; .324] | |
| Similar evaluative criteria (H2c) | **.407** [.207; .415]\* | **.385** [.207; .404]\* | .295 [-.359; .639] | **.389** [.207; .405]\* | |
| ***Interaction (H8)*** |  |  |  |  | |
| Time trends (linear) |  | .079 [-.059; .262] | **.083** [.021; .171]\* | **.144** [.063; .235]\* | |
| x Same candidate preference |  | **.051** [.038; .071]\* |  |  | |
| x Similar evaluative criteria |  |  | .046 [-.176; .242] |  | |
| x Similar policy preference |  |  |  | -.095 [-.253; .214] | |
| ***Endogenous structural effects*** |  |  |  |  | |
| Isolates | **1.019** [.793; 1.264]\* | **1.003** [.793; 1.264]\* | **1.005** [.793; 1.264]\* | **1.005** [.793; 1.264]\* | |
| Reciprocity (H7?) | **.769** [.507; 1.068]\* | **.768** [.507; 1.068]\* | **.768** [.507; 1.068]\* | **.768** [.507; 1.068]\* | |
| Multiple path closure (H4a) | .058 [-.053; .125]**†** | .057 [-.053; .125] | .057 [-.053; .125] | .057 [-.053; .125] | |
| Multiple cyclic closure (H4b) | **-.066** [-.080; -.060]\* | **-.066** [-.080; -.061]\* | **-.066** [-.080; -.061]\* | **-.066** [-.080; -.061]\* | |
| Multiple activity closure (H5a) | **.036** [.033; .053]\* | **.035** [.033; .053]\* | **.035** [.033; .053]\* | **.035** [.033; .053]\* | |
| Multiple popularity closure (H5a) | **.115** [.082; .232]\* | **.113** [.082; .232]\* | **.113** [.082; .232]\* | **.113** [.082; .232]\* | |
| Multiple two-paths | .003 [-.007; .009] | .003 [-.007; .009] | .003 [-.007; .009] | .003 [-.007; .009] | |
| Activity spread | **-4.350** [-4.557; -3.994]\* | **-4.395** [-4.557; -3.994]\* | **-4.392** [-4.557; -3.994]\* | **-4.392** [-4.557; -3.994]\* | |
| Popularity spread (H6) | **-4.049** [-5.342; -3.259]\* | **-4.123** [-5.342; -3.259]\* | **-4.120** [-5.342; -3.259]\* | **-4.121** [-5.342; -3.259]\* | |
| \* = zero outside the 95% confidence interval, † = zero outside the 90% confidence interval (all using 1000 replications). All models control for age, gender (including homophily), education, regional origins (including homophily), offline talk frequency, media use frequency, and candidate preference. | | | | |

Table 2. Bootstrapped TERGM estimates (95% percentile confidence intervals within brackets).

*Figure 1*. Parameter estimates and 95% confidence intervals from the final model.



Note. Significant model terms are denoted in red.

**Panel A: transitive closure and cyclic closure.**



*Note*: Positive transitivity closure and negative cyclic closure means node i is more likely than chance to send a tie to j, but j are less like than chance to send a tie back to i, suggesting network has a hierarchical structure.

**Panel B: Activity closure and popularity closure.**



*Note*: Positive shared activity closure and shared popularity closure means that node i and node j are selecting and being selected by many common actors, suggesting that they are in common in terms of certain nodal characteristics. This signifies structural bases of homophily in their characteristics.

# References

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McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social Networks. *Annual Review of Sociology, 27*, 415-444.

1. ERGM framework requires all key nodal covariates to be complete in estimation, therefore any missing values on nodal covariates are not allowed. To address the missingness in our data, we have also estimated an identical model with multiple imputation technique on candidate preference (imputation N = 5), yet the substantial conclusion has not been changed by the inclusion or exclusion of those 22 missing cases. [↑](#footnote-ref-1)
2. Since participants’ key characteristics such as candidate evaluations and preferences were rather highly stable across survey waves (mean correlations across waves = .61 to .89), we regard participants’ characteristics may drive the creation of network ties, but not the other way around. This also assumes that participants’ characteristics are relatively hard to be changed within such a short period of time as a function of mere message exposure online, which is rather a standard assumption to make (Lazer, 2001). [↑](#footnote-ref-2)
3. Instead of arbitrarily partitioning the behavioral log data into three-wave panel survey dates, we also estimated models with daily slices of log data and found largely the same results with minor discrepancies in estimated coefficients and significance level. Combined with multiple imputation results, our robustness check results suggest that our results and conclusions are reasonably robust against potential model misspecification and methodological issues in construction of the networks. [↑](#footnote-ref-3)
4. Items include: “I am competent at presenting my own opinions in a discussion,” “I can express my ideas in a coherent manner,” “I make full use of my subject knowledge in a discussion,” and “I feel competent persuading others in a discussion” [↑](#footnote-ref-4)