Selection Homophily in Dynamic Political Communication Networks: An Interpersonal Perspective

Dissertation

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

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2021

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Abstract

Political homophily, or the tendency for relationships or discussion ties to form more frequently between like-partisans than between people with differing political identities, is a well-studied phenomenon in the political communication and social networks literatures. Such political similarity has been observed in a variety of contexts, including in work environments, church congregations, universities, romantic relationships, neighborhoods, and online social media. Homophilous network structures have profound effects on normative democratic outcomes, such as participation and exposure to diverse sources of information. However, comparatively little attention has been paid to the antecedent processes which give rise to political homophily.

This dissertation advances the concept of political selectivity, or the degree to which one's decisions about the status of ties in a political discussion network favor discussion partners who one perceives to be similar (i.e., shared party identity) to themselves. The culmination of networked theories of homophily, along with interpersonal theories of relational uncertainty and topic avoidance, together provide a holistic view of how the dyadic and network structures co-evolve over time. The goals of this dissertation are threefold: to isolate selection from other generative mechanisms, to explain individual variances in selectivity, and to provide a framework with which interpersonal processes, like topic avoidance, affect selection in dynamic discussion networks.

To these ends, a five-phase, two-condition quasi-experiment was conducted in which participants shared political opinions with one another and made decisions regarding who they would like to continue discussing political matters with. Subjects ($n = 366$) were recruited from Amazon's Mechanical Turk participant pool into 24 cohorts. In condition 1, participants shared their opinions with each of their alters; in condition 2, participants were permitted to decide from among their alters who they would like to disclose their opinion to.

Results broadly support the selection homophily hypotheses that people are more likely to form political discussion ties with others who hold similar opinions to themselves. However, this process did not scale to the network-level in the form of political identity assortativity, as conventional wisdom suggests. In condition 1, selection homophily was found to produce relationships which were significantly more similar regarding withheld opinions on related issues that had been discussed in the dyad. However, such similarities do not extend to new topics. In condition 2, averaged similarity on previously-discussed topics was found to predict disclosure of the current opinion. However, the generative role of selection homophily was not found to significantly differ between networks with selective disclosure and networks in which all opinions were shared with network alters. These findings bring new insight to the study of generative mechanisms and point to a growing need to integrate theory and practice across interpersonal and social network disciplines.

Dedication

To Lavender: for your persistence in pushing me to be my better self.

Acknowledgments

This and every project of mine throughout my graduate experience (research and otherwise) would amount to little without the immense support and thoughtful criticism of those around me. My graduate and professional careers have been indelibly shaped by many, and I will inevitably neglect to list most of them here.

Among my many mentors and colleagues, none have been more supportive or helped push me into new and exciting areas of research more than my advisor, Rob Bond. Whether as an instructor, coauthor, mentor, or friend, the job of advisor requires one to wear many hats, and Rob never faltered in any one of them. He graciously offered to back this project with his own research funds at a time when it was unknown whether the study would actually work. He, along with my committee members Skyler Cranmer, Chip Eveland, and Hillary Shulman helped shape this dissertation in profound ways, every one for the better. I am immensely grateful for your help – more than these words can convey.

While it takes a committee to push a Ph.D. student towards completion of the dissertation, it takes a village of faculty to train and mentor a Ph.D. student on the many other facets of their graduate career. While they did not serve on my committee, Jason Coronel, Lanier Holt, Dave Deandrea, Joe Bayer, Dave Melamed, and Kylie Jackson all left a lasting impact on my research and teaching, or helped in a variety of often unseen ways in my time at Ohio State. Almost everyone in the COPS (Communication, Opinion, and Political Studies) group and Communication and Cognitive Systems lab has heard me talk about this project on more than one occasion and offered insightful feedback as many times. I am a better student, teacher, researcher, and communicator for having each of you in my corner.

To everyone at the 2018 Complex Systems Summer School at the Santa Fe Institute, I cannot thank you enough for your cross-disciplinary insight on my work. In particular, Thushara Gunda deserves a tremendous amount of credit for my present career path. Without sticking her neck out for me, I would not have had countless opportunities to integrate my social-scientific acumen with broader applied and complex research tasks as Sandia National Laboratories. Asmeret Naugle later took up this mantle and her mentorship at Sandia has been invaluable as well.

Finally, and most important of all, I owe every ounce of my successes to my best friend and partner, Lavender McKittrick-Sweitzer. Without you, I would have never thought that any post-graduate education was in the cards, let alone that I would be finishing a Ph.D. Through every hardship or bout of imposter syndrome, you have guided me to the light at the end of this long tunnel. When I got buried in my work, your love and support has lifted me up and given me the courage to push through. I can think of no one I would rather have by my side as we traverse the unknown together.

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Field of Study

Major Field: Communication

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Chapter 1: Homophily and Political Discussion

How and why do people choose to discuss political matters with one another? This question arises perennially in political communication research; some of the earliest work in the discipline was concerned with the effect of a person's informal political discussion with their social contacts on their decision-making in the lead-up to the 1940 and 1948 presidential elections (Berelson, Lazarsfeld, & McPhee, 1954; Lazarsfeld, Berelson, & Gaudet, 1944). Largely, subsequent research and theorizing has taken place within subfields of the discipline. Interpersonal scholars, to the small extent that they have studied discussion about politics, have theorized about and studied the psychological and dyadic processes that occur. Social networks scholars have more recently focused on the methodological and – to a lesser extent – theoretical concerns regarding interdependent interactions that take place on a larger scale. Though there have been many calls for converging theory across dyadic- and network-levels in the field (e.g., Eveland, Morey, & Hutchens, 2011; Felmlee & Faris, 2013; Huckfeldt, Johnson, & Sprague, 2005; Parks & Eggert, 1991; Pietryka et al., 2017), few theoretical additions have come to the fore which detail the specific mechanisms through which socially-networked processes and dyadic communication can be integrated.

A large part of the challenge of integrating these perspectives is the complexity and dynamic nature of political discussions. Moreover, the dissolution of the boundaries between what is explicitly "interpersonal" and "networked" communication requires definitional assimilation as well. That said, uniting these two perspectives creates a more comprehensive picture of the communicative processes in the broader public sphere. The focus of this dissertation is on the dynamic nature of interaction in political discussion contexts, with an emphasis on the processes of tie formation and dissolution.

Specifically, this dissertation advances the concept of political selectivity, or the degree to which one's decisions about the status of a tie in the political discussion network favors discussion partners who one perceives to be similar (i.e., shared party identity) to themselves (Lazarsfeld & Merton, 1954). The culmination of networked theories of homophily, along with interpersonal theories of relational uncertainty and topic avoidance, together provide a holistic view of how the dyadic and network structures co-evolve over time. A tightly-controlled quasi-experiment was conducted which distinguishes the process of selection. I then advance this framework by both examining explanations for variance in selectivity between different people, and by introducing the well-documented interpersonal phenomenon of topic avoidance to study its effects on the social information environment and the relational decision-making process which follows. This study may serve as a foundation for future research to better ascertain the role of group-, dyadic-, or individual-level effects in political interactions.

In the remainder of this chapter, I discuss selection homophily, paying specific attention to the theoretical processes underlying social decision-making in interpersonal interactions. In chapter 2, I introduce interpersonal selection and derive the hypotheses and research questions which guide the study to follow. Chapter 3 introduces the 5-phase networked quasi-experimental design and provides examples of the software used to conduct the study. Chapter 4 provides descriptions of the participant pool and the networks constructed in each iteration of the study, and previews the analytic strategy used in later chapters. Chapters 5 and 6 provide detailed results of the hypothesis tests conducted on quasi-experimental conditions 1 and 2, respectively. Finally, I close in chapter 7 with a review of the findings and their implications for theorizing and researching political homophily, strengths and limitations of the study design, and future directions for this line of research.

Deliberative Democracy and Discussion Networks

Underpinning much of the recent work on political discussion networks is the notion of deliberative democracy. This is a normative theory of political systems which holds that the laws and regulations which govern a society are best formed through a discursive process in which two or more sides, holding opposing moral viewpoints, justify their perspective to one another with reasons which could be accepted by free and equal persons seeking cooperation (Cohen, 2002; Fishkin, 1991; Habermas, 1990, 2002). Other definitions, such as the one provided by Gutmann and Thompson (2004), include "... the aim of reaching conclusions that are binding in the present on all citizens but open to challenge in the future" (p. 7). While many of the early proponents of deliberative democracy, such as Jürgen Habermas, (1990) and John Stuart Mill (Thompson, 1976), argue that the tenets of the theory need only apply to formal institutions (e.g., Congress) in democratic societies, later expansions by theorists such as Joshua Cohen (2002) and Jane Mansbridge (1999) extend the normative ideal to citizens as well.

Of particular importance for network scholars is the notion that deliberative democracy works best when people actively engage in discussion of topics on which there is moral disagreement (Gutmann & Thompson, 1998, 2004). That is, deliberative systems thrive under conditions where a diversity of viewpoints are freely expressed. Specifically, when people encounter opinions which differ from their own, they should practice tolerance (Galson, 1999), mutual respect, and reciprocity (Gutmann & Thompson, 2004). Such an approach to interaction, even in informal settings, fosters not only better outcomes for democracy, but also a greater understanding of the multitude of viewpoints which may exist on an issue (Mansbridge, 1999).

There are several critiques of the application of deliberative theory to informal interactions among citizens, including whether such interactions can "live up to" the ideals of well-reasoned argumentation, free and equal participation, and binding decision-making. I argue that these critiques miss the point of ideal theories like deliberative democracy insofar as they relate to describing the conditions of real-world interactions. Nevertheless, applications in the communication networks literature use deliberative theory as a means to an end: to justify investigations of whether and to what degree people encounter differing points of view in their social interactions about political matters. Whether this fixation on deliberative theory is a productive means of investigation is another matter (Eveland et al., 2011).

That said, the focus on encountering difference in interpersonal interaction is an important conceptual perspective in the literature. The roots of interpersonal difference in the field extend as far back as Gordon Allport's work on the so-called "contact hypothesis," or more formally: intergroup contact theory (1954). The hypothesis states that, under the right conditions, contact between majority and minority members can reduce stereotyping and prejudice. A recent application of this theory in a political context indeed found that discussion between dissimilar partisans increases moral and affective evaluations of out-group members (Bond, Shulman, & Gilbert, 2018). More generally, Huckfeldt, Johnson, and Sprague (2004) argue that:

> ... tolerance, compromise, and engagement are anchored in the personal experience of political diversity. In this way, the benefits of deliberation depend on disagreement, where disagreement is defined in terms of interaction among citizens who hold divergent viewpoints and perspectives regarding politics. ...
>
> [B]oth tolerance and deliberation lose meaning absent disagreement. (p. 3-4)

This definition of disagreement is worth highlighting, both because it is more or less paraphrased in much of the discussion network literature, and because it leaves room for a number of operational interpretations (Lupton & Thornton, 2016).[1] Communication networks, broadly considered, are "the patterns of contact that are created by the flow of messages among communicators through time and space" (Monge & Contractor, 2003, p. 3). While studies of communication networks examine broad patterns of interactions, not all conceptions of political discussion networks necessarily reduce communication networks to dyadic interaction in the political domain, nor do they necessarily examine the discourse between discussants to evaluate whether differing viewpoints are expressed.

Disagreement, in my view, is the clearest term to refer to interaction between two people with opposing viewpoints, as it connotes to some degree a communication of viewpoints in the dyad. However, not all studies using the term "disagreement" measure expression of opinions. For example, Parsons (2010) used a survey item from a so-called "name generator" task (see Klofstad, McClurg, & Rolfe, 2009) in which participants self-reported their perception of their alter's opinions. Whether those perceptions are formed through communication of opinions or through attributions on the part of the participant is unknown (see Heider, 1958 for a review of attribution). Others use terms like "cross-cutting" (e.g., Blau & Schwartz, 1984; Mutz, 2002, 2006; Mutz & Mondak, 2006; Wojcieszak & Mutz, 2009), which implies interaction across party lines, or "difference" (e.g., Brundidge, 2010; Eveland, Appiah, & Beck, 2018; Scheufele, Hardy, Brossard, Waismel-Manor, & Nisbet, 2006), which could be broadly construed to apply even in circumstances where two people who hold divergent opinions on a political topic interact in some apolitical way.[2]

One thing left out in much of the discussion of disagreement (or many of the other terms used in this literature) and its operationalizations is whether the measurement of diverging viewpoints reflects how people communicate with one another about politics. Specifically, it is often assumed that by using difference on a broad party identity or ideological scale, we can capture whether people are likely to encounter disagreement when any number of specific issues arise. This perhaps has also grown out of the ease with which difference can be operationalized in this way using a variety of research methods, including survey measures (Klofstad et al., 2009) or with large observational data sets (Barberá, 2015; Barberá, Jost, Nagler, Tucker, & Bonneau, 2015; Bond & Sweitzer, in press). This is not entirely unfounded either, given the strong correlation of party identification with specific policy preferences (Carsey & Layman, 2006; Layman & Carsey, 2002). However, there may be very specific instances where a policy preference does not neatly conform to the rest of one's identity. An example of this in the American context would be the pro-life Democrat or the Republican in favor of strict gun legislation.

Regardless of the definition used, that people tend to interact with similar alters (whether similarity is expressed or implied) is perhaps one of the most robust findings in social science in recent years. In a networked context, this phenomenon is referred to as "homophily".

Networked Homophily

The first to use the term "homophily" to describe the systematic structures of social networks were Lazarsfeld and Merton (1954). They wrote of "a tendency for friendships to form between those who are alike in some designated respect" (p. 23). Homophily, then, is a social scientific term for the idiom "birds of a feather flock together". The social processes of homophily can have profound effects on the structure of interactions: not only do similar people tend to group together in tight clusters (think balance theory,[3] scaled up), but ties between dissimilar people tend to dissolve at higher rates than among similar dyads (McPherson, Smith-Lovin, & Cook, 2001). This has implications for the flow of information in a network, one's exposure to diversity, and the influence of social relationships on opinion formation.

Importantly, the term "homophily" can be used to describe two related phenomena: both the *process* of networked interactions becoming more likely or frequent among similar pairs, and the *state* of a network structure exhibiting more ties in similar dyads than in dissimilar ones. The latter is also sometimes referred to as "assortativity", as that is formally the metric used to measure a network's *state* homophily.[4] Often, researchers will use a measure of *state* homophily as in indicator that *process* homophily has occurred. This is common in cross-sectional, observational, or survey studies which often have limited capacity to examine the process of network formation.

In interpersonal political discussions in the American context, homophily manifests as a tendency for Democrats (or liberals) to discuss politics with other Democrats (liberals), and Republicans (or conservatives) with other Republicans (conservatives), but with relatively few cross-partisan or ideological connections.[5] In operational terms, a positive correlation (a measure of assortativity) of party identity among all connected pairs in a political discussion network is expected. Importantly, Lazarsfeld and Merton (1954) developed two types of homophily: status-homophily, or the similarity of observable characteristics inclusive of network position among dyads, and value-homophily, or the similarity of interactors' opinions. Research on partisan homophily in political discussion networks implicitly uses the latter, as similarity is often operationalized using attitudinal or party identification measures. Since those early studies of the structure of Americans' interactions about politics, homophily has become a well-studied characteristic of discussion networks.

Many communication studies of homophily in political discussion networks have focused on describing the prevalence of homophily, or the extent to which it is attenuated in various contexts. In particular, recent research has found that online discussion spaces, as with offline contexts, facilitate value-homophily (Bond & Messing, 2015; Bond & Sweitzer, in press; Colleoni, Rozza, & Arvidsson, 2014; Goel, Mason, & Watts, 2010; Himelboim, Smith, & Shneiderman, 2013), but that is attenuated when the primary function of the discussion space is apolitical (Brundidge, 2010; Wojcieszak & Mutz, 2009). In offline discussions, the same attenuation seems to occur when the primary function of the social space is apolitical, such as in work environments (Mutz & Mondak, 2006), student interest groups (Eveland & Kleinman, 2013; Song, 2015), and churches (Scheufele, Nisbet, Brossard, & Nisbet, 2004). I will return to attenuation in a later section.

Further communication research has instead focused on the effects of homophily for individuals embedded in such network structures. For example, homophily has been found to affect normative democratic outcomes such as participation (Mutz, 2002; Nir, 2011; Sinclair, 2012), knowledge of political facts (Eveland & Hively, 2009), and the flow of political information (Bakshy, Messing, & Adamic, 2015; Feezell, 2016). However, comparatively little research has been conducted on the origins (i.e., generative processes) of homophilous structures in discussion networks.

Generative Mechanisms

In the literature, there are three generally-accepted systematic mechanisms which are theorized to produce (state) value homophily in social networks above chance (summarized in, among other works: Cowan & Baldassarri, 2018, Kossinets & Watts, 2009, and McPherson et al., 2001): influence, structure, and selection (sometimes referred to as "choice"). To be clear, while each mechanism may produce measurable similarity among connected dyads in a network, that is not to say that they correspond to the process of homophily, which is typically used to describe only the selection mechanism. Likewise, there are idiosyncrasies to each mechanism which may result in heterophily, or the formation of relationships between dissimilar people. I will unpack each of these mechanisms in turn.

Influence Homophily. Influence occurs when two people who share a network connection become more similar, over time, due to one or both people adopting the opinions or behaviors of the other individual. This may occur through overt persuasion on the part of one or both discussants, or through subversive or subconscious processes. As dyads converge on a shared issue position, ideology, or party identification, the average of dyadic differences at the network-level should decrease over time, resulting in measurable political homophily.[6]

The notion of interpersonal influence should be very familiar to communication researchers, as some of the foundational studies in the field examined the process of ideological convergence through political discussion (Lazarsfeld et al., 1944). While much of this early work focused on the "two-step flow" of communication, linking mass media messages to the public through influential "opinion leaders", Katz and Lazarsfeld (1955) also wrote of a reinforcement effect in which "... person-to-person influences may coincide with mass media messages and thus either counteract or reinforce their message" (p. 45). More recent work on influence has found that a person's opinions are susceptible to influence when those opinions are more weakly-held, are of low-dimensionality, are inconsistent with the person's behaviors, or when a person positively evaluates characteristics of the source, such as trustworthiness (for a review, see Crano & Prislin, 2006). Obvious attempts at persuasion can lead to resistance to the influence attempt, and can even strengthen existing opinions (McGuire, 1964).

Studies of influence homophily tend to isolate this mechanism for study by holding the relationships among people constant and observing some change (for example, in an issue position or behavior) from one individual to the next (e.g., Nickerson, 2008).[7] However, political networks often involve complex, multi-level influence processes as well, in part because the dynamic structure of social networks constrain the information and sources one has access to (Huckfeldt et al., 2005). A more holistic approach, or one which seeks to identify other mechanisms as well, thus needs to allow the structure of the network to change over time. This latter approach contrasts considerably with prior studies of the influence mechanism, and it informs this dissertation.

Structure Homophily. Structural processes come into play in political discussion networks when the context of an individual's associations, which are not ostensibly linked to politics, is nevertheless spuriously associated with the measure of assortativity (i.e., party identification). For example, suppose that Sam and Nasrin are both well-educated and wealthy. They may, by virtue of these features, live in similar neighborhoods, work at the same organization, or travel in social circles with a great deal of overlap. They may, therefore, be more likely to engage in any discussion than if they did not share these characteristics. To the extent that wealth and education correlate with values, ideologies, and thus party identification, their connection in the political discussion network, even if political discussion arises coincidentally, would therefore increase the observed level of state value homophily. In this way, politically homophilous interactions may be a byproduct of selection decisions that are made in domains which are not expressly political, but which are correlated with party identification. The breadth of potential characteristics which may drive structural foundations of political homophily and their variable effects makes this mechanism very difficult to quantify in observational studies.

Baked into this definition are two separate, but related phenomena: availability and selection on correlated characteristics. Availability refers to the prevalence of different values of the characteristic on which homophily is operationalized (Blau, 1977; Feld, 1982). This perspective argues that people are limited in the number of social relationships they can feasibly maintain; this is generally supported in social scientific research (e.g., Dávid-Barrett & Dunbar, 2013). Given that assumption, the constraints placed on one's opportunities for interaction are quite strong: arithmetically, as the distribution of the characteristic of interest becomes skewed, it is much easier for members of a majority to find similar alters and comparatively more difficult for members of a minority to do so (Blau, 1977, axiom 1). This may be further enhanced by both physical and networked proximity of similar people, such as through shared acquaintances or the structure of workplace or neighborhood relationships.

The availability dimension of structural processes may also produce heterophily in circumstances where the structure which provides opportunities for interaction is comparatively diverse. Take, for example, the student body at a university (examples of students samples in political homophily research include Eveland & Kleinman, 2013 and Song, 2015). Universities in the modern era make a concerted effort to increase the diversity (e.g., race, nationality, sex, socio-economic status, etc.) of the student body. This provides tangible benefits in the classroom, and also makes the school more desirable for prospective students (Morphew, 2009). To the extent that any of the characteristics that the admissions committees select applicants on also correlate with party identification, the university is also orchestrating (perhaps unintentionally) the distribution of political opinions in the student body. University classes, dorms, greek life, and other extracurricular activities all provide opportunities for students to interact with one another. Given that the university opportunity structure is more diverse compared to, for example, a student's prior school or neighborhood, they are comparatively more likely to form politically heterophilous relationships.

The second, less often cited, form of structural homophily is homophilous selection on correlated characteristics. Relationships between individuals are characterized by similarity on a wide array of traits, such as race, sex, education, income, and interests (McPherson et al., 2001). Increasingly, political identities have been found to be correlated with seemingly apolitical characteristics, such as tastes in music (Long & Eveland, 2021), what kind of car a person drives, or where they get their coffee (Hetherington & Weiler, 2018). People may choose to engage with another person based on shared similarity of any number of these seemingly apolitical characteristics, and without even engaging in political discussion, be situated in politically homophilous relationship networks. This is sometimes referred to as the "latent variables" component of structural homophily (Handcock, Hoff, & Raftery, 2002; Kossinets & Watts, 2009).

This consolidation of different facets of a person's identity into an increasingly cohesive picture which incorporates political identity ("parameter consolidation"; see Blau, 1977) makes social interactions more navigable, in part because this phenomenon makes predicting the outcome of interactions under conditions of relational uncertainty much easier (Berger & Calabrese, 1975). In other words, if you know some set of characteristics about a person, you can predict above chance whether you will agree with this person on some political issue. That said, because this mechanism could apply to any number of unmeasured characteristics, this component of structural homophily is difficult to quantify. To know how structural processes produced homophily in a network, researchers must be able to know what socially-supplied information people had about their alters when they chose to form those relationships.

In my view, relationship networks (e.g., coworker, friendship, etc.) which are often apolitical in purpose are most susceptible to this form of structural homophily, as this process does not require discussion of politics to occur. This is, to me, one of the biggest shortfalls with studies which operationalize ties as some relationship other than political discussion and which argue that the selection mechanism, described below, doesn't occur (e.g., Sinclair (2012)). While this conclusion may hold true for apolitical relationships, one cannot be certain that selection didn't occur without ascertaining whether political information was shared and whether that information was explicitly discarded when the tie was considered. This shortcoming is obviated if we instead consider ties in a political discussion network as obtaining when a dyad discusses political matters – it inherently involves the sharing of political information. The study conducted for this dissertation operationalizes ties as engagement in sharing political opinions in order to constrain this form of structural homophily, and to focus instead on how political information is shared and used in selective decision-making.

Selection Homophily. The final mechanism, selection, concerns an individual's decision – conscious or otherwise – to engage in political discussion with another person on the basis of shared opinions. This mechanism was established first by Lazarsfeld and Merton (1954): "[People] tend to *over-select* similars as friends and, at the extreme, to confine their friendships to individuals of like kinds." (emphasis original, p. 27). In other words, if given a choice, people will prefer to interact with others who are similar to themselves (Byrne, 1971). The degree to which the preferences of individuals to interact with similar others inform a person's decision to engage in political discussion with another individual is called *selectivity*. If selectivity is the norm among individuals in the network, then at a high level there will be many more connections between similar partisans and many fewer connections across partisan divides. This selection of similar alters using domain-relevant information is usually what is meant by process definitions of homophily (e.g., Aral, Muchnik, & Sundararajan, 2009).

To be clear, the view that selection on expressly political characteristics occurs in real-world networks and explains the observed homophily within them is not uncontested. For example, Sinclair (2012) argues, "[t]hat individuals prefer to belong to groups with homogeneous preferences is clear from their selection of a social network. These choices are governed not by political preferences, however, but by social preferences" (p. 6). Results often cited in support of this argument include studies like those of Lazer, Rubineau, Chetkovich, Katz, and Neblo (2010), which found insufficient evidence of a generative role of political opinion similarity in communication networks. Similarly, Klofstad et al. (2009) argues that because social network data collected using two different name generator techniques ("important matters" versus political discussion) have a great deal of overlap, that means people do not actively select like-partisans. These studies, and others like them (e.g., Kossinets & Watts, 2009), use an existing peer network and often operationalize ties in a broader context than political discussion (e.g., name generator with "getting together socially", "getting together for academic work", or more generally "discuss important matters with").

This approach, I argue, conflates structural and selection mechanisms, and political discussion ties with a broader category of social ties. Others view political discussion as a constituent of, yet distinct from social ties more broadly (e.g., Scheufele, 2000). This comports with a multiplex perspective of social relationships: Smith, Menon, and Thompson (2012), for example, found that people "activate", or bring to mind, different subsections of their network that are relevant to a particular decision-making process. In this view, people may opt into and out of political discussion with others in their network without necessarily affecting other aspects of their relationships (Cowan & Baldassarri, 2018; Settle & Carlson, 2019). For example, one might avoid discussing politics at work or with a family member; those coworker or familial relationships can remain unchanged, but their ties in a network composed only of political discussion relationships would be severed. If one considers political discussion networks as a separate constituent of these broader social networks, it follows, then, that information relevant to the context of social selection in a political discussion context (i.e., the political opinions of other discussants) may be used in the relational decision-making process (Lazarsfeld & Merton, 1954).

Distinguishing Mechanisms

Distinguishing between these mechanisms can be challenging, particularly when networks are dynamic and researchers often only have access to one or a few time points after the network has already been formed (Aral et al., 2009; Shalizi & Thomas, 2011). Specifically, conventional network study designs such as name generator (e.g., Klofstad et al., 2009) or observational studies on social media platforms (e.g., Bond & Sweitzer, in press) are well-suited to describe the extent of political homophily in a given context, but rarely are they able to elucidate the generative processes that resulted in the observed network structure. That is not to say that research in this area has been entirely unable to distinguish generative processes.

A growing body of literature (see for example, Aral et al., 2009; Eckles, Kizilcec, & Bakshy, 2016; Lewis, Gonzalez, & Kaufman, 2012; Steglich, Snijders, & Pearson, 2010) advances complex methodological techniques, such as matched sample estimation or stochastic actor models, to distinguish influence from other mechanisms. In a different study, Kossinets and Watts (2009) examined networks of college undergraduates for patterns of selection and two forms of structural homophily: cyclic and focal closure. Cyclic closure, of which triadic closure (i.e., "friend-of-a-friend") is a constituent, refers to when individuals are more likely to form a tie as a result of interconnected social circles. Focal closure, on the other hand, occurs when individuals are more likely to interact because of a shared connection to some other kind of network node in a bipartite network (e.g., students enrolled in the same class, as used in Kossinets & Watts, 2009). Because they studied homophily of invariant and observable attributes (e.g., gender, age, academic major), the authors argued, they need not consider influence as a generative mechanism. Compared to such demographic characteristics, the study of how discussion of political opinions shapes party identity is more complicated. This is because opinions can shift over time as a result of network-endogenous and exogenous factors, and because political opinions are a level of abstraction from party identity.

Other works closer to the fields of political science and communication isolate influence as well. For example, Nickerson (2008) and Bond et al. (2012) studied the propagation of voting behavior in pre-existing networks. By focusing on networks which have already been subject to structural and selection processes, coupled with invariant tie structure and random assignment to experimental conditions, the authors are able to control for the other mechanisms. Similarly, Sinclair (2012) wrote that "the sole means of identifying [influence] effects is to control for those characteristics by which the network relationships were formed" (p. 80). These paradigms, however, often either conflate selection and structural processes or ignore the structural mechanism altogether.

Whereas prior work argues that influence and process homophily (i.e., selection) are confounded in contemporary research (Aral et al., 2009; Shalizi & Thomas, 2011), I argue that structural and selection mechanisms are likewise confounded. One feature of network data that is required to distinguish influence and selection is a longitudinal representation of structure. The current work on mechanistic parsing argues that this is necessary to show changes in the network structure which result from selectivity. To distinguish selection from structural processes, researchers must also have 1) information about the prevalence of the characteristic of interest among all individuals in the network prior to data collection (availability), and 2) a complete accounting of the information individuals have about each other which may influence their relational decision-making (latent variables).[8] Current research methods make it difficult to quantify how selective people are on explicitly political characteristics, what kinds of domain-specific information are relevant to selective decisions, how selectivity varies systematically between members of the same network, or what role other communicative processes play in selective decision-making.

While the first component is relatively easy to quantify, the latter is very challenging from a methodological standpoint – not only would the research have to measure every potential source of similarity and its relation to the characteristic of interest (e.g., political party identification), but this approach may also require participants to accurately self-report what information was used in the decision-making process. Given the social desirability of heterophily on certain characteristics stemming from a desire not to appear prejudiced (Fisher, 1993), and the poor accuracy with which people are able to attribute other characteristics to their discussion partners (Goel et al., 2010), it is likely that any self-reported measure of information used in relational decision-making would be unreliable. Constraining the information available to subjects of the study to politically-relevant characteristics seems, to me, like a more accurate approach to the study of selectivity, as it limits the potential confounds of selection on other characteristics.

This dissertation offers a framework to isolate selection homophily in political discussion networks. This framework examines dyadic interactions situated within broader discussion networks with a limited information environment. Then, building upon these interactions by permitting discussants to constrain the information they make available to their discussion partners through topic avoidance, this dissertation begins to develop a more holistic view of complex selection in dynamic networks.

Isolating selection processes remains an important methodological contribution in communication. Selection is an inherently interpersonal communicative process: We convey information about ourselves to others through political discussion. Our discussion partners then use this information to form a judgment about whether to continue interacting with us in political contexts. At the same time, the inverse direction in the dyad also occurs – that is, our discussion partners share information with us and we make a decision about whether to continue interaction. Critically, with the same paired set of information, two discussion partners may reach different conclusions about the future status of their political discussion relationship. These decisions affect the patterns of interaction in the network as a whole, and thus have normative implications for political outcomes.

There are, in my view, three constituencies of communication researchers to whom this dissertation offers theoretical advances. For other political communication scholars, this framework is able to isolate communicative processes involved in politically selective decision-making. While the framework presented here could be applied outside of the domain of politics (for example, entertainment media preferences), the political application has normative implications (such as participation in the democratic process; e.g., Nir (2011)) which extend beyond the individual, dyad, or network. For interpersonal scholars, the theoretical linkages made below between relational uncertainty, topic avoidance, and relational decision-making provide a greater understanding of the intricacies of dynamic interaction around political issues. Further, this dissertation investigates the goals of selective decision-making in political discussion. Finally, for small group communication scholars, this dissertation offers a theoretical framework to show the emergence of dyadic processes to the group-level. The methods employed in this dissertation, presented in a later chapter, could also be used to test the interplay of inter- and intra-group theories.

Chapter 2: Interpersonal Selection

Selectivity, or the degree to which people actively choose to form relationships with other, like-minded people, is the process behind selection homophily. Selection is an "adjustive" process (Lazarsfeld & Merton, 1954): "By selective and adjustive processes in friendship we mean patterned sequences of social interaction between friends in which each phase generates and regulates the subsequent phase in such manner as to give rise to the observed patterns of friendship between people of designated kinds" (p. 25). In other words, selection plays out over time as interactions in the political discussion network provide discussants more information about their discussion partners with which to form judgments concerning the preferred status of the tie. Political discussion networks are thus dynamic, and so a dynamic theory of selection is called for. To investigate selection, I begin with a review of the myriad interpersonal communication accounts of why selection of similar discussion partners is thought to occur.[9]

Why We Select Similar Alters

Selective Exposure. Three theories are frequently cited in explications of selection homophily: selective exposure, cognitive dissonance, and uncertainty reduction. Though typically utilized in research to address an individual's selection of news media sources, selective exposure theory (Sears & Freedman, 1967) was formulated to apply to a broad array of information sources. Selective exposure to interpersonal communication sources applies in the context of political discussion networks, because an individual's tie decisions concern whether they talk about political matters with another person (for a review of early interpersonal applications, see Zillmann & Bryant, 1985). Recent applications of selective exposure theory in interpersonal contexts, for example, examine decisions to "follow" a like-partisan on social media (e.g., Himelboim et al., 2013). The theory argues that people are discerning when it comes to sources of political information. Specifically, they prefer to engage with those sources of information which they expect will comport with their existing opinions, and which will reaffirm those opinions in future interactions with the source. Just as in mediated settings, where Democrats tend to watch MSNBC and Republicans tend to watch Fox News, in interpersonal contexts, partisans discuss political matters with other, like-partisan people. This constrains the information they may be exposed to in much the same way as mediated selective exposure (Feezell, 2016; Halberstam & Knight, 2016). The perception that an information source will reaffirm one's political identity stems from, among other things, previous interactions with the source. In this way, selective exposure theory accounts for the longitudinal nature of selective processes outlined by (Lazarsfeld & Merton, 1954) – interactions with a source that reaffirm one's beliefs begets future interactions with that same source.

Implied in this theory, and confirmed in later studies (e.g., Garrett, 2009), are two complementary, but distinct processes: a tendency to engage with opinion-reaffirming sources, and a tendency to avoid opinion-discrepant sources. Applying this to a political discussion network context, one can see how these processes might result in homophily. When a person avoids discussing political matters with someone who they think will disagree with them, the tie is either severed or ignored in the network.[10] Likewise, when a person chooses to engage with people who are similar to themselves, the tie is either maintained or formed in the network, reinforcing homophilous relationships. If these processes are normative across individuals in the network, then the overall network structure will evince assortativity.

Cognitive Dissonance. Cognitive dissonance theory (Festinger, 1957) holds that people experience psychological stress when they encounter beliefs or values which contradict a personally-held belief or value. The negative affect experienced with dissonance can be felt even in the absence of aversive consequences like interpersonal disagreement (Harmon-Jones, 2000). Related psychological perspectives, such as the action-oriented model (Harmon-Jones, Peterson, & Vaugh, 2003) hold that cognitive discrepancies produce dissonance specifically when they interfere with efficient belief-consistent actions. In a political discussion network context, a person's action of engaging in belief-consistent political discussion with an alter draws on information that is relevant to the decision to engage the alter (i.e., form a tie in the political discussion network). The information in this context is one's perceptions (whether accurate or inaccurate) of their alter or prospective alter's political identity. Dissonant information – differences between one's own beliefs and the perceived beliefs of their alter – results in action avoidance.

This psychological stress is thought to be a substantial cost of maintaining ties with dissimilar others in the discussion network (Kossinets & Watts, 2009). People are motivated to relieve this stress, either by adapting their beliefs to more closely align with the encountered contradictory information,[11] or perhaps more likely, remove the source of this discomfort. In political discussion contexts, this manifests as avoidance of political discussion when interacting with dissimilar others – in other words, severing the tie in the political discussion network. Rational individuals turn instead to other, more agreeable sources of socially-supplied information (Downs, 1957).

Uncertainty Reduction. Uncertainty reduction theory (URT; Berger & Calabrese, 1975) argues that interpersonal relationships, and particularly those early in the lifecycle ("entry phase", although see Berger & Gudykunst, 1991) are filled with uncertainty. This uncertainty stems from a desire to predict the outcomes of interactions with the other person; if we know little about them or if the information we do know could lead to a wider variety of outcomes from continued communication, then this uncertainty reduces our liking of this individual and we may avoid communicating with them (axiom 7, Berger & Calabrese, 1975, p. 107). Similarity between interactors helps reduce uncertainty (axiom 6, Berger & Calabrese, 1975, p. 106), in part because it reduces their need to justify to themselves and others the continued existence of the relationship (Koenig, 1971). By "justify", Koenig (1971) means that we feel desire, due in part to social norms, to justify our dislike of others. Conversely, dissimilarity (encountered through disagreement in discussion) increases uncertainty in the relationship because there are a greater number of potential outcomes in future interactions and because we feel a greater need to justify the existence of the tie in spite of disagreement stemming from the "... large number of alternatives for explaining behavior" (Berger & Calabrese, 1975, p. 106).

One of the ways uncertainty has been operationalized in prior studies of URT is through attributional confidence (Clatterbuck, 1979), or the assessed confidence one has in their ability to predict what their discussion partner thinks about an issue. This, the theory argues, helps people assess the outcome of discussing that issue with an alter (e.g., agreement or disagreement). Similarity, the argument goes, aids the attribution process because people are able to extrapolate from their own personal experiences (in this case, political experiences) to form more concrete projections of their alter's political identity. This helps reduce the potential number of outcomes that result from discussion, and thus makes it more likely that the person will choose to engage in discussion (Berger & Calabrese, 1975). Hereafter, I refer to the decision to engage in discussion as an "*associative*" tie choice. On the other hand, dissimilarity of expressed political opinions increases uncertainty, and should result in the person choosing to avoid political discussion with their alter in the future. Hereafter, I refer to this relational decision as the "*disassociative*" tie choice.

Perceptions of similarity in URT may be derived in a number of ways, including through domain-relevant information shared in previous interactions with the person, through shared alters (axiom 8, Berger & Gudykunst, 1991), and even readily learned information about a person that does not require interaction, such as their race or gender. These other characteristics often (through parameter consolidation, see Blau, 1977) give us some indication (however imperfect) of our potential political compatibility. The purpose of this dissertation is to isolate selection of alters on expressly political characteristics, and the latter two sources of perceived similarity pertain to structural sources of homophily. Thus, the first of those sources – expressed, domain-relevant information (i.e., shared political opinions) – is used in this study. Given that all three theories, however imperfectly applied in interpersonal contexts, arrive at the same conclusion – that similarity begets tie formation and maintenance while dissimilarity begets tie dissolution in a political discussion – the following hypothesis is formed:

H1: Similarity of expressed opinions in the dyad will lead ego to choose the associative tie choice concerning alter.

While this dissertation emphasizes the role of interpersonal communication processes, it is also worth noting here that small group communication theories would also conclude that people make associative relational decisions concerning similar alters. Social identity theory (Tajfel & Turner, 1979, 2004) posits that a self-concept derived from membership in a social group results in social categorization of others into in-group members and out-group members. This is made salient in American political contexts by political party identities (Greene, 1999, 2004). The theory further states that people form positive evaluations of in-group members and denigrate out-group members. While this generally leads to selection, social identities can also produce intergroup conflict which may further divide the social space (Brewer, 2001). Even though both small group and interpersonal perspectives reach the same conclusion, I opted to focus on implementation of interpersonal theories for this dissertation as a matter of operational consistency.

Discussion and Selection as Dynamic Processes

Recall that selection homophily was described by Lazarsfeld and Merton (1954) as an "adjustive process", meaning that the structure of relationships plays out over time and the relational decisions at any given time affect the structure at subsequent time points. People learn more information about their discussion partners and update their network connections in accordance with their assessment of similarity with their alter. Political discussions are also dynamic; people tend to discuss issues which are salient at a given point in time (Roberts, Wanta, & Dzwo, 2002). However, the tenets of selection homophily simply state that people prefer similar alters, but do not posit how multiple pieces of information regarding an alter's similarity (or disimilarity) are aggregated or weighed against one another. In most cases, given the consistency of political identity in the American political landscape (Layman & Carsey, 2002), it is likely that new information comports with old information. For example, a Democrat who told their discussion partner that they support strong gun legislation is also likely to take a similarly liberal position if the topic shifts to taxation or abortion. What happens, though, when new information conflicts with prior information? How do people resolve those differences of opinion? If only the current topic matters to relational decision-making, then when that Democrat later tells their similarly Democratic discussion partner that they are pro-life, does their discussion partner use only this one opinion to inform their decision (likely disassociative), or do they weigh that one difference of opinion against previously discussed similar opinions (likely associative)? Answering how relational decision-making plays out in a complex, dynamic social information environment may advance the current simplistic understanding of selection.

> *RQ1: Are multiple pieces of information (i.e., expressed opinions) about the alter aggregated by ego to reach an associative or disassociative tie decision?*

Given that people will tend to form relationships with similar discussion partners (H1), and that selective decision-making (tie formation and dissolution) is informed by similarity in expressed opinions over time, in some form or another, it stands to reason that the connections between discussion partners will create a network structure that evinces (state) homophily over time as well.[12] That is, early in the formation of the network, when people have little information about their discussion partners and they have made few relational decisions, the correlation of a characteristic such as party identification across all connected dyads in a network should be quite low, accounting for structural availability. However, over time as people learn more of their discussion partners' opinions and make relational decisions which affect the structure of the network as a whole, this correlation should begin to increase. This phenomenon of individuals affecting dyads and dyads affecting network structure is called "microdeterminism" (Monge & Contractor, 2003). Answering when, over the course of several topic discussions, selection produces assortativity at the network-level above chance levels (and accounting for other mechanisms) may help future researchers design dynamic selection studies with some expectation of the outcomes. Additionally, investigating what proportion of observable assortativity may be attributed to selection, as opposed to other sources of homophily, will allow researchers to better understand how networks in cross-sectional studies likely form.

H2: Over time, network-level assortativity of party identity will exceed chance.

RQ2: After how many topic discussions does the network-level assortativity of party identity exceed levels expected by chance?

Interpersonal Consequences of Selection

The emphasis on anticipated outcomes of interaction is prevalent throughout interpersonal communication theories, but particularly among theories of initial interactions, such as URT (Berger & Calabrese, 1975; Berger & Gudykunst, 1991). In URT, the cognitive effects of relational uncertainty in early stage interactions are the direct result of the inability to predict how an interaction will transpire. Moreover, similarity is thought to reduce the number of potential outcomes by virtue of agreement. In other words, selection of similar discussion partners should beget both attribution of an agreeable position on as-yet-undisclosed issues, and greater attributional confidence (Gudykunst, 1985). It is thus hypothesized that:

H3: Selection results in connected dyads which have similar opinions on topics not discussed.

Testing this hypothesis has the additional benefit of answering whether people's attributional certainty which results from selection of similar alters is warranted. In other words, if the hypothesis is not supported, then perhaps people should not use similarity on previously discussed political topics to project similarity on future topics of discussion.

Somewhat relatedly, network research regularly finds that homophilous ties tend to be more stable over time in a variety of contexts (Felmlee, Sprecher, & Bassin, 1990; Kossinets & Watts, 2009; Leenders, 1996). Aspects of the selection process laid out thus far can help explain why this might be the case. In interpersonal research, Holmes and Rempel (1989) find that uncertainty reduction results in increased trust in interpersonal relationships. Given that similarity reduces uncertainty (Berger &

Calabrese, 1975; axiom 6), it follows that selection of similar discussion partners results in greater trust between them. It may thus be easier for people to maintain the trusting relationships they have as opposed to seeking new political discussion contacts. Dissimilarity, on the other hand, produces competition, and so strong relationships are less likely to form among dissimilar individuals (Nebus, 2006; Reagans, 2005). All else being equal, the selectivity of networked discussants should produce more lasting relationships:

> *H4: Dyadic selection produces greater relational stability compared to sociality alone.*

Individual Variance in Selectivity

Issue publics. The theory of issue publics (Krosnick, 1990) concerns people's tendency to act on those political issues which are most salient or important to them. The theory stems from the psychological concept of "cognitive misers." This perspective argues that people have a limit to their cognitive capacities, and as such, will constrain the amount of effort they invest in understanding and acting on related, but comparatively undervalued concepts (i.e., heuristic processing; for a review see Fiske & Tayler, 2013). For example, a Republican may be more invested in either social or fiscal issues, and disproportionately so in the subsumed issues, such as gun ownership, abortion policy, or law enforcement. The Republican who considers gun ownership to be the most important issue may then be more likely to sign a petition concerning gun rights or to join the National Rifle Association than they are to canvas in support of abstinence education.

More recent research integrating issue publics and selective exposure theories finds that partisans are more selective when the information pertains to an issue that is of high subjective importance (Kim, 2009). In other words, perceived discrepancies between one's opinion and the viewpoint of the information source are *magnified* when the issue is important to them, but *lessened* when the issue is of lower importance. This augmented perception influences selection of an information source. This comes into play in political discussion networks when individuals are evaluating the level of similarity they have with another person and how it affects their decision to form or dissolve a tie in the discussion network. That is, people may feel that small dissimilarities on really important issues weigh heavier on their tie decisions than do larger dissimilarities on comparatively less important issues. As Huckfeldt et al. (2004) put it: "political disagreement typically becomes less tolerable when political passions are more intense" (p. 23). In conjunction with selective exposure, the theory of issue publics provides a way in which differences of opinion may be magnified or diminished depending upon the concerns of the individual making the tie choice.

It may help to consider an example. Imagine that two people, Sam and Nasrin, share a tie in the political discussion network. Over time, they discuss three topics: healthcare, education, and foreign policy. As they discuss their opinions with each other, they ascertain the difference of their discussion partner's opinions relative to their own. If Sam's opinions on the specific topics were projected on a 1-7 Likert scale, they might look like the set: $\{1, 4, 6\}$. Nasrin's opinions might similarly be expressed on a 1-7 scale as the following: $\{1, 3, 2\}$. To both Sam and Nasrin, the absolute difference between their positions on each of these issues is (assuming there are no errors in their perception of their alter's positions): $\{0, 1, 4\}$. For the first two discussion topics, Sam and Nasrin's opinions were relatively close. However, when the topic of foreign policy comes up, they find that they have very different opinions on the matter. If both Sam and Nasrin consider foreign policy equally important or unimportant, then they might reach the same conclusion about the status of the tie.

Let's imagine that they weigh the importance of the discussed issues differently. Sam thinks that healthcare is very imporant, is somewhat tepid about education, and does not care about foreign policy. If issue importance was similarly measured using a 7-point scale with response options ranging from very unimportant (1) to very important (7), then Sam's ratings of these issues might look like this set: $\{7, 3, 1\}$. Meanwhile, Nasrin thinks that healthcare and education are somewhat important issues and foreign policy is very important: $\{5, 5, 7\}$. In their discussion of the first two topics, it wouldn't matter much that Sam and Nasrin consider the importance of healthcare and education differently, since their opinions on those issues are relatively close. Sam's perceived difference with Nasrin, weighted by the importance of healthcare and education to Sam, after the first two topics are discussed is 1.5, while Nasrin's weighted perceived difference with Sam is marginally higher at 2.5. These scores are both relatively low, and so even if both Sam and Nasrin were highly selective, they would still both likely reach the same conclusion about the discussion tie after discussing two topics: that they want to continue political discussion.

After Sam and Nasrin discuss their third topic of foreign policy – a topic on which their opinions differ more compared to their previous discussions – their assessments of their political differences differ dramatically. Because Sam does not think foreign policy is an important issue, their weighted perceived difference with Nasrin increases only slightly to 2.33. If Sam is deciding whether or not to discuss a fourth political issue with Nasrin, they would likely reach the same conclusion they had before: maintain the tie. However, for Nasrin, foreign policy is a very important issue. After discussing foreign policy with Sam, Nasrin's weighted perceived difference with Sam increases drastically after discussing this topic to 11. If Nasrin is weighing whether to continue discussing politics with Sam, they might reach a different conclusion (under conditions of selectivity): they may dissolve their political discussion tie with Sam.

> *H5: Issue importance to ego will moderate the relationship between (dis-)similarity of expressed opinions and the tie decision reached by ego concerning alter such that smaller differences of opinion on highly important issues to ego will result in disassociation with alter.*

Affective Polarization. Political scientists in recent years have been raising the alarm over increased political polarization, both in American contexts and abroad (e.g., Lee, 2005; Lelkes, 2016). While some scholars (e.g., Binder, Dalrymple, Brossard, & Scheufele, 2009) have focused on explaining polarization using attitudinal or identity extremity – for example, by "folding" the commonly-used 7-point scale of party identity – others have focused on a somewhat related conceptualization called *affective polarization.* This conceptualization draws from small group theories of communication, such as social identity theory (Tajfel & Turner, 2004), to explore polarization as a combination of both positive feelings about an in-group (e.g., other members of the same political party) *and* negative feelings about an out-group. By measuring the difference between two feelings thermometer scales, researchers can assess the polarization of individuals as a degree of preference for one's in-group versus their out-group (Iyengar, Sood, & Lelkes, 2012; Iyengar & Westwood, 2015; Lelkes, 2016).

Affective polarization can have dramatic effects on one's willingness to engage in a political conversation with someone they may not agree with. A recent study conducted by Hutchens, Hmielowski, and Beam (2019) examined the reciprocal reinforcing effects of affective polarization and discussion with like-partisans over time. In two 3-wave studies, they find support for the hypothesis that affective polarization leads to discussion with increasingly similar alters. This is a somewhat stronger argument than a similar argument put forth by Bello and Rolfe (2014): that one's strength of party identification is associated with selective discussion. That is because affective polarization accounts for *both* an in-group preference (and thus associative tie decisions on similar alters) *and* an out-group derogation (and thus disassociative tie decisions on dissimilar alters). This is akin to the dual-process perspective of selective exposure theory (Garrett, 2009). Whereas the application of selective decisions in Hutchens et al. (2019) was limited to self-reported discussion on a survey, this dissertation investigates the role of affective polarization on selectivity in a dynamic networked context.

> *H6: Individuals high in affective polarization are more selective compared to individuals who are less affectively polarized.*

Disclosure and Topic Avoidance in Discussion

I turn now to the interpersonal process of topic avoidance, sometimes referred to as "selective disclosure" in the political networks literature (e.g., Cowan & Baldassarri, 2018). Cognitive dissonance theory holds that we feel a great deal of mental discomfort when we encounter opinions which differ from our personally-held opinions (Festinger, 1957). To remedy this discomfort, we engage in a variety of strategies in our interactions (Huckfeldt et al., 2004, p. 10). Among the most impactful strategies of dissonance resolution is the avoidance of discussion of the topic (MacKuen, 1990). This process treats the decision to engage in interpersonal political discussion as a strategic game (MacKuen, 1990) – a recent study conducted by Settle and Carlson (2019) even found that participants were willing to pay more to avoid discussion when they anticipate partisan disagreement. People will anticipate the outcome of discussion of the topic (Berger & Calabrese, 1975), perhaps by extrapolating their discussion partners' opinion on the matter from previously discussed political topics. If their assessment is that they are likely to encounter disagreement if they discuss the issue, they may choose not to disclose their opinion on the matter in order to avoid the mental anguish of confrontation.

Other interpersonal theories mentioned previously also suggest that topic avoidance is the rational choice. Uncertainty reduction theory (Berger, 1987; Berger & Calabrese, 1975; Berger & Gudykunst, 1991) argues that relational uncertainty brought about by the inability to accurately predict the outcome of interactions (and by attributed dissimilarity; Berger & Calabrese, 1975, axiom 6) results in great psychological discomfort, which once again can be eased by avoiding communication. URT also goes one step further: in situations where discussants are similar and uncertainty is reduced (axiom 6), reciprocity rates are generally lower (axiom 5, Berger & Calabrese, 1975). This indicates that it would be socially acceptable for a person in an established relationship to avoid disclosing their opinion on a topic with their discussion partner, even though the discussion partner disclosed their opinion.

Topic avoidance fundamentally changes the social information environment – if others in the network are evaluating the opinions of a person who avoids discussion of a topic, then they will only be able to form their evaluation from other previously-discussed topics. The person's true views on this issue are obscured from their discussion partners. In other words, the opinions which one expresses to their discussion partners are more likely to be those which the discussion partner agrees with.[13] Avoided topics are difficult to measure in observational studies (Huckfeldt & Sprague, 2000), as the absence of communication could be deliberate or unintentional, making quantifying the role of topic avoidance in networked selection very challenging.

It is worth noting here, too, that other theories of communication would also predict the avoidance of disagreement, albeit through a slightly different process. Spiral of silence theory (Noelle-Neumann, 1974), for example, argues that people use a perception of the distribution of opinions held by others (known as a "quasi-statistical sense") to inform their decision to reveal their opinions to society. A person who holds an opinion which they perceive to be in accordance with the majority-held opinion in society is likely to discuss their opinion on the matter with others. Conversely, if they feel as though their opinion is only consistent with a minority of societal members, then the person is much less likely to reveal their opinions to others in discussion. This is motivated, Noelle-Neumann (1993) argues, by a fear of isolation. They instead may turn to other tactics, such as asking others what they think about the topic (both as a diversion, and perhaps also to confirm their quasi-statistical sense), or expressing uncertainty or ambivalence about the topic (Hayes, 2007). In this macro communication perspective, the decision to either express one's opinion or to avoid discussion of the topic involves information about societal-level distributions of an opinion.

In contrast, the interpersonal perspective contends that this decision occurs at the dyad-level, meaning that people may decide to disclose or withhold their opinions from different alters in their network using information that is specific to the alter. For example, suppose Sam and Nasrin are considering whether to engage in discussion about foreign wars. In spiral of silence theory, Sam would consider whether their hawkish stance is broadly popular before deciding to share this opinion. In the interpersonal sense, Sam needs only to consider whether Nasrin is likely to agree with them on this topic. If they have discussed several issues before and agreed often, then Sam can conclude from those prior discussions that Nasrin will likely agree with them on matters of foreign wars.[14]

> *H7: People are more likely to withhold their opinion from an alter with whom they have greater dissimilarity on previously discussed topics.*

Research applying issue publics theory (Krosnick, 1990) to interpersonal communication finds substantial variation in the willingness to discuss certain topics. Principally, important issues are much more likely to be discussed in informal conversation (Krosnick, Boninger, Chuang, Berent, & Carnot, 1993). This coincides with the notion that our positions on these subjectively important issues are considered more central to our identities (Krosnick, 1990). People weigh the benefits of disclosure (e.g., identity expression, uncertainty reduction) against the costs of conflict, and for comparatively less important issues, the benefits do not outweigh the costs (Roloff & Ifert, 2000). On the other hand, subjective issue importance may help us overcome the cognitive implications of disagreement.[15]

> *H8: Issue importance will moderate the relationship between ego's prior dissimilarities with alter and their decision to disclose their opinion on the current topic to the alter such that greater issue importance will reduce the negative effect of dissimilarity on disclosure of the current topic.*

As mentioned previously, topic avoidance has tremendous implications in networked discussion, as it constrains the information one has about their alters to more agreeable issue positions. This may lead people to think that their discussion partners are more similar to themselves than they actually are. This may be an unsurprising conclusion, given that people often overestimate the rate of agreement between themselves and their political discussion partners in name generator social network studies (Goel et al., 2010). Given that perceived similarity among dyads in the discussion network increases with the inclusion of topic avoidance, the role of attitudinal difference in network generation should be reduced compared to a discussion network in which topic avoidance is not permitted:

> *H9: The generative role of selection homophily is lower when people have the option to withhold their opinions compared to when they do not have that option.*

Assuming that H9 is supported, it may interest deliberative and network scholars alike to know whether selection still produces network-level (state) homophily above chance:

> *RQ3: Does selection in networks where selective disclosure is permitted still produce network-level partisan assortativity above chance?*

With many of the intricacies of selection homophily explicated, I turn now to the methodological component of this dissertation. The study presented here isolates selection homophily in a tightly-controlled quasi-experiment.

Chapter 3: Quasi-Experimental Design

While the basics of selectivity and its relation to network-level homophily are straight-forward, the specific intricacies of this relationship can be quite complex, as the culmination of the hypothesized relationships above suggests. The distribution of expressed opinion differences, weighted by issue importance and affective polarization, updates with each dyadic interaction over time. Individual decisions about breaking a tie may not only affect the composition of their ego network, but may result in meaningful changes in the topology of the broader network. A person's decision to avoid a topic of discussion which they are likely to disagree on fundamentally changes the information their alters have to inform their relational decisions. It is thus unknown how sensitive the homophilous structure of the network may be to changes in an individual's behavior. To this end, the methodological component of my dissertation is a human subjects quasi-experimental design which addresses each of the hypotheses and research questions listed in the previous chapter. The goals of this approach are threefold: to isolate selection from other homophilous mechanisms, to explain individual variances in selectivity, and to provide a framework with which interpersonal processes, like topic avoidance, affect selection in dynamic discussion networks. This framework is readily expandable to incorporate additional processes in future studies.

As mentioned before, selection homophily has largely gone unstudied, in part because it is difficult to isolate selection from influence and structural mechanisms using more conventional social-scientific methods (Shalizi & Thomas, 2011). Using the framework detailed here, this study can successfully isolate selection by 1) allowing the structure of the network to change over time as a function of participants' decisions concerning the status of ties, 2) not permitting the opinions or party identities of participants to change after interaction (i.e., influence homophily), and 3) limiting the non-political information participants have about the other participants, such as race, gender, or the underlying network structure (i.e., structural homophily). While these restrictions will produce interactions in the study that aren't necessarily reflective of the full complexities of real-world political discussion, the limitations in ecological validity are counterbalanced by a focus on internal validity with this design. Such a treatment of political discussion is necessary to isolate the process of selection in dynamic networks as a first-order goal. Then, additional processes and information about one's discussion partners can be added to this framework to begin to make the interactions in the study more naturalistic. This strategy, I argue, is essential if this research paradigm is to provide a meaningful contribution to the selection homophily literature.

The study utilizes Breadboard, a software platform designed for network experiments (McKnight & Christakis, 2019). This particular platform has a number of unique advantages, including built-in integration with the Amazon Mechanical Turk (MTurk) participant pool – the pool used for this study – and flexibility with regard to study design. Subjects can be recruited to participate in the study concurrently – groups of participants (hereafter, "*cohort*") are able to interact with one another. Because simultaneous recruitment is necessary, each cohort of participants is randomly assigned to one of two conditions as a group (hence *quasi*-experiment). The two conditions are alike in most respects, except where outlined below. In the following pages the 5-phase, 2-condition study conducted in fulfillment of this dissertation is detailed.

Study Design

The entire study – both conditions – is divided into five phases: waiting room, opinion survey, discussion rounds, demographic survey, and chat room. Participants are held at several points within each phase as well as at the end of each phase so that the entire cohort can progress to the next step at the same time. If at any time a participant is faced with some sort of action (e.g., selecting a response option in either survey phase, or making a tie decision), but they fail to make a decision within 60 seconds, they are dropped from the study. This rule is enforced to prevent the other participants from waiting for an inactive player. This information is displayed prominently in the instructions of each section. Additionally, when the first 30 seconds of inaction have transpired, a 30 second countdown displays at the top of their screen. Exactly how these participants are dropped depends on the current phase of the study – during the first two phases participants are dropped completely. During the final 3 phases the participant is replaced with an autonomous agent (hereafter, "*bot*"). Bots' actions will be detailed in the respective phase subsections below. The only exceptions to the 60 second drop rule are 1) participants are not dropped from the waiting room phase until the administrator activates the button to proceed to the second phase, 2) participants who have completed a step and are waiting on other participants to finish the same step are considered continually active, and 3) after the links for the chat rooms are displayed, the 60 second rule is turned off for all participants.

Participants are instructed that completing the study will take approximately 60 minutes. All but two cohorts (1A and 2A) finished in less than 60 minutes, though the total time spent in the study varied between cohorts depending on the number of active participants and internet connectivity speeds. Subjects earn pro-rated remuneration for taking part in the study up to $15.00. The incentive structure is detailed in each of the phases described below.

At the start of data collection, the study administrator enters a number of parameters into the Breadboard dialog. This includes the order of the ten discussed topics as well as which version of each topic question is to be shared in the corresponding round. This allows for the randomization of the order of topics between different iterations of the study (i.e., each cohort discusses the same 10 topics, but the order and which version of the topic is discussed is randomized between cohorts). Once the parameters are entered, the Breadboard software sends a “HIT”, or “human intelligence task,” to a central listing page which provides MTurk “workers” with a link to join the study. A maximum of 35 “HITs” were permitted per instance of the study in order to account for attrition and to reach the target of approximately 15 participants in the network phase of the study. The study software was hosted on a server provided by The Ohio State University’s College of Arts and Sciences. See Appendix E for more details regarding software and code availability.

Phase 1: waiting room. The waiting room phase is designed to hold participants in a ready state until enough participants have joined the study. This section of the study is not timed. Participants are welcomed and shown the consent form. They may read the consent form at their own pace and select from “accept” and “decline” options. Participants who select “decline” are dropped immediately.[16] During this step, participants are assigned a randomly-generated unique identifier consisting of two letters and a number (e.g., “MK5”) which allows other participants to be able to identify them on a network graph and connect that information with disclosed opinions which appear to the right of the graph. The two letters are screened against a blacklist of options provided to the software which prevents colloquial abbreviations, such as states (e.g., “OH”), from being assigned. This identification format was chosen to allow participants to be identifiable to one another, while also limiting social selection of a participant because of a meaningful identifier, such as if a person’s first name was used.

Participants who accept the consent form are instructed to wait patiently for more participants to join. On the administration side, the node of a participant in the graph[17] changes from red to green, indicating that they have accepted the consent form and are ready to participate. Once approximately 25 participants accept the consent form, the administrator activates the second phase of the study. At this point, a button displays on all participants' screens and the 60-second time limit becomes active. They must press this button within 60 seconds to proceed to the next phase and to earn the initial show-up payment of $1.00. Participants who do not press this button are dropped from the study. This practice is common among Breadboard studies, particularly those using MTurk, as it helps weed out people who are not paying attention or bot accounts which are holding a person's place in the study.

Phase 2: opinion survey. At the start of the opinion survey phase, participants' user interface changes (see Figure 1). The left-hand side of the screen contains a network graph, at this point occupied only by the participants' own node. The right-hand side contains the text for any instructions, survey questions, or actions required. At the top of this section is a counter indicating how much money a participant has earned at any given time. If a participant drops out at any point when a value is shown here, they are paid that amount for their participation up to that point in time.

The instructions indicate that participants are about to fill out a public opinion survey and that some of their responses will be shared with other participants in the study. After reading the instructions, participants are held in place while the remaining participants finish reading the instructions. This hold is also repeated after each set of topic questions in the survey. This way, faster participants are forced to wait in many smaller increments, rather than one longer period at the end, ideally making it less likely that they will drop out or become distracted.

The first question in this survey is "Generally speaking, do you usually think of

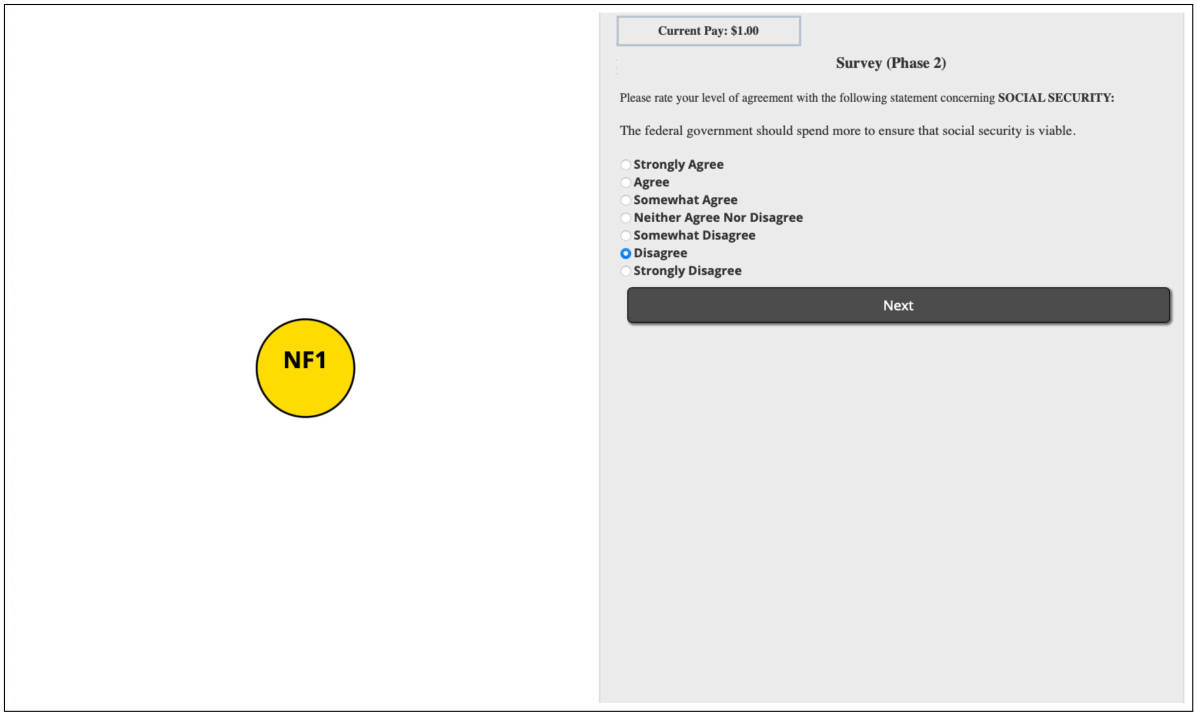

Figure 1. Example of the participant user interface on Breadboard.

yourself as a Republican, a Democrat, or an Independent?" Participants who respond "Republican"("Democrat") are shown a followup: "Would you consider yourself a strong Republican(Democrat), or not a very strong Republican(Democrat)?". Participants who selected "Independent" are shown the followup: "Do you think of yourself as closer to the Republican or Democratic party?" In addition to those two response options, Independents are shown a "neither" response option. The combined results of these measures is used to construct a single 7-point scale of *party identification*. This is the variable which is used to determine the amount of assortativity (state homophily) in the networks. Additionally, *ideology* is measured using a 7-point scale from "Very Liberal" to "Very Conservative". This latter question is not used in any of the analyses that appear in this dissertation, but will be used to describe the participant pool in the next chapter. Answers to both the party identity and ideology scales are not shared with other participants. However, answers to the remaining public opinion questions in this survey may be shared.

The opinion survey is 45 questions long, and broken down into 15 topic categories: the economy, terrorism, immigration, foreign policy, healthcare, gun policy, social security, international trade policy, education, race, abortion, the environment, LGBTQ matters, tax policy, and crime. These topics were chosen specifically because they were listed among the most important issues to American voters at least once in the previous year of public opinion polls when this study was being designed (Gallup, 2019; Pew Research Center, 2019). Each topic contains three questions: an A version, a B version, and an importance question. The importance question is phrased similarly for each topic: "How important is the following issue to you: **TOPIC**?", where "**TOPIC**" is replaced with the topic name listed above. Responses to this question range on a 7-point scale from "not at all important" to "very important" and are not shared with other participants. The A and B versions are public opinion questions which pertain to a specific problem or policy proposal in the corresponding topic. Specific problems or policy proposals were chosen in order to reduce nuance in the meaning of a response option. That is, participants reading the response options of others should have a clearer understanding of where that person stands on an issue than if the public opinion questions were more general in nature. Response options to these questions range on a standard 7-point Likert scale from "strongly disagree" to "strongly agree". See Table 1 for the complete list of questions.

In the discussion phase that follows, participants have their responses to one version of ten topic questions – the economy, immigration, gun policy, social security, international trade, race, abortion, LGBTQ matters, taxes, and crime – shared with

Table 1

Public Opinion Survey

Topic	Version	Question Text
1 - Economy	A	Reducing regulations on businesses is an effective way to address problems with the economy.
	B	The federal government should spend more on retraining programs to help people get jobs.
2 - Terrorism†	A	The U.S. should NOT invest time and resources hunting terrorist groups in other countries.
	B	The Islamic religion encourages violence more than other religions around the world.
3 - Immigration	A	The U.S. should deport all immigrants who are here illegally, regardless of their actions.
	B	The U.S. should create a path to citizenship for immigrants who are here illegally, but who are otherwise model citizens.
4 - Foreign Policy†	A	Sanctions and diplomacy are more effective than military actions.
	B	The U.S. should not have to contribute more financial resources than other countries to alliance networks like NATO.
5 - Healthcare†	A	The federal government should leave healthcare to the insurance companies.
	B	The healthcare system would be improved if the government used a single-payer system like in Europe or Canada.
6 - Gun Policy	A	The lax gun laws in this country contribute to the likelihood of mass shootings like Sandy Hook.
	B	Concealed-carry of guns makes the public safer.
7 - Social Security	A	Social security should be privatized.
	B	The federal government should spend more to ensure that social security is viable.
8 - International Trade	A	Free trade deals have been a GOOD thing for jobs in the U.S.
	B	Placing tariffs on goods from another country is an effective negotiating tactic.
9 - Education†	A	Parents should be given school vouchers so their kids can attend any school they want.
	B	The U.S. should provide free college tuition for low income students.
10 - Race	A	Police agencies should receive training to reduce racial discrimination.
	B	Affirmative action policies designed to increase the number of minorities at colleges or places of work should be abolished.
11 - Abortion	A	The federal government should not provide funding to agencies which conduct abortions, like Planned Parenthood.
	B	Employers should provide employees with healthcare plans that cover contraception or birth control at no cost.
12 - Environment†	A	The U.S. should invest in renewable sources of energy, like wind or solar.
	B	Climate change is NOT influenced by human actions.
13 - LGBTQ	A	Businesses should be allowed to refuse service to gay/lesbian couples on religious grounds.
	B	Laws which restrict which bathroom a transgender person can use are discriminatory.
14 - Taxes	A	The wealthiest people in this country do not currently pay their fair share in taxes.
	B	Corporate taxes should be reduced to help create jobs.
15 - Crime	A	Sentencing guidelines for routine drug offenses should be strictly enforced.
	B	Life imprisonment is a better punishment than the death penalty.

Note: †Topic was not discussed across all cohorts, regardless of parameter randomization.

their alters (i.e., discussion partners). The same ten topics are shared in every cohort, but the order and the version shared is randomized between cohorts. This helps ensure that any ordering effects in terms of the topic discussed are insignificant in aggregate. The other 5 topics (both versions; terrorism, foreign policy, healthcare, education, and the environment) and the unshared versions of the ten discussed topics are withheld for additional analyses, described in chapter 5.

Additional payments in this phase of $1.00 each occur after answers are provided to the 7th (social security) and 15th (crime) topics. Once all participants have either completed the opinion survey phase or have been dropped due to inactivity, all remaining participants will start the third phase of the study.

Phase 3: discussion rounds. The third phase is the longest and most complicated phase. This phase is also the only part of the study in which the two quasi-experimental conditions differ. In both conditions, there are ten "discussion rounds" in this phase – the specific number of rounds was chosen after examining the results of a prior agent-based modeling study I conducted which follows a similar design to determine when an equilibrium state had been reached by the agents in the model. The total number of discussion rounds is not shown to participants in order to mitigate any changes in behavior as the end of the discussion phase draws closer.

Prior to the start of the first round, participants are placed into an Erdős-Rényi (1959) random graph in which approximately 20% of the possible edges are realized (hereafter, "*random assignment*"). This randomization, and the relatively low initial network density, ensures that any assortativity exhibited in the network at this stage is purely to due to chance. Verification of the chance homophily levels at this random assignment stage will occur in chapters 5 (condition 1) and 6 (condition 2). If participants can transition from a network with random connections to one where the network structure definitively shows evidence of homophily, then the strategy that produces such a result can be said to be influential in the formation of dyadic relationships within that structure (see Lazarsfeld & Merton, 1954, p. 29).

At this point in the study, the left-hand side of participants' user interface shows several other nodes, each showing their alters' unique identifier, and lines connecting the participant's node to their alters'. Participants are informed of their own identifier, the quantity of alters they have, and each of their alters' identifiers to help familiarize them with the graph. Importantly, these graphs depict *only* their connections to their alters (i.e., their ego network) and not any other ties in the network – including ties between their alters. This ensures that participants do not have information about the social structure (e.g., shared alters) which might influence their tie decisions; this is a form of structural homophily.

At the beginning of each round, participants see an instruction at the top of the right-hand side of their screen indicating the current round's topic, as well as the question text for the randomly-selected version and a reminder of how they responded to the question. Below that, participants are shown a table containing all of their current alters' answers to the same question in the form of the Likert response (e.g., "somewhat agree"). If a participant does not currently have any network neighbors (i.e., they are a network isolate), they will see the instruction: "You do not have any social contacts to discuss the current topic with. Please press the 'Next' button below to proceed to the next step." Once each participant presses the "next" button to advance, they are asked to wait while the remaining participants finish reading the responses.

Next, 20% of all of the possible ties in the network, both currently active and inactive, are selected at random to update in the round. By constraining the amount of updates per round, the study limits the time it takes to complete the round, and – more importantly – the dynamics more closely mirror the “viscous” nature of real-world social relationships (Harrell, Melamed, & Simpson, 2018; Nishi, Shirado, & Christakis, 2015; Rand, Arbesman, & Christakis, 2011). The total number of updates in the round is calculated with the equation:

$$\frac{n * (n-1)}{2} * .20 \tag{1}$$

where n is the number of participants in the cohort at the start of the discussion phase. If a dyad is selected to update in a round, one participant in the dyad is selected at random to make a decision about the status of that tie. Each dyad may be selected up to twice in a given round. When the dyad is selected for the second time, the tie decision is automatically assigned to the participant who did not make the prior tie decision. When a participant is faced with a tie decision, they may see one of three different things, depending on the nature of the relationship. The instructions on the right-hand side are color-coded (purple for the participant, yellow for the discussion partner[18]) in coordination with the network graph on the left-hand side to help facilitate interpretation of the decision at hand. Additionally, the tie connecting the nodes on the graph becomes much thicker than the other ties and change color and line type to signify the current status of the relationship (solid black for active, dashed grey for inactive). Figure 2 shows an example of a tie decision.

If the tie selected is currently active, the participant is shown a table with two columns and a number of rows equal to the number of rounds for which the dyad had an active tie. Each row pertains to the topic(s) which the two participants have shared their opinion(s) on. In the first column, the participant are shown their discussion

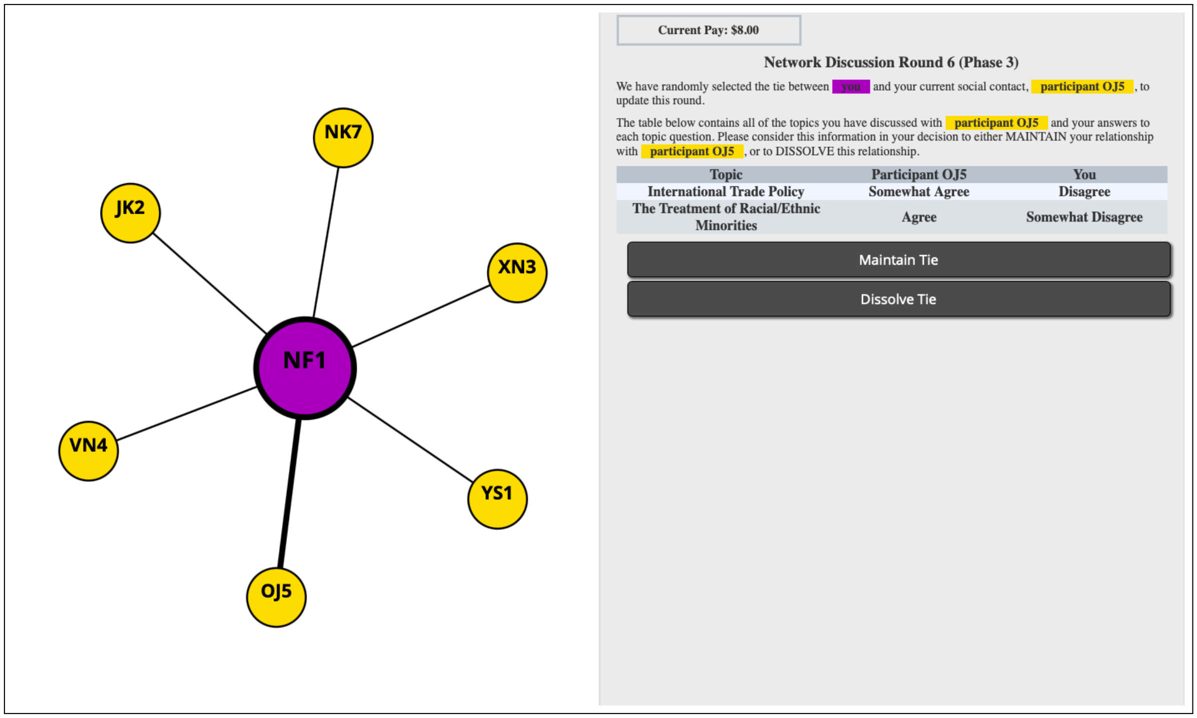

Figure 2. Example of the user interface on Breadboard during the discussion phase. The decision faced by participant NF1 concerns their *existing* relationship with participant OJ5.

partner's answers to each of those topics. In the second column, they are reminded about their own answers to the same set of questions. This table format was chosen so that every participant had a complete accounting of the discussion history in the dyad; that is, this study assumes that people have accurate and complete memory of prior discussion in order to reduce participant variability in the information used to make tie decisions. This decision is elaborated on in the discussion chapter at the end of this dissertation.

The selected participant will then be tasked with the decision to either *maintain* or *dissolve* the existing tie. The former will result in continued communication between the pair in subsequent rounds (i.e., an "associative" decision), while the latter will cease communication at least until the next time the dyad is randomly selected to update (i.e., a "disassociative" decision).

If the tie selected is currently inactive, but the two participants have shared their responses to at least one prior topic, the selected participant is shown a similar table. Each row corresponds to each of those previously discussed topics. Additionally, a new row is appended to the bottom of the table indicating the prospective alter's and the participant's opinions on the current round's topic. The selected participant faces a different decision between *add* or *ignore* the currently inactive tie. Selection of the former option results in the participant rekindling their discussion tie with the alter ("associative"), while the latter signifies continued non-communication ("disassociative").

Finally, if the tie selected is currently inactive and the two participants have not shared their responses on any previous topic, the participants are shown each other's responses to the current question. Whereas the instructions to the previous two circumstances omitted the question text to save space in the user interface, the instructions in this scenario will include the question text. This represents a kind of initial political interaction between the two participants. Like the prior scenario, the selected participant will choose between *adding* ("associative") and *ignoring* ("disassociative") the new tie with the prospective alter.

Importantly, all participants are given the instruction at the start of this phase: "At the end of the study, you will have the opportunity to join a chat room to discuss political matters in more detail with your social network. Your decisions about who you include in your social network will determine who you talk to directly at the end of the study. **Please consider other participants' political opinions as they are shared and try to make tie decisions as you would in real-life situations.**"

This instruction is intended to give participants a sense that their tie decisions are consequential. If participants don't want to talk to a particular person in the chat room, they should avoid a network tie with them. Conversely, if they would like to communicate directly with another participant in the chat room, they should foster a network tie with them. Importantly, while participants are instructed to consider the political opinions of others and to treat this information in a similar manner to how they would treat real-life political conversations, participants are *not* told what to do with this information (i.e., they are not told to be selective). Participants are also instructed that they may have as many or as few network ties as they prefer. The implications of these instructions will be discussed in the final chapter.

The graph on the left-hand side of the user interface updates instantly when a tie decision is made. If *maintain* or *add* are selected, the nodes revert to the standard yellow color and the tie becomes the same color and thickness as the ones connecting the participant to each of their other alters. If *dissolve* or *ignore* are selected, then the tie that was connecting the two nodes (including the temporary dashed grey one for currently inactive ties) disappears and the alter about whom the decision concerns is flung off the screen. This visual representation of the changes to the relationship status should help convey the consequences of participants' decisions.

At the end of each discussion round, participants are shown two synopsis screens. The first reminds them of all of their tie decisions in the round (e.g., "You maintained a relationship with AB1 and CD2"; one line each for maintain, dissolve, add, and ignore decisions). The second synopsis screen shows all of the decisions that other participants made about them (e.g., "FG3 ignored a potential relationship with you"). Once everyone has read the synopses, all participants earn \$1.00 and the next round begins. At the end of round 10, the demographic phase starts.

The description above pertains to the first quasi-experimental condition. The second condition is similar in all but one respect: the option to avoid discussion of a topic with particular alters. Prior to the part of this phase when participants are shown the questionnaire answers from each of their alters (at the beginning of each round), participants are shown the topic of discussion for the round. Then, they are asked with whom they would like to share their opinion on that topic. A list of all of their current alters is then displayed and a share/don't share response option is displayed for each alter – the default option for each is to share the opinion with all alters, meaning participants have to *actively* decide to avoid discussion of a topic with an alter. Once all disclosure decisions have been made, the remainder of the phase will proceed as it does in the first condition. Figure 3 shows an example of a disclosure decision.

If a participant drops out of the study due to inactivity at any point during the discussion phase or after, they are immediately replaced by an autonomous agent, or bot. The use of bots in human subjects designs on the Breadboard platform is not new (e.g., Shirado & Christakis, 2017). In this study, the purpose of replacing dropped participants is to maintain the same network size and rough structure in order to cause as little harm to the realism of the study as possible for the remaining participants. Whenever a bot replaces a participant, a line is written to the output indicating the exact time of this change and they are flagged for removal from the data. During the discussion phase, bots are programmed to make as few changes to the network structure as possible. Specifically, when a dyad containing a bot is selected to update in a round, and the bot is selected to make the tie decision, they will first defer to the other discussion partner to make a tie decision. Only in two circumstances will the bot not defer: when the alter is a participant and the alter has already made a decision concerning the status of the tie (i.e., no repeat decision-making in the same round), or

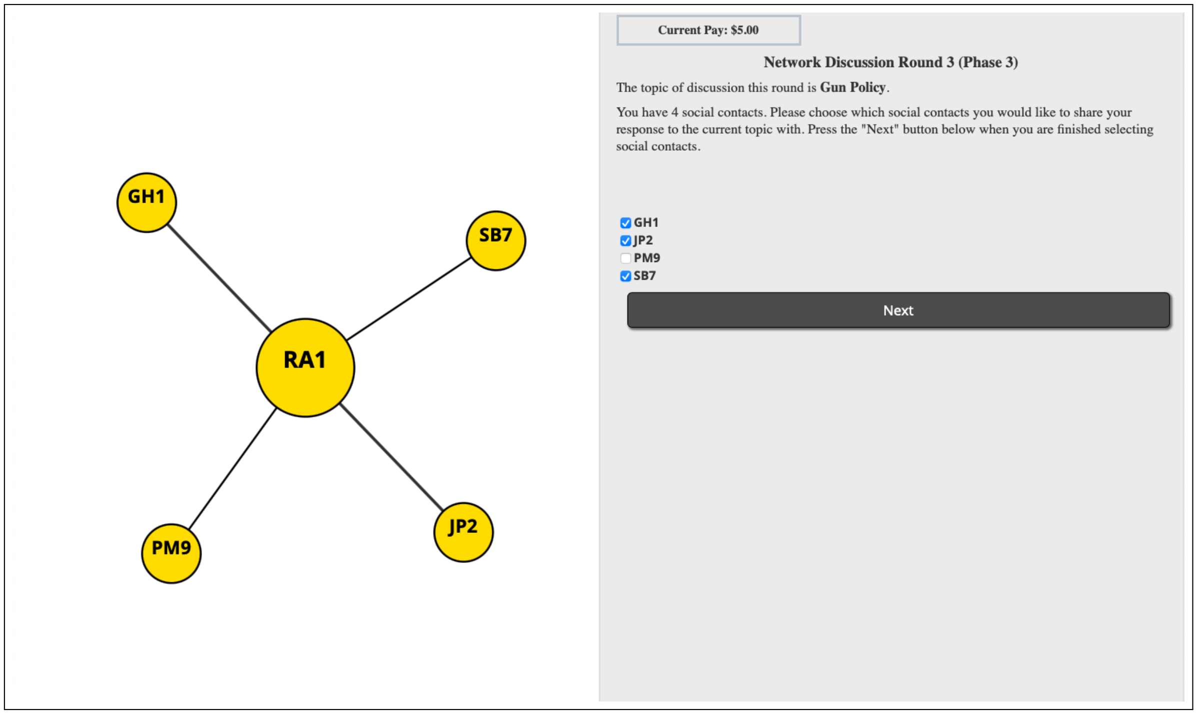

Figure 3. Example of the user interface on Breadboard during the discussion phase in condition 2. In this screenshot, participant RA1 has chosen to disclose their opinion on gun policy to participants GH1, JP2, and SB7. They chose to withhold their opinion on gun policy from participant PM9.

when the alter or prospective alter is also a bot. In both cases, bots are programmed to maintain the status quo. That is, if the tie currently exists, the bot will choose to *maintain* the tie. If the tie does not currently exist, the bot will choose to *ignore* the tie.

In the two remaining phases, bots will select response options randomly from a uniform distribution to maintain the realism of the study for other participants. In the chat phase, bots will select one of the two rooms randomly, but they will not participate in the chat on the separate website (described in more detail below). All bots and their associated data are removed from the analyses in later chapters, as many of the data points needed for analysis are missing.

Phase 4: demographic survey. The next phase contains a short demographic survey. At the start of this phase, the network structure is saved and all ties are temporarily removed. This serves to clear the left-hand side of the user interface and coincides with the instruction: "Your answers to questions in this phase will NOT be shared with other participants." This step is necessary, as it helps constrain response biases present if participants thought that their responses in this phase would not be kept private.

First, participants are asked four questions pertaining to their feelings about others (generally) who identify with a political party. The question phrasing will depend upon participants' answers to the first party identity question. The first two questions are: "Generally speaking, how to you feel about people who also identify as a(n) (Republican/Democrat/Independent)?" and "Generally speaking, how to you feel about people who do NOT identify as a(n) (Republican/Democrat/Independent)?". Response options to these questions range on a 7-point scale from "overwhelmingly negative" to "overwhelmingly positive". Together, these two questions are used to construct the measure of *affective polarization* by subtracting the latter out-group measure from the former in-group measure. Two additional out-group measures were taken: "Generally speaking, how to you feel about people who identify as a(n) (Republican/Democrat/Independent)?", and "Generally speaking, how to you feel about people who identify as a(n) (Republican/Democrat/Independent)?". These measures do not appear in any analyses in this dissertation.

The next set of questions ask about a participant's political experiences. The first question, "How often do your everyday social interactions include discussions of political issues?" uses a 5-point response from "never" to "always". The next block of questions follow the format "In the past four years, have you ____________" and response options are either “yes” or “no”. The blank is filled with the following political behaviors:

- Voted in a local election
- Voted in a national election
- Signed a petition
- Donated to a political campaign
- Attended a political rally
- Emailed, called, or sent a letter to a politician
- Displayed a political sign or bumper sticker
- Been a member of a political organization
- Worked on a political campaign
- Signed up for an email newsletter from a politician or political organization
- ‘Liked’ a politician or political organization on Facebook
- ‘Followed’ a politician or political organization on Twitter
- ‘Followed’ a politician or political organization on Instagram

‘Yes’ responses are coded as 1, ‘No’ responses as 0, and a summative index is created to indicate a participant’s *political participation*. Frequency of political discussion and democratic participation are presented in this dissertation to describe the participant pool, but they may be valuable controls or avenues for further investigation of subjective differences in selectivity in additional research using the data collected here.

The final questions gather demographic information about the participants. *Age* was reported with a text field that accepted integers ranging from 12 to 120.[19] Participants are then asked to report their *gender* using the response options “male”, “female”, “transgender or non-binary”, and “prefer not to say”. Their *race* and/or ethnicity is measured categorically with the following groups: “Asian”, “Black / African American / African”, “Latinx / Hispanic / Chicanx”, “Middle Eastern”, “Native American / First Nations / Aleut”, “Pacific Islander”, “White / European / Caucasian”, “Mixed-race”, “Other”, and “Prefer not to say”. Highest level of *education* is measured on an 8-point ordinal scale ranging from “Less than a high school education” to “Doctoral degree”, along with a ninth option for “prefer not to say”. Annual household *income* is also measured ordinally on an 8-point scale from “Less than $20,000” to “$200,000 or more”, along with an additional response option for “prefer not to say”. Participants earn $1.00 at the completion of the demographic survey phase.

Phase 5: chat room. The final phase of the study is the chat room phase. Recall that participants are instructed at the start of the discussion phase that their tie decisions would affect who they would speak to in the chat room phase. This instruction is included in order to convey to participants that their tie decisions are consequential and that they ought to treat these tie decisions in the online study as they would treat real-world interactions around politics. However, because of technical limitations, it is all but impossible to construct a chat room in which the full network structure is represented. I therefore settled on an alternate plan which involves another instance of participant selection.

The study has two chat rooms, named the “green room” and the “orange room.”[20] At this point, the network structure which was saved at the start of the demographic survey phase is reinstated. Participants are then asked to choose between the green and orange rooms. Once every participant has made a selection, all of the nodes in the participants’ graphs change color to reflect their chat room decision. Participants can then decide whether they would like to keep their chat room selection, or switch to the other chat room. This decision to either maintain or swap rooms is important because it will likely be affected by the room choices of their alters. Once all participants have made a selection, they are shown a link to either the green or the orange room (see Figure 4).[21] At this point, the 60-second timer is turned off for all participants. The chat rooms open in a separate browser window. After 60 seconds, the Breadboard user interface changes to show the “submit HIT” screen, allowing MTurk workers to be paid for their participation and provide comments to the administrator. Participants may continue to discuss with each other in the chat room while this change is made to the Breadboard window in the background.

The chat rooms, for both technical and security purposes, are both hosted on a WordPress website on a separate Ohio State Arts and Sciences server. Both webpages use a WordPress plugin called “Wise Chat” (Kainex Web Solutions, 2019). The plugin requires users to input their participant identifier (displayed prominently on the last instruction screen on the Breadboard website), which is used to validate participation in the final phase and matched with the MTurk Worker ID provided in the Breadboard interface to send payment for the chat phase ($1.00). Critically, participants are instructed that they must enter the identifier correctly to receive credit for participating in this phase. The input field is capped at 3 characters to limit deviations from this instruction. The recorded content of this chat room phase is beyond the scope of this dissertation.

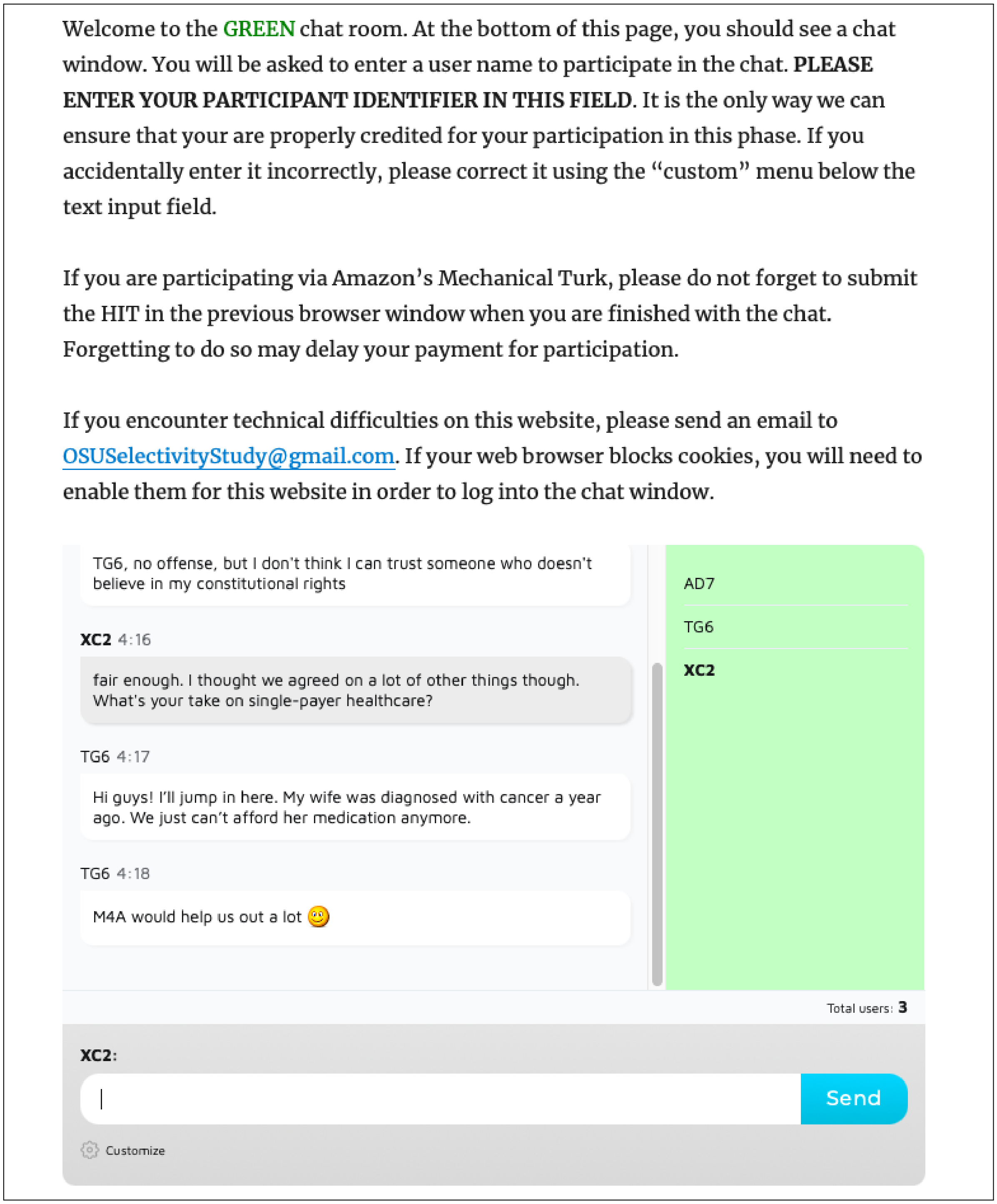

Figure 4. Example of the Wise Chat user interface. Note: discussion was simulated and does not represent collected data.

Chapter 4: Participant and Network Characteristics

Amazon's Mechanical Turk (MTurk) subject pool was used to recruit all participants for this study. Because Breadboard (McKnight & Christakis, 2019) has built-in support for the MTurk subject pool, the overwhelming majority of published studies using the Breadboard platform use participants from MTurk (e.g., Rand, Nowak, Fowler, & Christakis, 2014; Rand et al., 2011; Shirado & Christakis, 2017). MTurk is a high-quality participant pool for human behavior experiments; replications of experiments using MTurk participants are reliable, and in general the reported demographics of participants are reliable across studies as well (Rand, 2012).

All participants were required to be 18 years or older and reside within the United States in order to be eligible to participate. These stipulations help ensure that participants are at least somewhat familiar with American politics, as some of the public opinion questions pertain to uniquely American political issues. Data were collected during and immediately following lock downs for the COVID-19 pandemic in late 2020 and early 2021. Additionally, data were collected following the 2020 U.S. Presidential election. This was a particularly contentious election in U.S. political history, and most data (but not all) were collected in the aftermath of the deadly events of January 6th, in which a group of protesters violently attempted to stop the certification of the election results in the U.S. Capitol building. I will discuss some potential implications that these factors have for the findings and the need for replication of this study in a different political climate in the final chapter.[22]

Each iteration of the study (cohort) was conducted between the hours of 10:00am and 10:00pm Eastern time and spread out throughout both weekdays and weekends in order to recruit a diverse participant pool. In total, 29 cohorts were collected – 14 for condition 1 and 15 for condition 2. However, in two of the condition 1 cohorts and 3 of the condition 2 cohorts, fewer than 10 participants remained at the end of the network phase. As this meant that a much larger proportion of participants in the network phase were bots – and their directive of always maintaining the status quo meant that very few changes were made in each round, and perhaps the tie decisions of remaining participants were affected – I elected to remove these five cohorts from the study, leaving 12 cohorts in each condition.

In the pages that follow, each cohort is identified with a number indicating the condition and a capital letter "A" through "L". "A" in both conditions (cohorts 1A and 2A) was reserved for both cohorts which exceeded the promised 60 minute study length so those results can be compared separately from the remaining cohorts. Alphabetically starting with B, each cohort was then ordered from high to low by the number of participants that remained after bots were removed from the data.

The target cohort size when recruiting participants was approximately 15 after accounting for dropped participants. Both data collection and computing time for the analyses increase exponentially with larger group sizes, so cohorts were required to be relatively small. This target cohort size is roughly in-line with prior experiments on the Breadboard platform. For example, Rand et al. (2011) used cohorts with an average of 19.63 participants. Likewise, Shirado, Fu, Fowler, and Christakis (2013) gathered cohorts with an average size of 16.99 participants. In total, $n = 441$ subjects participated in these 24 cohorts; $n = 75$ participants were dropped from the study at some point before the chat room selection, and so they were removed from analysis leaving $n = 366$ participants across all cohorts (Condition 1 $n = 192$; Condition 2 $n = 174$). Average cohort size was $M = 15.25$ participants ($SD = 3.11$). Importantly, cohort size did not differ significantly between condition 1 ($M = 16.00$, $SD = 3.10$) and condition 2 (M = 14.50, SD = 3.06; $t(22) = 1.19$, $p = .25$).

Demographics

Participants in this study ranged in age from 19 to 65 (M = 34.10, SD = 9.24; Condition 1 M = 34.68, SD = 9.25; Condition 2 M = 33.45, SD = 9.10). 60.38% of participants identify as male, 39.34% female, and 0.27% as transgender / non-binary. Participants' racial identity broke down as follows: 14.48% Asian, 7.65% Black / African American / African, 9.56% Latinx / Hispanic / Chicanx, 0.27% Middle Eastern, 4.10% Native American / First Nations / Aleut, 59.84% White / European / Caucasian, 3.55% multiracial, 0.27% other, and 0.27% preferred not to say. No participants identified as Pacific Islander.

When asked about their highest completed education, no participants said that they had not completed high school, 5.74% had a high school diploma or GED, 11.20% had some college or professional training but no degree, 10.38% had completed a two-year college degree, 47.27% had completed a four-year college degree, 5.19% have attained some post-graduate education without a degree, 19.40% held a Master's degree, 0.27% held a PhD, and 0.55% preferred not to say. In terms of annual household income, 19.40% make less than $20,000 per year, 24.04% between $20,000 and $39,999 per year, 25.96% between $40,000 and $59,999 per year, 14.75% between $60,000 and $79,999 per year, 7.92% between $80,000 and $99,999 per year, 5.19% between $100,000 and $149,999 per year, 2.19% between $150,000 and $199,999 per year, and 0.55% make $200,000 or more per year.

Party identity was measured using a two-part survey question. The first asked participants whether they think of themselves as a Republican, a Democrat, or an Independent. A follow-up question asked Democrats and Republicans whether they consider themselves a strong or not very strong Democrat/Republican. Independents were asked whether they considered themselves closer to the Republican party, the Democratic party, or neither. These answers were combined to form a 7-point scale: strong Democrat (1), not strong Democrat (2), independent lean Democrat (3), independent neither (4), independent lean Republican (5), not strong Republican (6), strong republican (7). Overall, participants tended to lean closer to the Democratic party (M = 3.25, SD = 2.27; Condition 1 M = 3.40, SD = 2.30; Condition 2 M = 3.08, SD = 2.24). *Political ideology* was measured on a single 7-point scale ranging from strong liberal (1) to strong conservative (7). Participants also tended to lean more on the liberal side of the scale (M = 3.56, SD = 1.95; Condition 1 M = 3.52, SD = 1.97; Condition 2 M = 3.61, SD = 1.93). The skewed nature of both measures of political leanings are not surprising given previous findings regarding the political makeup of MTurk samples (Huff & Tingley, 2015; Levay, Freese, & Druckman, 2016), although the standard deviations indicate that at least some political diversity can be encountered. That said, this dynamic does mean that the availability component of structural homophily may be operating to some extent even at the random assignment at the start of the discussion phase. Analyses relating to homophily expected by chance (H2 and RQ3; presented in chapters 5 and 6 respecively) take this distribution into account. *Party identity* is used in all of the analyses that follow regarding network assortativity.[23]

Participants were asked to rate on a 5-point scale from never (1) to always (5) how frequently their everyday social interactions include discussions of political issues. *Political discussion* was a somewhat frequent occurrence for individuals (M = 3.49, SD = 1.00). Political participation was measured by asking a variety of yes or no questions about recent political behaviors. Over the last 4 years, 94.81% of participants have voted in a local election, 95.63% have voted in a national election, 52.73% have signed a petition, 36.61% have donated money to a political campaign or organization, 42.35% have attended a political rally or speech, 37.98% have contacted a politician, 37.16% have displayed a political sign or bumper sticker, 33.61% were members of a political organization, 27.60% have worked or volunteered for a political campaign or cause, 40.98% have signed up to receive a newsletter from a politician or political organization, 71.04% have "liked" a politician or political organization on Facebook, 68.85% have "followed" a politician or political organization on Twitter, and 68.85% have "followed" a politician or political organization on Instagram. A summative index of *participation* was then created by adding up the number of items a participant had completed in the last 4 years (range 0 to 13); overall, participants are somewhat active in politics, but the measure was quite varied (M = 7.08, SD = 3.60).

Finally, to measure *affective polarization*, a somewhat novel approach is employed. Affective polarization has been primarily operationalized in previous studies using three methods, all of which compare feelings thermometer ratings of two groups. Iyengar et al. (2012) used both a comparison of "Democrat/Republican" ratings and "liberal/conservative" ratings. Hutchens et al. (2019), on the other hand, compared evaluations of the two major party candidates: in the 2012 study between Barack Obama and Mitt Romney, and in the 2016 study between Hillary Clinton and Donald Trump. Critically, all three of these operationalizations exclude one important group which was part of the sample included in this dissertation: political independents. For both Democrat and Republican participants, political independents are an out-group. Likewise, for political independents, constituents of both parties (Democrats and Republicans) are out-group members. Recall that the hypothesis which relies on this measure (H6) states that individuals that are highly affectively polarized are more selective compared to less affectively polarized individuals.

A recent study by Klar, Krupnikov, and Ryan (2018) found that weak and leaning partisans typically opt out of political discussion, regardless of the party identification of the discussion partner. Their argument is that this phenomenon should be classified as a distaste for partisanship more broadly construed, rather than as affective polarization per se, because the avoidance of discussion signifies low evaluations of both in-group and out-group members. Consistent with partisan operationalizations of affective polarization (e.g., Iyengar et al., 2012), feelings thermometer ratings of both in-group (independents) and out-group (partisans) should both be low in this case, and thus there should be little difference between evaluations (i.e., low affective polarization). That independents avoid all discussion of politics suggests this avoidance occurs regardless of the level of similarity they may have with their discussion partner (i.e., low selectivity). If, on the other hand, affording independents the opportunity to rate in-group feelings toward independents provides a more accurate representation of the political identity of being independent (e.g., Klar, 2014) and they demonstrate in-group preferences akin to partisans (i.e., high affective polarization), then it stands to reason that they might demonstrate some selective preferences when it comes to discussion ties. It may be the case that both descriptions of the way that independents feel about in- and out-group members are true – some people may feel ambivalent, while others may feel affectively polarized. In either case, the conclusion regarding independents' selectivity is consistent with H6, and so independents are integrated into this test along with Democratic and Republican participants.

This requires a slight modification of Iyengar's (2012) party identity approach to measuring *affective polarization*. Rather than asking Democrats to rate Republicans and vice versa, I instead chose to ask both partisan groups to rate both "people who also identify as a (Democrat/Republican)" and "people who do NOT identify as a (Democrat/Republican)." Using this approach for independents, the in-group measure asks them to rate other independents and the out-group measure asks them to rate non-independents (i.e., partisans). Thus, by subtracting the out-group measure (M = 4.03, SD = 1.46) from the in-group measure (M = 5.93, SD = 0.81), one can arrive at a single measure of *affective polarization* that works for both independents and partisans (M = 1.90, SD = 1.71). Importantly, while Democrats (M = 1.96, SD = 1.78) and Republicans (M = 2.08, SD = 1.63) had higher average *affective polarization* scores than the average independent (M = 1.61, SD = 1.61), a one-way ANOVA revealed that these differences were not significant ($F(2, 11) = 1.89$, $p = .15$). This suggests that the latter interpretation of political independents as a political identity separate from partisan groups, but with in-group preferences akin to partisans likely describes the average independent participant in this study.

Public Opinion Questionnaire

All participants provided answers to 30 public opinion questions and 15 issue importance questions regarding 15 different topics. The descriptive statistics for these questions are provided in Table 2. For question text, refer back to Table 1. Interestingly, the most divisive issues (i.e., largest standard deviation) are the statements "Businesses should be allowed to refuse service to gay/lesbian couples on religious grounds." and "The federal government should leave healthcare to the insurance companies." The latter issue in particular is surprising, given that the study was conducted during a world-wide pandemic in which the U.S. government was offering free vaccinations. Healthcare was not one of the ten discussed topics in the discussion phase, however.

Participants rated Healthcare as the most important issue (m = 6.57, sd =

Table 2

Public Opinion Survey - Descriptive Statistics

		Overall		Condition 1		Condition 2	
Topic	Version	*M*	*SD*	*M*	*SD*	*M*	*SD*
1 - Economy	A	4.73	1.81	4.56	1.88	4.93	1.75
	B	5.77	1.23	5.76	1.34	5.77	1.19
2 - Terrorism†	A	4.29	1.80	4.18	1.86	4.41	1.74
	B	4.43	1.95	4.20	1.97	4.68	1.91
3 - Immigration	A	4.11	2.22	4.08	2.30	4.14	2.14
	B	5.54	1.48	5.59	1.48	5.49	1.49
4 - Foreign Policy†	A	5.54	1.32	5.56	1.38	5.52	1.27
	B	4.79	1.74	4.74	1.75	4.84	1.73
5 - Healthcare†	A	3.99	2.30	3.74	2.32	4.25	2.25
	B	5.72	1.47	5.80	1.41	5.63	1.53
6 - Gun Policy	A	5.25	1.80	5.18	1.86	5.32	1.74
	B	4.10	2.02	4.07	2.02	4.13	2.03
7 - Social Security	A	4.11	2.22	3.89	2.26	4.36	2.16
	B	5.95	1.17	5.93	1.16	5.97	1.18
8 - International Trade	A	5.43	1.35	5.32	1.45	5.56	1.22
	B	5.08	1.57	5.05	1.62	5.11	1.52
9 - Education†	A	5.31	1.71	5.14	1.77	5.49	1.63
	B	5.92	1.43	5.96	1.51	5.89	1.34
10 - Race	A	6.17	1.25	6.06	1.37	6.29	1.10
	B	4.48	2.09	4.47	2.16	4.49	2.03
11 - Abortion	A	4.28	2.19	4.20	2.25	4.36	2.12
	B	5.39	1.74	5.26	1.87	5.53	1.58
12 - Environment†	A	6.40	0.89	6.36	1.03	6.43	0.71
	B	3.16	2.26	3.14	2.27	3.19	2.26
13 - LGBTQ	A	3.74	2.38	3.68	2.38	3.80	2.38
	B	5.20	1.73	5.24	1.75	5.16	1.72
14 - Taxes	A	5.72	1.55	5.70	1.63	5.75	1.46
	B	4.63	2.04	4.46	2.09	4.82	1.97
15 - Crime	A	4.98	1.90	4.82	2.03	5.16	1.74
	B	5.46	1.50	5.53	1.51	5.40	1.49

Note: $n = 366$ (192 condition 1; 174 condition 2). †Topic was not discussed across all cohorts, regardless of parameter randomization.

0.79), followed by Education (m = 6.46, sd = 0.91), the Environment (m = 6.39, sd = 0.94), the Economy (m = 6.33, sd = 0.88), Social Security (m = 6.10, sd = 1.09), Taxes (m = 6.08, sd = 0.97), Race (m = 6.05, sd = 1.21), Crime (m = 5.91, sd = 1.17), Gun Policy (m = 5.79, sd = 1.31), Immigration (m = 5.77, sd = 1.22), Foreign Policy (m = 5.73, sd = 1.17), International Trade (m = 5.67, sd = 1.30), LGBTQ matters (m = 5.60, sd = 1.50), Abortion (m = 5.45, sd = 1.63), and Terrorism (m = 5.11, sd = 1.83). That social issues, like access to abortion and LGBTQ matters, are rated consistently below domestic services, like healthcare and the economy, during a global pandemic and subsequent economic recovery is not surprising.

Discussion Networks

The social network data provided by the Breadboard study include eleven points in time for each cohort (total of 264 networks) – one network for the random assignment at the beginning of the discussion phase, and one network at the conclusion of each of the ten discussion rounds. Ties in these networks represent a political discussion relationship between two participants; the status of these ties (present or absent at the end of the round) are governed in part by the tie decisions described in the previous chapter. Recall that associative tie decisions made in a round result in the tie obtaining in the network, while disassociative tie decisions result in that tie being absent in the network. With the exception of tests regarding Hypotheses 7 and 8 (described in chapter 6), all analyses described in the following pages will utilize these networks.

Importantly, these networks are undirected in principle, meaning that all dyadic relationships are reciprocated – if participant MG8 discusses politics with HL3, then HL3 also discusses politics with MG8. However, because certain tests described in the following two chapters rely on covariates which are inherently directed (asymmetrical;

e.g., MG8 discloses their opinion to HL3, but HL3 does not disclose their opinion to MG8), these networks had to be constructed as symmetric directed networks in order to conduct the necessary analysis. This difference should have little bearing on the results, as every tie in the directed version is always reciprocated just as in the undirected version.

Graphs of each of these networks across time are provided in Appendix A. Vertices (circles) in these graphs represent each participant in the cohort and their color (shades of blue, white, and red) correspond to the participant's party identity on the 7-point scale described above. Gray lines connecting two vertices together indicate that the two participants share a tie in the political discussion network in the corresponding round. If participants were to form assortative networks, this would be evidenced in network graphs by an increasing separation between blue and red vertices. That separation would indicate that, for example, Republican participants are choosing the associative tie decision with greater frequency among other Republican alters compared to independent and Democratic participants.

Figure 5 depicts the assortativity (or Pearson's correlation among connected dyads) of party identity over time for each of the 24 cohorts as well as the condition averages. The y-axis is to be interpreted as a correlation coefficient; 1 would mean only connections between exactly similar alters are present, -1 would mean that only connections between dissimilar alters are present, and 0 represents no political party similarity among connected pairs. As shown in the graph, all 24 cohorts tended to measure somewhere between -0.2 and 0.2 on this scale. This indicates that there is little if any tendency for connections between like-partisans to form more frequently in the network compared to dissimiliar-partisans. If any one of these networks were collected in an observational study and assortativity (a measure of state homophily) was used to determine whether selection (process) homophily generated the network, one might conclude that selection on party identity did not occur. I will return to the assortativity metric in tests of H2, RQ2, and RQ3.

A possible explanation for this non-finding could be that participants simply preferred interaction of any kind with others in the cohort. That is, people may generally prefer to make the associative tie decision with greater frequency than the disassociative tie decision. This could be for a number of different reasons; I will return to this in the final chapter of this dissertation. One way that this associative preference could be evidenced is with the density network statistic. This statistic returns the proportion of all possible ties ($\frac{n*(n-1)}{2}$) which are present in the network. If participants make the associative tie choice with greater frequency, then this statistic should steadily increase over time. Figure 6 shows how the density statistic changes over time with each cohort, as well as the condition averages.

As expected, network density does increase considerably over time in all cohorts, indicating that participants broadly preferred to make associative tie decisions with greater frequency than disassociative decisions. That said, the rate of increase in these trend lines does begin to lessen after rounds 3 or 4. This indicates that there is a theoretical limit to associative attachment below a density of 1 (every participant is connected to every other participant), and that leaves room for some disassociative decisions resulting from selectivity to occur. While network-level assortativity may be obfuscated by increased network density, generative dyad-level selectivity may yet be identifiable, particularly if participants' desire to have a lot of ties can be controlled for.

Analytic Strategy

The first quasi-experimental condition is, in my view, a clean representation of selection in a dynamic, information-constrained environment. The second condition,

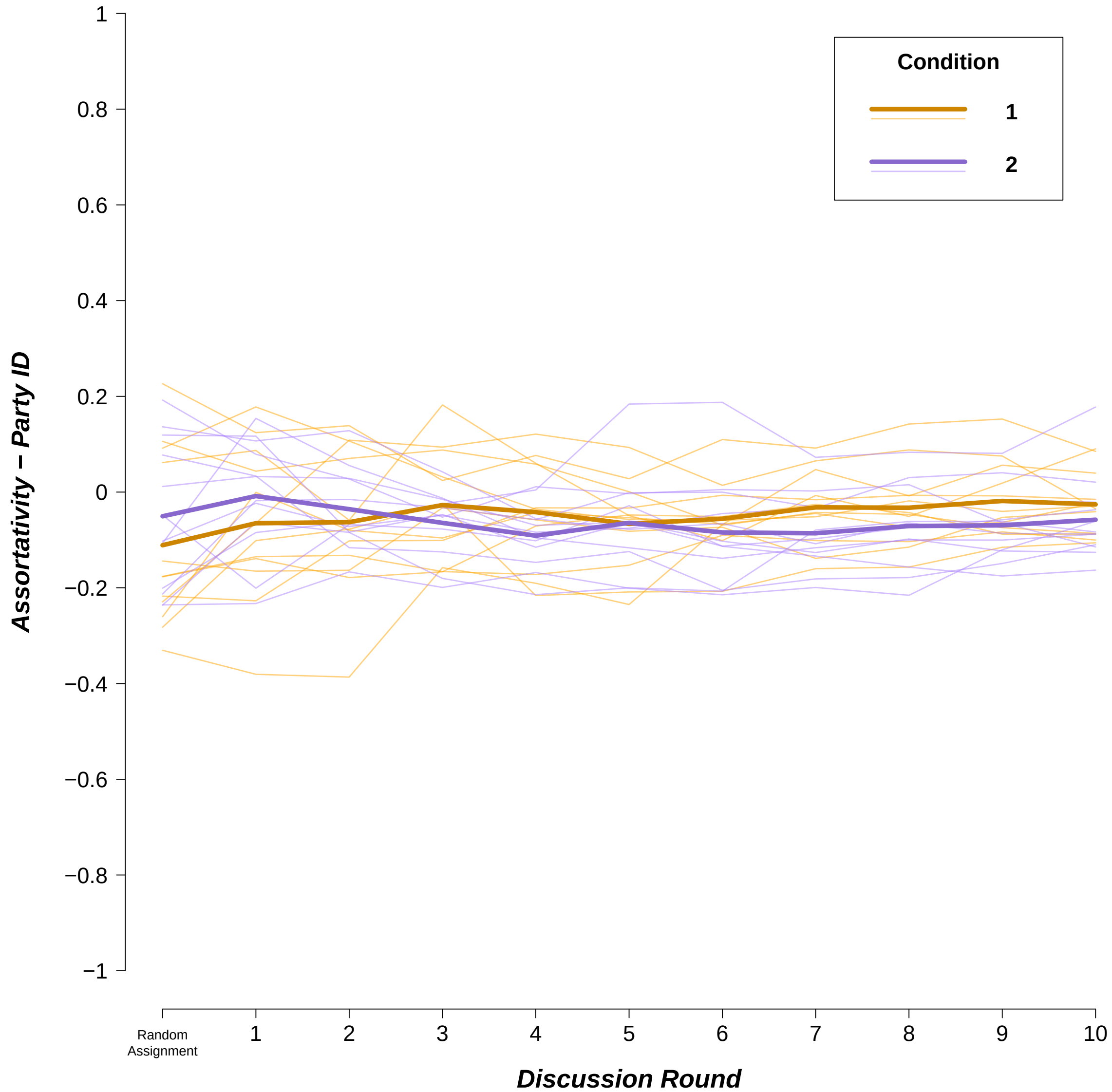

Figure 5. Assortativity (Pearson's correlation of among connected dyads) of participants' party identity of each network from random assignment through round 10. Line colors represent the condition a cohort was assigned to. Thin lines represent each individual cohort, while thick lines represent the average of all twelve cohorts in each condition.

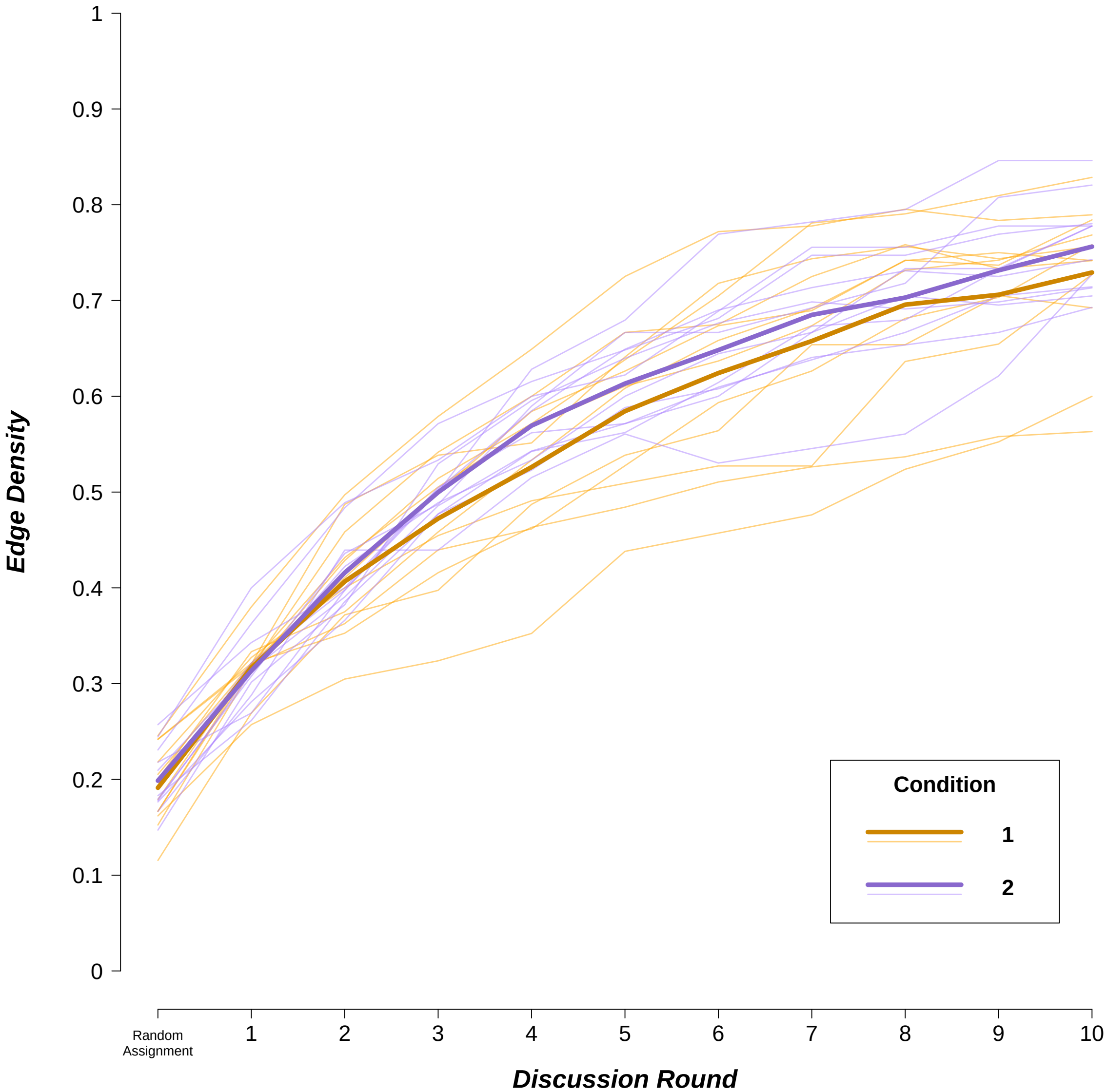

Figure 6. Density (proportion of all possible ties which are present) of each network from random assignment through round 10. Line colors represent the condition a cohort was assigned to. Thin lines represent each individual cohort, while thick lines represent the average of all twelve cohorts in each condition.

which adds the decision to express or withhold one's opinions on a topic, adds a theoretically-relevant process. However, the second condition, in my view, also fundamentally changes the information one may use to inform their tie decisions. As such, I will separate data from these two conditions for most analyses: Hypotheses 1 through 6 and research questions 1 and 2 are addressed using data from condition 1 cohorts. Hypotheses 7 and 8, as well as research question 3, are addressed by data from condition 2 cohorts. Finally, hypothesis 9 is addressed by comparing results of similar tests from condition 2 against those of condition 1. This last analysis is thus the only one which benefits from the quasi-experimental design – otherwise, these conditions could be treated as separate studies. The analyses of these networks all take place at the cohort-level; I do not present an aggregate analysis of all of the iterations of the study combined, but instead display the results of each cohort together. This is a common means of reporting the results of network experiments in which many distinct cohorts were collected (e.g., Nishi et al., 2015; Rand et al., 2011, 2014; Shirado et al., 2013; Shirado & Christakis, 2017; Song, 2015), as many of the inference methods used in social network analysis measure the effects of features which are endogenous to each network being studied (Cranmer, Desmarais, & Morgan, 2020). Those network-endogenous generative processes tend not to translate well between models of different networks, particularly when they are of different scales or if some omitted variable is generative in one network but not another (Duxbury, 2021). While some meta-analytic techniques exist for combining results across networks (see for example, Song, 2015), I am hesitant to use them for this dissertation as I am uncertain that such techniques are appropriate for this data.

The majority of the hypothesis tests presented in the following two chapters rely on a network analytic modeling procedure called Bootstrapped Temporal Exponential

Random Graph Models, or "BTERGMs" (Leifeld, Cranmer, & Desmarais, 2018). This was accomplished using the *btergm* package in the R statistical software (Leifeld, Cranmer, & Desmarais, 2019). BTERGMs are a member of the exponential random graph family of statistical models used for inference. This family of methods involves comparison of an observed network's structure against the space of possible alternate network structures by generating many random graphs. The observed tie structure is treated as the dependent variable, and a variety of parameters including endogenous network characteristics (e.g., transitivity), directed or undirected edge values, and node-level attributes are used to explain this structure. Like more conventional inferential models, such as linear regression, BTERGMS are susceptible to omitted variable biases, and causal claims depend largely on the underlying theory being tested and the temporal ordering of variable measurement in the study design (i.e., cause precedes effect). In the exponential random graph models presented here, omitted variable biases are unlikely as tie decisions were made in heavily constrained information environments – participants did not have access to the network structure beyond their own ego network, nor did they know other characteristics of their alters beyond political opinions. Hypotheses which make causal claims, such as H1 predicting the opinion differences in the current round would predict the tie decision reached in that round, are supported by the temporal ordering of the study design – in this example, opinions on the current topic are shared prior to each tie decision. Unlike more conventional statistical models, ERGM family techniques can account for the interdependence of observations in networked data (Cranmer & Desmarais, 2011). An additional procedure, described below, can be conducted which will help determine if the data violate the independent and identically distributed (IID) assumptions of methods like regression.

The estimates produced by ERGM models represent the log odds of a tie obtaining in the observed network given a one-unit increase in the modeled statistic. There are two characteristics of a BTERGM that set this technique apart from a standard exponential random graph model. The "B" in BTERGM means that the parameter estimates are bootstrapped to produce 95% confidence intervals of the estimates – should this interval exclude zero, the parameter is a significant generative process of the network. This also allows for simple comparison of the generative roles of a parameter across models – if the estimates in one network lie outside the bounded confidence intervals of the same estimate in another network, the generative role of that parameter is significantly different between cohorts. For this dissertation, 10,000 bootstraps were used in each model so that estimates are more accurate. The "T" in BTERGM means that the model can assess changes in the observed network's structure over time. In the analyses to follow, I include an edge memory covariate which conditions the results on the status of the tie in the previous round. This helps account for the fact that 80% of the edges are not updated in a given round, and instead turns the focus toward the tie decisions of participants (i.e., which processes produce *changes* in the tie structure from round to round).

The parameters used in each model are kept consistent within each hypothesis test across all cohorts in the condition being tested. This ensures that the results are generally comparable between cohorts. Likewise, except where hypotheses call for respecification of a key parameter, the variables are kept constant between different hypothesis tests to allow for better comparison of the effects of that respecification. The controls used in each model are as follows: For each BTERGM which uses the political discussion network as the dependent structure (all but hypotheses 7 and 8), whether the opinion was disclosed in a given round was included to account for the fact that some dyads have no measured opinion differences because they have not had a discussion tie. In models where opinion differences are averaged over multiple rounds, this control is also measured temporally as the number of topics discussed in the dyad. I also included a term in each model called "two-stars" which adds a network statistic for each two-edge triad in the network (e.g., i has a tie with both j and k). This helps account for local edge density resulting from subjective differences in ego network size preferences (i.e., sociality; see Figure 6). Each model also includes an "edges" term, which is the ERGM equivalent of an intercept in regression.

Another network analytic technique used in this dissertation for tests of hypothesis 2 and research questions 2 and 3 is a conditional uniform graph (CUG) test (Butts, 2008). This method is a three step technique for assessing the significance of some network-level statistic relative to chance. First, one creates many random networks which all have a similar characteristic or set of characteristics to the observed network. In these tests, I created 1,000 networks for each of the cohorts at the conclusion of each discussion round, or 10,000 randomly-generated networks for each cohort. Each randomly-generated network contained the same number of nodes, the same number of edges (i.e., accounting for sociality), and the same distribution of the 7-point political party identity scale (i.e., accounting for the availability component of structural homophily) as the observed network which it tests. Next, one measures some descriptive network-level statistic in each of the randomly-generated networks; in tests of H2, RQ2, and RQ3, I used assortativity of the party identity measure. Finally, one compares the statistic measured in the observed network against the distribution of that same statistic in the randomly generated networks. In this way, the proportion of randomly-generated networks which have higher or lower values of the measured statistic compared to the observed network acts as a pseudo one-tailed p-value indicating the significance of the observed levels of that statistic relative to what would be expected by chance.

This same procedure can also be used to determine whether networked data violate IID assumptions of conventional approaches to inference, in which case a network-analytic inference model such as BTERGMs is required. In this application, a single characteristic of the observed network is needed to form the randomly-generated networks – I elected to use edge density following the descriptive finding that all observed networks demonstrated increasing sociality over time.[24] For the comparison statistic, I used transitivity, or the proportion of all two-edge triads (e.g., $i \leftrightarrow j \leftrightarrow k$) for which the third edge is also present (e.g., $i \leftrightarrow k$). This statistic is an important characteristic, as it both demonstrates the interdependence of participant observations, and it is frequently found to occur in homophilous networks as triadic balance describes clusters of similar alters (Heider, 1958, 1979; McPherson et al., 2001). Appendix B contains a selection of the test results. Figures presented there depict the pseudo null distribution of the transitivity statistic compared to the same statistic in the observed network. Considering that every cohort across both conditions had at least one round in which the transitivity of the network significantly differed from chance, a network analytic approach to hypothesis testing is warranted.

Chapter 5: Condition 1 Results

Hypothesis 1

The core hypothesis addressed in this dissertation is H1, that participants are more likely to make associative tie decision regarding politically similar alters. Because this design eliminates influence processes and limits the information one has about their discussion partners to expressly political characteristics, one need only to test whether similarity of expressed opinions is a generative feature of the network. To this end, I have estimated a bootstrapped temporal exponential random graph model (or BTERGM, Leifeld et al., 2018) on the observed condition 1 networks using the *btergm* package in R (Leifeld et al., 2019). This test is able to assess the generative role of specified parameters in the network using many simulated networks, conditioning on the status of the tie at time $t - 1$.

The key parameter in this test is the absolute difference of opinion scores for the corresponding round – a negative coefficient is expected, indicating that larger differences of opinion reduce the likelihood of a tie being present in the dyad. Opinion differences are parameterized as a list of matrices, one for each discussion round (random assignment is excluded), containing the edge-wise absolute difference for the current round. Included in the model is a similar list of edge covariate matrices indicated whether (1) or not (0) the topic is discussed in the dyad. Recall in condition 1 that all opinions in the current round are shared with one's alters from the network produced at the end of the previous round. The addition of this control helps account for the fact that disconnected dyads which also are not selected to update in the current round do not share their opinions, and thus won't have a difference score to affect the status of the tie at the end of the round.

Also included in the model specification is an edge memory parameter to

Table 3

BTERGM Results - Hypothesis 1

Parameter	Cohort 1A	Cohort 1B	Cohort 1C	Cohort 1D	Cohort 1E	Cohort 1F
Opinion Difference	−0.010 [−0.050, 0.028]	−0.040* [−0.067, −0.012]	−0.006 [−0.022, 0.015]	−0.004 [−0.019, 0.014]	−0.045* [−0.070, −0.028]	−0.032* [−0.059, −0.010]
Disclosed Opinion	53.90* [53.77, 54.04]	54.20* [54.05, 54.37]	54.05* [53.96, 54.14]	54.09* [53.96, 54.23]	54.20* [54.02, 54.43]	54.11* [53.97, 54.26]
2-stars	0.054* [0.037, 0.068]	0.031* [0.019, 0.038]	0.036* [0.028, 0.047]	0.043* [0.032, 0.052]	0.039* [0.030, 0.047]	0.058* [0.043, 0.075]
Edge $\text{Memory}_{(1)}$	0.25* [0.20, 0.30]	0.38* [0.33, 0.44]	0.28* [0.26, 0.31]	0.33* [0.28, 0.38]	0.39* [0.32, 0.47]	0.31* [0.23, 0.39]
Edges	−27.18* [−27.37, −26.98]	−27.28* [−27.49, −27.02]	−27.36* [−27.53, −27.21]	−27.39* [−27.54, −27.26]	−27.28* [−27.46, −27.06]	−27.40* [−27.58, −27.25]
	Cohort 1G	Cohort 1H	Cohort 1I	Cohort 1J	Cohort 1K	Cohort 1L
Opinion Difference	−0.012 [−0.040, 0.020]	−0.031* [−0.051, −0.016]	−0.020 [−0.052, 0.008]	−0.001 [−0.034, 0.024]	−0.026 [−0.052, 0.002]	−0.010 [−0.029, 0.010]
Disclosed Opinion	54.09* [53.98, 54.23]	53.92* [53.81, 54.05]	53.88* [53.73, 53.99]	53.91* [53.83, 54.00]	53.77* [53.70, 53.87]	53.67* [53.59, 53.75]
2-stars	0.050* [0.036, 0.067]	0.049* [0.033, 0.067]	0.050* [0.034, 0.067]	0.058* [0.042, 0.071]	0.043* [0.026, 0.057]	0.054* [0.037, 0.071]
Edge $\text{Memory}_{(1)}$	0.31* [0.28, 0.35]	0.31* [0.25, 0.39]	0.28* [0.21, 0.33]	0.28* [0.22, 0.33]	0.18* [0.14, 0.22]	0.18* [0.15, 0.21]
Edges	−27.38* [−27.52, −27.26]	−27.20* [−27.37, −27.10]	−27.18* [−27.31, −27.02]	−27.29* [−27.40, −27.15]	−27.05* [−27.19, −26.90]	−27.05* [−27.20, −26.92]

Note: Estimates shown with 95% confidence intervals drawn from 10,000 bootstraps. *Significant result.

account for the imposed viscosity of the network across rounds, and a statistic called "2-stars" which adds 1 network statistic for each pair of edges adjacent to the same vertex and helps account for participants' tendency to prefer associative decisions (see chapter 4). These additional parameters help improve model fit as well (Leifeld et al., 2018). Where possible, the remaining BTERGMs will use the same set of parameters so that results are more readily compared between models. The results of the BTERGM testing H1 are presented in Table 3.

The results of this test provide mixed support for hypothesis 1. Four of the twelve networks in condition 1 (1B, 1E, 1F, and 1H) show significant evidence that participants were less likely to choose the associative tie in a given round when their current or prospective discussion partner expressed a different opinion from their own. The remaining eight cohorts (1A, 1C, 1D, 1G, 1I, 1J, 1K, and 1L) did not have significant coefficients for the opinion difference parameter, however all of those coefficients were in the predicted (negative) direction. Perhaps using only opinion differences from the current round of discussion is too limited. I turn now to the research question intended to investigate the aggregation of several rounds of discussion.

Research Question 1

Research question 1 asks whether pieces of information about an alter's opinions discussed over several rounds are aggregated by the ego when reaching a decision about the tie. Relatedly, although not explicit in this proposition, the question of whether aggregated differences are *more* predictive of tie status than a single round is relevant to this investigation.

In order to aggregate opinion differences over time, I created 10 matrices, 1 for each discussion round, and filled them with the average dyadic differences of all prior discussed topics iteratively. In the first matrix, the opinion differences are identical to those used in the test of H1, as there has only been one topic to discuss. The opinion difference matrix for round 2 takes on the value of the differences discussed in round 2, as well as the average of round 1 and 2 in the dyad if the pair discussed both topics. In subsequent rounds, it is possible that not all of the prior rounds would get averaged together. For example, if MK1 and JI8 discussed topics 1 and 2, dissolved their tie for a few rounds, and then picked up their discussion again in round 7, the difference value in round 7 would be the average differences between MK1 and JI8 on topics 1, 2, and 7. In this way, the difference measure effectively takes the average of the table of opinions shown to participants when they are making tie decisions.

The disclosure control used in H1 was also changed for RQ1 to reflect the history of the relationship in a similar manner to opinion differences. Instead of values in this matrix representing whether (1) or not (0) the current round's topic was disclosed in the dyad, the value in this version is the number of topics that have been disclosed in the dyad. This change still allows this parameter to act as a constraint on dyads which have not disclosed information to one another, but it also serves to control for how much information a participant is asked to consider in cases of long-standing relationships. The same 2-star and edge memory covariates which appeared in the tests of H1 are retained for the tests of RQ1. The results of this BTERGM are presented in Table 4.

When opinion differences are averaged across all discussed topics, the generative role of political difference is noticeably stronger in some cohorts. In these tests, nine of the twelve cohorts had significant negative estimates for average opinion difference (1A, 1C, 1D, 1F, 1G, 1H, 1J, 1K, and 1L). Two of the remaining three cohorts had non-significant results in the predicted direction (1B and 1E) – curiously both of these cohorts had significant results in the tests of H1, suggesting that differences on only the current round was a better predictor of tie changes among those participants. One cohort had a positive estimate, but it was not significant. In answering the second part of the question mentioned above, the estimates from the significant models in tests of H1 all fall outside the upper bounds of the confidence intervals from the significant models in tests of RQ1. In other words, the significant effects in RQ1 exceed the significant effects in H1. In sum, aggregating opinion differences with a simple average does appear to be a better predictor of tie decisions than the current round alone; however, the results are still not conclusive across all twelve cohorts.

Table 4

BTERGM Results - Research Question 1

Parameter	Cohort 1A	Cohort 1B	Cohort 1C	Cohort 1D	Cohort 1E	Cohort 1F
Avg. Opinion Difference	-0.39* $[-0.78, -0.11]$	-0.20 $[-0.67, 0.14]$	-0.37* $[-0.50, -0.26]$	-0.35* $[-0.56, -0.17]$	-0.21 $[-0.66, 0.19]$	-0.45* $[-0.90, -0.12]$
# Disclosed Opinions	0.48* $[0.21, 1.91]$	0.44* $[0.21, 2.25]$	0.23* $[0.12, 0.60]$	0.47* $[0.25, 1.77]$	0.36* $[0.14, 3.61]$	0.33* $[0.11, 1.88]$
2-stars	-0.142 $[-0.456, 0.085]$	-0.024 $[-0.113, 0.087]$	0.024 $[-0.010, 0.061]$	-0.035 $[-0.113, 0.049]$	-0.052 $[-0.158, 0.038]$	-0.108 $[-0.201, 0.008]$
Edge $\text{Memory}_{(1)}$	1.83* $[0.40, 2.52]$	2.01* $[0.39, 2.48]$	2.14* $[1.66, 2.42]$	1.96* $[0.85, 2.19]$	1.98 $[-0.67, 2.30]$	2.04* $[0.74, 2.57]$
Edges	1.65 $[-0.68, 3.05]$	0.62 $[-1.20, 1.57]$	0.33 $[-0.34, 0.75]$	1.02 $[-0.23, 1.44]$	1.13 $[-2.33, 1.86]$	2.00* $[0.20, 3.27]$
	Cohort 1G	Cohort 1H	Cohort 1I	Cohort 1J	Cohort 1K	Cohort 1L
Avg. Opinion Difference	-0.39* $[-0.56, -0.18]$	-0.49* $[-0.82, -0.22]$	0.05 $[-0.26, 0.44]$	-0.39* $[-0.62, -0.18]$	-0.33* $[-0.48, -0.18]$	-0.28* $[-0.66, -0.01]$
# Disclosed Opinions	0.47* $[0.30, 1.17]$	0.69* $[0.32, 2.18]$	0.71* $[0.31, 2.74]$	0.54* $[0.23, 1.46]$	0.29* $[0.08, 1.14]$	0.20* $[0.11, 0.42]$
2-stars	-0.054 $[-0.239, 0.058]$	-0.072 $[-0.161, 0.019]$	-0.104 $[-0.218, 0.013]$	-0.042 $[-0.119, 0.039]$	-0.031 $[-0.159, 0.055]$	0.043 $[-0.093, 0.140]$
Edge $\text{Memory}_{(1)}$	1.96* $[1.23, 2.24]$	1.71* $[0.43, 2.16]$	1.80* $[< 0.01, 2.92]$	1.54* $[0.73, 1.99]$	2.00* $[1.05, 2.49]$	2.13* $[1.89, 2.50]$
Edges	0.32 $[-0.33, 0.92]$	1.21 $[-0.32, 1.99]$	0.60 $[-1.73, 1.74]$	0.47 $[-0.66, 1.32]$	0.80 $[-0.30, 1.48]$	0.49 $[-0.22, 1.64]$

Note: Estimates shown with 95% confidence intervals drawn from 10,000 bootstraps. *Significant result.

Hypothesis 2 and Research Question 2

Hypothesis 2 states that, assuming dyadic selectivity occurs (H1), the microdeterministic nature of dyadic selection homophily should scale to the network-level in the form of significant assortativity of party identity. Relatedly, research question 2 asks at what point along the ten discussion rounds do the networks evince party identity assortativity above chance. As mentioned previously, one way that structural homophily manifests is through the constraints of availability (Blau, 1977). If the distributions of party identification or ideology are skewed, it will be easier for people in the majority to find like-partisans to interact with compared to members of the minority. Because MTurk participants tend to lean more Democratic compared to nationally-representative samples (Huff & Tingley, 2015; Levay et al., 2016), observed network-level assortativity of party identity may be, in part, driven by the increased likelihood of a Democratic-leaning person encountering other Democratic-leaning participants with greater frequency. To assess what amount of assortativity could be expected by chance in a cohort, simulated networks which have the same distribution of party identity as the cohort's members are needed to generate a null distribution of party identity assortativity against which the observed network can be tested. Both H2 and RQ2 were tested using the same technique that involves a variation on the conditional uniform graph test used to test for IID assumptions in chapter 4.

Recall that a conditional uniform graph test (Butts, 2008) randomly generates several networks with the same key characteristics of the observed network. A descriptive statistic is calculated on each of the randomly-generated networks, and a null distribution is formed against which the same statistic on the observed network is compared. The CUG tests constructed for this hypothesis/research question extract three features of the observed network and apply them to the randomly-generated networks: 1) the number of vertices, 2) the number of edges (i.e., density), and 3) the distribution of party identity among the participants. The descriptive statistic being compared between the randomly-generated networks and the observed networks is the assortativity of party identity. The R code used to conduct this test is presented in Appendix E. The results of these tests across twelve cohorts at random assignment and each of the ten discussion rounds are presented in Table 5.

This table can be interpreted as the psuedo *p*-value of a one-tailed test of party identity assortativity above chance. The results of these tests do not support hypothesis 2. Among the 132 combinations of cohort and discussion round, only on 7 occasions was the observed network significantly more assortative than chance, and that was never sustained for longer than three consecutive discussion rounds in the same cohort. Moreover, at several points, cohorts evinced significantly *less* assortativity compared to the randomly-generated networks. This was most readily apparent in the three smallest cohorts (1J, 1K, and 1L) in the later discussion rounds. With H2 unsupported, the answer to RQ2 is unclear. This result follows from the observed levels of assortativity over time previewed in Figure 5. Given that the observed networks become denser over time, the simulated networks contain more and more edges as well, and so the number of possible combinations of ties which differ from the observed network is comparatively diminished. Useful to the other components of this study, though, are the results in the random assignment rows; here, the Erdős-Rényi (1959) random graphs used to assign ties at the start of the study did not produce networks which were either significantly more or less homophilous than chance.

Hypothesis 3

The tests of H3 and H4 are interesting because they rely on assumptions drawn from interpersonal theories of communication. Specifically, these tests answer whether

Table 5

Conditional Uniform Graph Test Results - Hypothesis 2

Round	Cohort 1A	Cohort 1B	Cohort 1C	Cohort 1D	Cohort 1E	Cohort 1F
Random Assignment	.234	.834	.277	.129	.199	.308
1	.503	.986†	.147	.048*	.218	.314
2	.561	.969†	.144	.270	.172	.143
3	.723	.883	.645	.247	.040*	.133
4	.096	.634	.496	.622	.025*	.494
5	.066	.469	.351	.628	.023*	.612
6	.036*	.460	.403	.800	.179	.618
7	.130	.527	.113	.778	.121	.786
8	.124	.802	.176	.856	.098	.682
9	.323	.598	.514	.868	.249	.350
10	.409	.739	.582	.846	.131	.358
	Cohort 1G	Cohort 1H	Cohort 1I	Cohort 1J	Cohort 1K	Cohort 1L
Random Assignment	.772	.166	.807	.093	.872	.389
1	.850	.736	.810	.032*	.882	.593
2	.577	.505	.908	.008**	.942	.915
3	.967†	.399	.963†	.267	.811	.925
4	.866	.612	.953†	.174	.936	.958†
5	.599	.570	.863	.073	.865	.943
6	.400	.479	.552	.552	.975†	.828
7	.758	.660	.724	.944	.995†	.910
8	.581	.460	.686	.833	.996†	.975†
9	.841	.540	.468	.980†	1.000†	.972†
10	.981†	.797	.343	.982†	.989†	.813

Note: Cell values indicate the proportion of 1,000 simulated networks which had higher values of party identity assortativity than the observed network. $^{*}p < .05$, $^{**}p < .01$. †Significantly *less* assortative than chance.

the theorized reasons *why* people are selective are reflected in the network data once selection has occurred. Understanding this dynamic may aid future research into the motivations behind selection. Hypothesis 3 states that people choose to discuss political matters with similar alters because it improves their ability to anticipate agreement in future discussions. To ascertain whether this anticipation is predictive of tie formation, two tests are conducted: one using the responses to the withheld versions of the same ten topics discussed in the study (e.g., if economy A was discussed in the cohort, economy B is used as the difference metric), and one using the ten responses to the five withheld topics (see Table 1). The former tests whether agreement should be anticipated on different facets of the same topic, while the latter tests whether individuals could expect to encounter agreement on issues which have not been discussed. Formally, both tests substitute the shared opinion differences in the test of H1 with the withheld opinion differences on the same topics over ten rounds (same order) and with opinion differences on the withheld topics overall.

Table 6 shows the BTERGM results of the first test using the non-discussed versions of the discussed topics as the difference measure. Of the twelve cohorts in condition 1, seven show significant, negative relationships between the tie obtaining in the current round and the dyad's difference of opinions on the non-disclosed versions of the discussed topic (1A, 1D, 1E, 1H, 1I, 1J, and 1K). This suggests that tie formation as the result of selection on a topic is likely to result in agreement on a different matter within the same topic should the dyad choose to discuss it. Of the five non-significant results, three are also in the predicted direction. Taken together, hypothesis 3 garnered mixed support, albeit with substantially more support compared to hypothesis 1.

Strangely, five cohorts (1A, 1D, 1I, 1J, and 1K) show significant results in this tests of H3, but the difference estimates were non-significant among these cohorts in

Table 6

BTERGM Results - Hypothesis 3, Same Topics

Parameter	Cohort 1A	Cohort 1B	Cohort 1C	Cohort 1D	Cohort 1E	Cohort 1F
Opinion Difference	-0.044* [$-0.073, -0.018$]	-0.007 [$-0.043, 0.024$]	-0.011 [$-0.022, < 0.001$]	-0.027* [$-0.047, -0.010$]	-0.030* [$-0.050, -0.016$]	-0.023 [$-0.055, < 0.001$]
Disclosed Opinion	53.92* [53.77, 54.04]	54.18* [54.06, 54.29]	54.02* [53.97, 54.08]	54.10* [54.01, 54.18]	54.06* [53.95, 54.21]	53.99* [53.85, 54.16]
2-stars	0.062* [0.044, 0.075]	0.031* [0.013, 0.040]	0.037* [0.029, 0.045]	0.043* [0.032, 0.052]	0.037* [0.024, 0.049]	0.068* [0.061, 0.076]
Edge $\text{Memory}_{(1)}$	0.28* [0.22, 0.34]	0.36* [0.32, 0.40]	0.31* [0.29, 0.34]	0.35* [0.30, 0.40]	0.36* [0.31, 0.41]	0.27* [0.20, 0.33]
Edges	-27.17* [$-27.28, -27.05$]	-27.33* [$-27.54, -27.00$]	-27.35* [$-27.45, -27.25$]	-27.33* [$-27.43, -27.18$]	-27.21* [$-27.33, -27.06$]	-27.44* [$-27.59, -27.31$]
	Cohort 1G	Cohort 1H	Cohort 1I	Cohort 1J	Cohort 1K	Cohort 1L
Opinion Difference	0.003 [$-0.024, 0.038$]	-0.035* [$-0.048, -0.018$]	-0.028* [$-0.053, -0.007$]	-0.011* [$-0.020, -0.002$]	-0.030* [$-0.055, -0.008$]	0.016 [$> -0.001, 0.040$]
Disclosed Opinion	54.09* [54.00, 54.18]	53.85* [53.77, 53.96]	53.84* [53.74, 53.91]	53.88* [53.74, 54.06]	53.84* [53.77, 53.91]	53.71* [53.62, 53.85]
2-stars	0.055* [0.043, 0.066]	0.061* [0.045, 0.074]	0.052* [0.029, 0.069]	0.059* [0.044, 0.070]	0.047* [0.029, 0.063]	0.062* [0.046, 0.077]
Edge $\text{Memory}_{(1)}$	0.30* [0.26, 0.34]	0.30* [0.27, 0.33]	0.25* [0.21, 0.30]	0.24* [0.22, 0.26]	0.22* [0.18, 0.27]	0.16* [0.13, 0.19]
Edges	-27.44* [$-27.54, -27.30$]	-27.24* [$-27.32, -27.17$]	-27.17* [$-27.28, -27.00$]	-27.27* [$-27.42, -27.09$]	-27.12* [$-27.24, -26.97$]	-27.20* [$-27.37, -27.05$]

Note: Estimates shown with 95% confidence intervals drawn from 10,000 bootstraps. *Significant result.

the tests of H1. It could be the case that the discussed versions of each question in these cohorts are less associated with specific political worldviews compared to the withheld version – that is, it may have been easier for participants to form a cohesive perception of their discussion partners' political party had they discussed the non-disclosed versions of each topic instead. I will return to this notion of one's perceptions of their alter's political identity in the final chapter.

The second test of H3 assesses whether participants form ties which are similar with regard to topics that are not discussed. The five held-out topics in all cohorts were terrorism, foreign policy, healthcare, education, and the environment. Each topic had two public opinion questions associated with it. In order to reduce any over-reliance on any one question to produce significant results, I averaged the dyadic differences across all ten responses. These differences are included in the model as a single, static matrix, rather than a list of matrices, as differences on the withheld topics do not vary over time with regard to the discussion round. The results of this test are presented in Table 7.

Across twelve cohorts, just three have a significant result (1B, 1H, and 1L) for averaged differences of opinion on the withheld topics, and all three of them are significant against the predicted direction – a negative coefficient is expected when greater differences reduce the likelihood of a tie obtaining in the network. In other words, participants in these cohorts formed ties with alters with whom they would be significantly *less* likely to agree on these five withheld topics (on average). The remaining nine cohorts (1A, 1C, 1D, 1E, 1F, 1G, 1I, 1J, and 1K) all had non-significant coefficients for the difference estimate, and they were about evenly split in direction: 4 positive and 5 negative. Taken together, the results of H3 suggest that people are more likely to form ties with alters with whom they might agree on a previously undisclosed

Table 7

BTERGM Results - Hypothesis 3, Withheld Topics

Parameter	Cohort 1A	Cohort 1B	Cohort 1C	Cohort 1D	Cohort 1E	Cohort 1F
Avg. Opinion Difference	0.005 $[-0.016, 0.026]$	0.016* $[0.004, 0.026]$	-0.002 $[-0.019, 0.015]$	0.016 $[-0.004, 0.035]$	0.007 $[-0.002, 0.016]$	0.025 $[-0.003, 0.046]$
Disclosed Opinion	53.41* $[53.36, 53.45]$	53.49* $[53.44, 53.54]$	53.45* $[53.43, 53.48]$	53.49* $[53.46, 53.53]$	53.48* $[53.44, 53.52]$	53.49* $[53.44, 53.54]$
2-stars	0.026* $[0.019, 0.033]$	0.015* $[0.006, 0.020]$	0.018* $[0.011, 0.024]$	0.024* $[0.019, 0.030]$	0.024* $[0.018, 0.028]$	0.034* $[0.026, 0.044]$
Edge Memory$_{(1)}$	0.094* $[0.071, 0.118]$	0.133* $[0.117, 0.147]$	0.108* $[0.098, 0.115]$	0.126* $[0.109, 0.146]$	0.111* $[0.091, 0.134]$	0.091* $[0.070, 0.113]$
Edges	-26.85* $[-26.91, -26.79]$	-26.92* $[-26.99, -26.78]$	-26.91* $[-27.00, -26.82]$	-26.96* $[-27.03, -26.90]$	-26.97* $[-27.01, -26.92]$	-27.05* $[-27.16, -26.98]$
	Cohort 1G	Cohort 1H	Cohort 1I	Cohort 1J	Cohort 1K	Cohort 1L
Avg. Opinion Difference	0.006 $[-0.023, 0.035]$	0.015* $[0.004, 0.023]$	-0.014 $[-0.034, 0.008]$	-0.001 $[-0.034, 0.032]$	-0.015 $[-0.033, 0.005]$	0.037* $[0.007, 0.065]$
Disclosed Opinion	53.50* $[53.45, 53.56]$	53.38* $[53.35, 53.41]$	53.37* $[53.35, 53.40]$	53.42* $[53.36, 53.49]$	53.34* $[53.31, 53.37]$	53.37* $[53.32, 53.41]$
2-stars	0.025* $[0.021, 0.032]$	0.016* $[0.010, 0.022]$	0.017* $[0.007, 0.026]$	0.023* $[0.014, 0.029]$	0.014* $[0.007, 0.020]$	0.017* $[0.004, 0.029]$
Edge Memory$_{(1)}$	0.113* $[0.099, 0.128]$	0.080* $[0.063, 0.096]$	0.093* $[0.076, 0.108]$	0.084* $[0.072, 0.093]$	0.058* $[0.040, 0.079]$	0.047* $[0.028, 0.061]$
Edges	-26.97* $[-27.04, -26.92]$	-26.83* $[-26.87, -26.78]$	-26.75* $[-26.85, -26.65]$	-26.84* $[-26.96, -26.70]$	-26.70* $[-26.75, -26.63]$	-26.85* $[-26.97, -26.72]$

Note: Estimates shown with 95% confidence intervals drawn from 10,000 bootstraps. *Significant result.

issue; however, that similarity on as-yet-undiscussed issue positions extends only to related issues within previously-discussed topics. In other words, if people are selective because, as URT (Berger & Calabrese, 1975) suggests, they want to form more confident predictions about future interactions, they may be justified in doing so when future interactions pertain to the same topic, but they may be mistaken for using selection to predict future interactions on new topics.

Hypothesis 4

Related to the theoretical assumptions at test in H3, similarity between discussion partners is thought to produce fewer possible outcomes from interaction, and thereby reduce the costs of continued communication. This, in turn, means that selection of similar alters ought to result in greater stability (Felmlee et al., 1990; Kossinets & Watts, 2009) and more reciprocity (Leenders, 1996) in interpersonal relationships. If this occurs as a function of selection in the political discussion cohorts, I would expect to see that the status of the tie at the prior time point would become increasingly predictive of the status of the tie at the current time point. While “edge memory”, or time-lagged tie status, is included in each of the BTERGMs detailed above, relying on this metric alone will not suffice for this hypothesis.

This is because the study design explicitly constrains the proportion of ties which are permitted to update in any given round. This was included in the study to both mimic the “viscosity” of social relationships (Harrell et al., 2018; Nishi et al., 2015; Rand et al., 2011), and to improve the pacing of the study for participants. In other words, some of the observed predictive power of relationship status at the prior time point is the result of the study design, and individual preferences for relational stability cannot be distinguished from these estimates. Instead, this analysis will assess the rates of what I refer to as choosing the “status quo” decision, or opting to retain the same relationship status. In decisions regarding a new discussion partner, the status quo decision is to *ignore* the tie. In decisions regarding an existing relationship, the status quo decision is to *maintain* the tie. The rate of status quo decision-making is thus calculated as the number of ignore decisions plus the number of maintain decisions, divided by the total number of tie decisions assigned in the round.

Figure 7 shows how rates of status quo decision-making vary over time in each of the twelve condition 1 cohorts. On average (shown as the thick line), participants selected the transformative tie decision (i.e., add a new tie or dissolve an existing tie) with greater frequency in rounds 1 and 2. From round 3 onwards, the majority of tie decisions resulted in the status quo option being selected. Indeed, in rounds 1 ($t(11)$ = -6.80, $p < .001$) and 2 ($t(11)$ = -2.31, $p < .05$), rates of status quo decision-making were significantly below 50% among all twelve cohorts. However, in rounds 4 ($t(11)$ = 3.22, $p < .01$), 6 ($t(11) = 4.18$, $p < .01$), 7 ($t(11) = 3.80$, $p < .01$), 8 ($t(11) = 3.14$, $p < .01$), 9 ($t(11) = 8.21$, $p < .001$), and 10 ($t(11) = 7.74$, $p < .001$) the twelve cohorts on average chose the status quo decision with significantly greater than 50% regularity.

While these trend lines and *t*-tests provide evidence in support of hypothesis 4, it is important to also consider that increases in status quo decision-making over time would coincide not just with selectivity, but also with a simple preference for many ties (i.e., network density). Assuming that people want only to discuss politics with many alters, the rates of status quo decision-making would follow a similar trajectory: early on, transformative decisions would be the norm as people add many new ties to their ego network. In later stages, people with many existing ties that formed in early rounds would want to maintain those ties, and so status quo decision-making would increase. To the extent that new tie decisions are faced in these later rounds, those decisions would still likely result in the transformative choice (i.e., add), but their

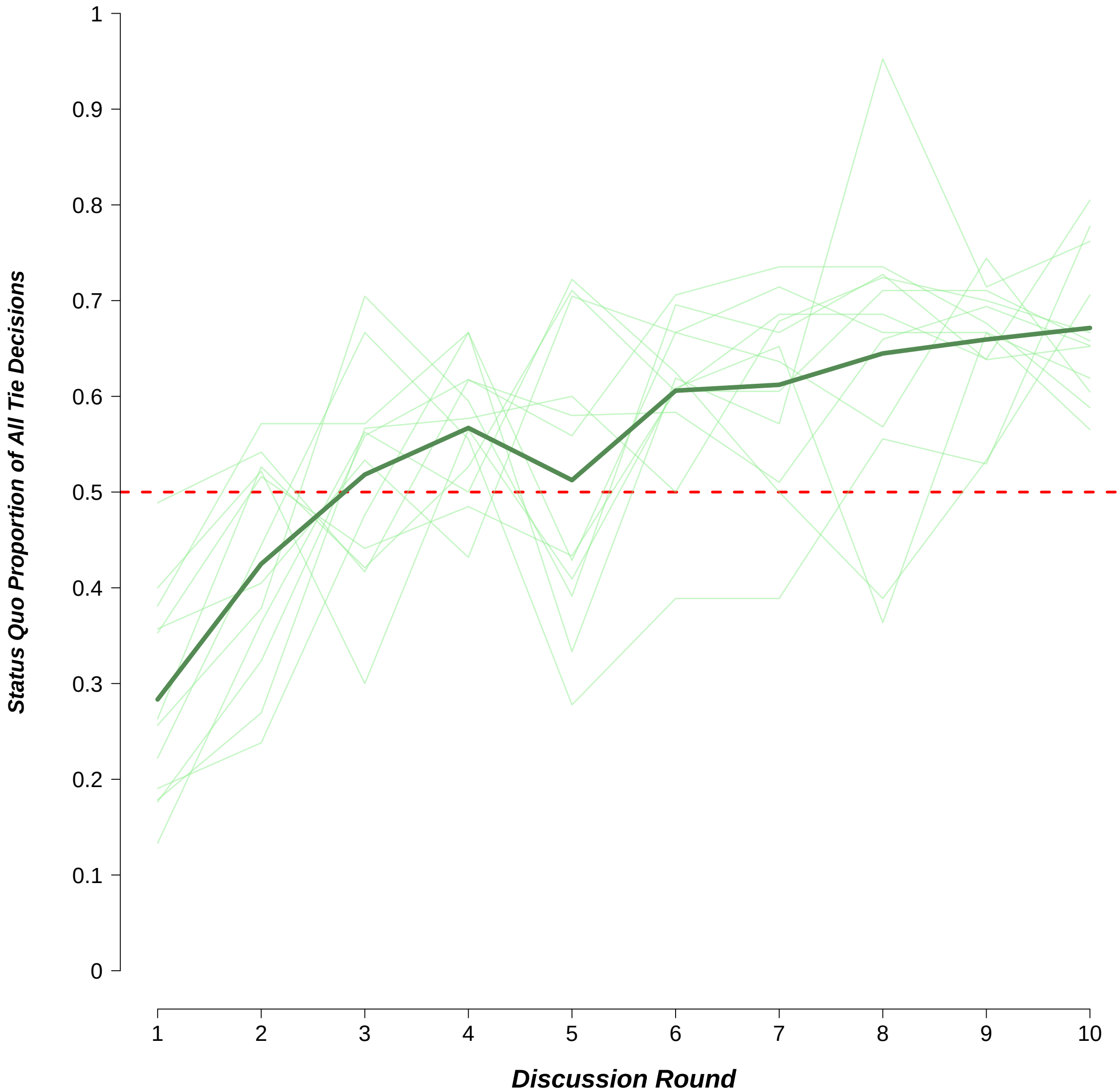

Figure 7. Proportion of all tie decisions which retain the same relationship status once made (maintain existing ties, ignore new ties). The red dashed line at 0.50 represents equal preference for status quo decisions as transformative decisions. Thin lines represent each cohort, while the thick line is the average across all twelve condition 1 cohorts.

relative infrequency should mean that the overall rate of status quo choices is likely to exceed 50%. Conversely, under conditions of selectivity, one would expect to find that the rates of status quo decisions for new and existing ties follow similar trends. At the start of the study, when participants are randomly assigned to network positions, new tie choices at first may be more likely to result in the addition of new ties as people search for like-partisans to interact with, but that should change quickly to status quo (i.e., ignore) as the number of available like-partisans dwindle.

To further investigate whether the increase in status quo decision-making observed above is the result of selective tie choices or rather the simple preference for many alters, I separated the tie decisions into two groups: those that concerned new relationships and those that concerned existing relationships. The rates of status quo decision-making in new tie decisions is the number of times "ignore" was selected divided by the total number of new tie decisions faced in a round. The rates of status quo decision-making in existing tie decisions is the number of times "maintain" was selected divided by the total number of existing tie decisions faced in a round. Figure 8 depicts these rates in separate graphs. These trends support the notion that participants tended to prefer to interact first and foremost with many others, and that preference for like-partisans, if present, was likely a secondary consideration. This comports with the descriptive findings in chapter 4, but does not support hypothesis 4.

Hypothesis 5

Hypothesis 5 states that, in accordance with issue publics theory (Krosnick, 1990), the importance of a particular issue or set of issues will affect relevant political behaviors. In the case of selection homophily in dynamic discussion networks, subjective issue importance should moderate the relationship between differences of opinion and a person's tie decisions. Here, I arrive at the first examination of

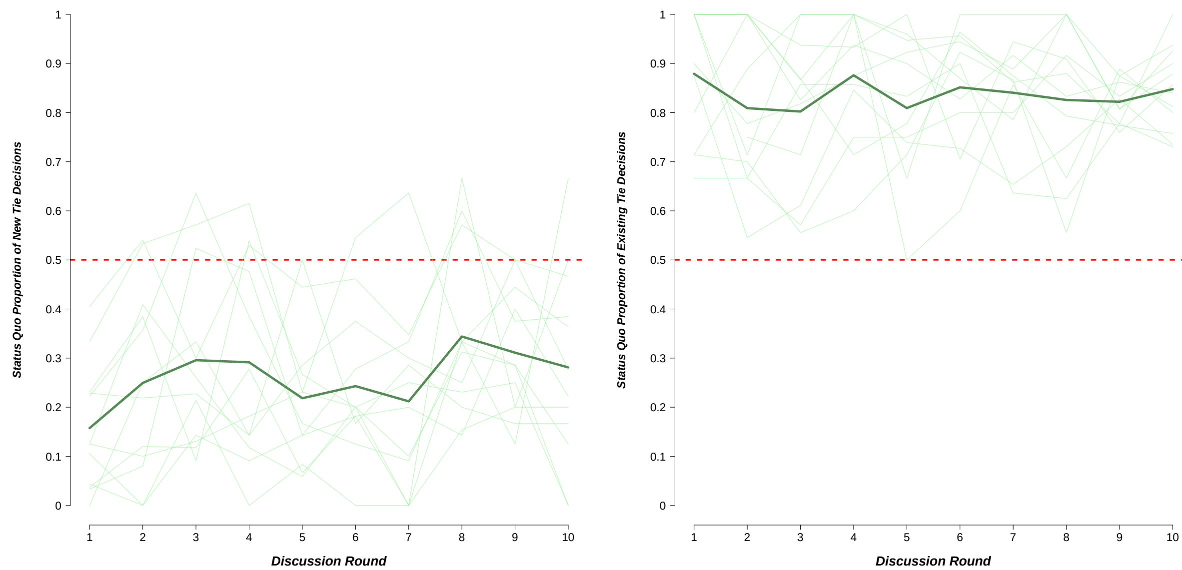

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Figure 8. Proportion of new (left panel; "ignore") and existing (right panel; "maintain") tie decisions which retain the same relationship status once made. The red dashed line at 0.50 represents equal preference for status quo decisions as transformative decisions. Thin lines represent each cohort, while the thick line is the average across all twelve condition 1 cohorts.

subjective variation of selectivity. In other words, this test may provide novel insight into why two people who have discussed the same set of issues with one another may reach a different conclusion about their willingness to continue discussion. Whereas the BTERGMs testing H1 and RQ1 used a symmetric edge covariate (opinion differences) for each discussion round, testing H5 will require an asymmetric (i.e., directed) edge covariate which interacts dyadic opinion differences with subjective importance of the relevant issues for each round.

Given that RQ1 showed that an average of discussed opinion differences is generally more predictive of tie status than the current issue considered alone (H1), H5 will use the following averaging equation to arrive at the interaction term:

$$\frac{\sum_{t=1}^{n}(|O_{jt} - O_{kt}| * I_{jt})}{n} \tag{2}$$

where O represents the expressed opinions of both ego (j) and alter (k) of topic t. This absolute difference is then multiplied by importance of topic t to ego j. This product is then averaged across the number of topics discussed in the dyad, or n. This procedure is followed to fill ten asymmetric matrices, one for each discussion round. The BTERGMs testing H5 includes this edge covariate alongside the difference edge covariate and average importance of discussed topics is included as an edge covariate. The same controls from the models in tests of RQ1 (number of disclosed opinions, 2-stars, and edge memory) are included in these tests as well. Table 8 provides the results.

Assessing these results, a negative coefficient for the interaction term is expected. This would indicate that as the importance of the issue discussed increases, the negative effect of opinion differences on the log likelihood of the tie obtaining in that round is magnified. Across twelve cohorts, just one (1A) shows evidence of a

Table 8

BTERGM Results - Hypothesis 5

Parameter	Cohort 1A	Cohort 1B	Cohort 1C	Cohort 1D	Cohort 1E	Cohort 1F
Importance x Difference	−0.32* [−0.46, −0.19]	0.18* [0.04, 0.31]	−0.02 [−0.12, 0.09]	0.06 [−0.02, 0.18]	0.07 [−0.22, 0.22]	0.01 [−0.25, 0.19]
Avg. Issue Importance	0.85* [0.55, 1.20]	< 0.01 [−0.45, 0.54]	0.28 [−0.15, 0.67]	−0.04 [−0.30, 0.26]	0.08 [−0.47, 0.98]	−0.13 [−0.58, 0.75]
Avg. Opinion Difference	1.30* [0.69, 2.06]	−1.06* [−1.87, −0.34]	−0.27 [−0.89, 0.28]	−0.69* [−1.46, −0.16]	−0.67 [−1.57, 1.19]	−0.50 [−1.52, 0.93]
# Disclosed Opinions	0.51* [0.22, 1.89]	0.45* [0.22, 2.25]	0.24* [0.12, 0.61]	0.47* [0.25, 1.71]	0.36* [0.14, 3.53]	0.33* [0.11, 1.90]
2-stars	−0.19 [−0.48, 0.02]	−0.04 [−0.12, 0.06]	0.01 [−0.03, 0.04]	−0.04 [−0.13, 0.05]	−0.06 [−0.16, 0.04]	−0.11* [−0.20, −0.01]
Edge $\text{Memory}_{(1)}$	1.81* [0.49, 2.51]	2.02* [0.47, 2.52]	2.13* [1.66, 2.42]	1.96* [0.91, 2.22]	1.99 [−0.62, 2.31]	2.04* [0.73, 2.58]
Edges	−2.49* [−5.59, −0.21]	0.61 [−2.62, 3.02]	−1.11 [−3.32, 1.18]	1.32 [−0.53, 2.52]	0.73 [−5.53, 3.75]	2.86 [−2.54, 5.18]
	Cohort 1G	Cohort 1H	Cohort 1I	Cohort 1J	Cohort 1K	Cohort 1L
Importance x Difference	0.10 [−0.06, 0.27]	0.12 [−0.04, 0.33]	0.10 [−0.08, 0.31]	−0.06 [−0.20, 0.17]	0.11 [−0.11, 0.25]	0.07 [−0.04, 0.29]
Avg. Issue Importance	−0.15 [−0.56, 0.35]	−0.13 [−0.59, 0.37]	−0.47 [−0.95, 0.12]	−0.09 [−0.47, 0.34]	−0.30 [−0.77, 0.44]	−0.26 [−0.72, 0.17]
Avg. Opinion Difference	−0.99* [−2.08, −0.03]	−1.23* [−2.73, −0.09]	−0.57 [−1.91, 0.65]	−0.04 [−1.56, 0.86]	−0.95 [−1.61, 0.16]	−0.70 [−2.24, 0.04]
# Disclosed Opinions	0.48* [0.30, 1.16]	0.71* [0.34, 2.19]	0.74* [0.33, 2.71]	0.54* [0.23, 1.44]	0.29* [0.08, 1.06]	0.20* [0.11, 0.43]
2-stars	−0.05 [−0.24, 0.07]	−0.07 [−0.16, 0.02]	−0.09 [−0.21, 0.03]	−0.03 [−0.12, 0.05]	−0.04 [−0.17, 0.05]	0.03 [−0.08, 0.12]
Edge $\text{Memory}_{(1)}$	1.95* [1.25, 2.25]	1.71* [0.47, 2.20]	1.78* [0.02, 2.92]	1.56* [0.74, 2.00]	2.02* [1.16, 2.54]	2.14* [1.91, 2.51]
Edges	1.16 [−2.19, 3.41]	2.02 [−2.24, 4.74]	3.29 [−0.40, 5.83]	0.96 [−1.82, 3.66]	2.49 [−1.57, 5.14]	2.14 [−0.46, 5.19]

Note: Estimates shown with 95% confidence intervals drawn from 10,000 bootstraps. *Significant result.

significant negative interaction. One further cohort (1B) shows a significant *postive* interaction, meaning that in this group, differences of opinion were tolerated more frequently on important issues than on less important issues. On the whole, estimates for the generative role of average opinion differences remained negative as in RQ1, with the exception of 1A, which evinced the significant negative interaction. Across three cohorts (1D, 1G, and 1H) which did not have a significant interaction between issue importance and differences of opinion, and in 1B, the average difference term was significant and negative. Taken together, these results suggest that, in most cohorts, the importance of the issue being discussed matters much less for the outcome of tie decisions than the average differences of opinions that are shared. That is, H5 is not supported.

Hypothesis 6

Hypothesis 6 posits that another characteristic may account for inter-subject variance in selectivity: *affective polarization.* Recall that this concept was measured using the difference between two variables: feelings ratings of in-group members minus feelings ratings of out-group members. Which political group (Democrats, independents, or Republicans) serves as the in-group for these measures was determined from participants' responses to the first question regarding party identification. This measure is not time dependent, meaning a single measure was constructed for each participant and will serve as a node covariate across all 10 networks in the BTERGM. To test for the interaction of affective polarization with opinion differences, the averaged differences matrices from tests of RQ1 were used. Specifically, each row in the matrix was multiplied by the corresponding participant's affective polarization score. The resulting matrix is asymmetric (directed), meaning that affective polarization may be one avenue through which two people who experience the same amount of differences in their shared opinions may nevertheless reach different conclusions about the status of the tie in a given round. Once again, the number of topics disclosed, 2-stars, and edge memory parameters were included in the models as controls. Table 9 shows the results of these tests.

Affective polarization is thought to magnify differences of opinion such that people who more disparately rate in-group and out-group members (positive score) weight differences of opinion more heavily than do people who more equally rate in- and out-groups. That is, a negative effect of the interaction between affective polarization and average differences of opinion is expected. Of the twelve cohorts in condition 1, just two (1A and 1E) showed evidence of a significant interaction. Among the 10 remaining cohorts, four (1C, 1G, 1I, and 1J) had estimates which were in the predicted direction. These results provide mixed, and tepid at that, support for hypothesis 6. Importantly, average opinion differences remained largely in the predicted direction (negative), and this effect was significant in eight of the twelve cohorts. Once again, differences of opinion appear to outweigh any subjective characteristics of the person making the decision when considering a tie in the political discussion network.

In the next chapter, I turn to investigations of an interpersonal communicative process called "selective disclosure." The following tests utilize data from cohorts which were assigned to the second quasi-experimental condition. The assumption that every opinion is automatically shared with all alters, as was the case with the condition 1 data in the prior analyses, will no longer apply.

Table 9

BTERGM Results - Hypothesis 6

Parameter	Cohort 1A	Cohort 1B	Cohort 1C	Cohort 1D	Cohort 1E	Cohort 1F
Affect x Difference	-0.054^{*} $[-0.101, -0.012]$	0.016 $[-0.016, 0.050]$	-0.013 $[-0.040, 0.016]$	0.006 $[-0.014, 0.032]$	-0.077^{*} $[-0.130, -0.026]$	0.004 $[-0.025, 0.024]$
Affective Polarization	-0.23^{*} $[-0.41, -0.11]$	0.032 $[-0.088, 0.169]$	-0.051 $[-0.137, 0.032]$	0.077^{*} $[0.008, 0.154]$	-0.071 $[-0.181, 0.045]$	0.059 $[-0.022, 0.131]$
Avg. Opinion Difference	-0.29 $[-0.72, 0.04]$	-0.22 $[-0.66, 0.10]$	-0.35^{*} $[-0.48, -0.22]$	-0.36^{*} $[-0.59, -0.18]$	0.01 $[-0.49, 0.40]$	-0.48^{*} $[-0.91, -0.16]$
# Disclosed Opinions	0.55^{*} $[0.24, 2.09]$	0.44^{*} $[0.21, 2.35]$	0.24^{*} $[0.12, 0.61]$	0.49^{*} $[0.27, 1.69]$	0.36^{*} $[0.13, 3.51]$	0.33^{*} $[0.11, 1.88]$
2-stars	-0.314^{*} $[-0.642, -0.080]$	-0.025 $[-0.114, 0.081]$	0.020 $[-0.016, 0.060]$	-0.036 $[-0.110, 0.038]$	-0.072 $[-0.192, 0.020]$	-0.108 $[-0.201, 0.001]$
Edge $\text{Memory}_{(1)}$	1.75^{*} $[0.32, 2.48]$	2.00^{*} $[0.35, 2.46]$	2.13^{*} $[1.64, 2.43]$	1.94^{*} $[0.92, 2.17]$	1.99 $[-0.51, 2.31]$	2.05^{*} $[0.81, 2.56]$
Edges	3.31^{*} $[0.88, 5.53]$	0.48 $[-1.41, 1.66]$	0.51 $[-0.44, 1.20]$	0.69 $[-0.49, 1.20]$	1.62 $[-1.56, 2.47]$	1.87^{*} $[0.07, 3.16]$
	Cohort 1G	Cohort 1H	Cohort 1I	Cohort 1J	Cohort 1K	Cohort 1L
Affect x Difference	-0.031 $[-0.081, 0.008]$	0.006 $[-0.008, 0.025]$	-0.003 $[-0.039, 0.037]$	-0.055 $[-0.124, 0.007]$	0.031 $[-0.041, 0.086]$	0.025 $[-0.038, 0.081]$
Affective Polarization	-0.086 $[-0.198, 0.039]$	0.070 $[-0.029, 0.159]$	-0.176^{*} $[-0.307, -0.030]$	-0.129 $[-0.298, 0.037]$	-0.235^{*} $[-0.351, -0.112]$	0.006 $[-0.172, 0.186]$
Avg. Opinion Difference	-0.36^{*} $[-0.56, -0.14]$	-0.50^{*} $[-0.83, -0.23]$	-0.03 $[-0.33, 0.37]$	-0.23^{*} $[-0.46, > -0.00]$	-0.43^{*} $[-0.65, -0.15]$	-0.34^{*} $[-0.78, -0.10]$
# Disclosed Opinions	0.47^{*} $[0.31, 1.16]$	0.70^{*} $[0.34, 2.16]$	0.78^{*} $[0.37, 2.67]$	0.58^{*} $[0.26, 1.58]$	0.31^{*} $[0.10, 1.12]$	0.20^{*} $[0.10, 0.41]$
2-stars	-0.058 $[-0.237, 0.052]$	-0.076 $[-0.171, 0.015]$	-0.106^{*} $[-0.219, -0.002]$	-0.061 $[-0.154, 0.016]$	-0.047 $[-0.184, 0.029]$	0.036 $[-0.118, 0.140]$
Edge $\text{Memory}_{(1)}$	1.95^{*} $[1.23, 2.24]$	1.70^{*} $[0.48, 2.16]$	1.75^{*} $[0.11, 2.80]$	1.53^{*} $[0.74, 1.97]$	1.98^{*} $[1.09, 2.49]$	2.13^{*} $[1.91, 2.52]$
Edges	0.77 $[-0.28, 1.64]$	0.94 $[-0.53, 1.50]$	1.20 $[-1.12, 2.53]$	1.02^{*} $[0.13, 1.95]$	2.20^{*} $[0.95, 3.23]$	0.51 $[-0.53, 1.99]$

Note: Estimates shown with 95% confidence intervals drawn from 10,000 bootstraps. *Significant result.

Chapter 6: Condition 2 Results

Condition 2 permitted participants to choose at the beginning of each discussion round which of their current alters they would like to share the current round's opinion with. Each participant was presented with a checklist containing all of their current alters. By default, all alters on this list were checked. Participants would have to manually choose to withhold their opinion from an alter, otherwise their opinion is shared with all of their alters as in condition 1. On average, participants chose to disclose their opinions to a large majority of their alters: Round 1 (M = 95.53%, SD = 19.17%), Round 2 (M = 97.03%, SD = 13.22%), Round 3 (M = 95.15%, SD = 15.38%), Round 4 (M = 97.38%, SD = 9.96%), Round 5 (M = 96.02%, SD = 13.02%), Round 6 (M = 96.59%, SD = 11.67%), Round 7 (M = 96.22%, SD = 14.09%), Round 8 (M = 97.81%, SD = 10.08%), Round 9 (M = 97.84%, SD = 8.84%), Round 10 (M = 96.46%, SD = 13.77%). That the rates of disclosure did not vary systematically over time suggests that participants thought more about the specific issue in the current round and their network alters, and less about study length or the amount of information one had about their alters, before deciding to disclose their opinion.

Hypotheses 7 and 8

Hypothesis 7 states that people are more likely to withhold their opinion from an alter with whom they are likely to disagree on the subject. Many interpersonal theories of the early and developmental stages of relationships regard the anticipated outcomes of interactions as critical to the decision to engage in dyadic communication. The avoidance of topics in interpersonal discussion is a goal-oriented decision (Afifi & Guerrero, 2000); we are motivated to have others, even unknowns others, evaluate us positively and we are hurt by rejection or exclusion (Eisenberger, Lieberman, &

Williams, 2003). We are more likely to avoid topics when there is more relational uncertainty (Knobloch & Carpenter-Theune, 2004; uncertainty perhaps brought about by dissimilarity, Berger & Calabrese, 1975, Axiom 6) in particular because we cannot rule out conflict as we try to anticipate the outcomes of engaging in conversation on that topic.

Testing hypothesis 7 requires both a different conceptualization of the tie in the network, and of opinion differences. First, because participants are asked each round who they would like to share their opinion with, there are functionally two sets of network ties: both the more persistent relational tie which is also present in condition 1, and the disclosure tie, which reflects the actual transferal of opinion information from one person to another. In condition 1, the second set of ties is congruent with the first, as all opinions are automatically shared. However, the second operationalization is quite different in the second condition, because participants may choose to withhold their opinion from any or all of their discussion partners. Moreover, this second operationalization of ties is directed, because disclosure of an opinion is not necessarily reciprocated in a given round. The test of H7 uses this latter network structure (disclosure ties).

Next, because the decision to disclose one's opinion on a particular issue takes place *before* their alters' opinions are revealed, participants must form some conception of what their alters' opinions would look like in order to form an expectation of agreement or disagreement in the future interaction. To account for this, rather than measuring opinion differences on the issue of the current round, as was done for the tests of H1, I instead create a measure of *alter's anticipated opinion* by averaging all of the opinions which alter has shared with ego in all prior rounds[25] to be used in the assessment of difference relative to ego's opinion.

Table 10

BTERGM Results - Hypothesis 7

Parameter	Cohort 2A	Cohort 2B	Cohort 2C	Cohort 2D	Cohort 2E	Cohort 2F
Avg. Opinion Difference Time $t-1$	-0.82^* $[-1.23, -0.42]$	-0.40^* $[-0.65, -0.23]$	-0.40^* $[-0.69, -0.17]$	-0.20 $[-0.43, 0.03]$	-0.16 $[-0.37, 0.04]$	-0.25^* $[-0.42, -0.07]$
2-stars	0.092 $[-0.045, 0.170]$	0.109 $[-0.021, 0.240]$	0.143^* $[0.036, 0.257]$	0.040^* $[0.005, 0.069]$	0.040 $[-0.022, 0.149]$	0.044 $[-0.059, 0.131]$
Edge Memory$_{(1)}$	2.88^* $[2.57, 3.38]$	2.45^* $[2.28, 2.76]$	2.26^* $[2.12, 2.53]$	2.12^* $[1.97, 2.32]$	2.57^* $[2.44, 2.80]$	2.33^* $[2.20, 2.53]$
Edges	1.95^* $[1.33, 3.13]$	0.45 $[-1.13, 2.20]$	-0.04 $[-1.38, 1.08]$	0.55^* $[0.01, 1.16]$	0.83 $[-0.26, 1.66]$	0.71 $[-0.28, 1.69]$
	Cohort 2G	Cohort 2H	Cohort 2I	Cohort 2J	Cohort 2K	Cohort 2L
Avg. Opinion Difference Time $t-1$	-0.35 $[-0.68, 0.05]$	-0.08 $[-0.62, 0.46]$	-0.35 $[-0.72, 0.24]$	0.23 $[-0.48, 1.39]$	< 0.01 $[-0.32, 0.47]$	-0.59^* $[-1.20, -0.21]$
2-stars	0.226^* $[0.118, 0.324]$	-0.001 $[-0.123, 0.123]$	-0.098 $[-0.420, 0.269]$	-0.014 $[-0.149, 0.038]$	-0.077 $[-0.202, 0.022]$	0.041 $[-0.115, 0.184]$
Edge Memory$_{(1)}$	2.22^* $[2.15, 2.46]$	2.41^* $[2.19, 2.80]$	2.81^* $[2.69, 3.18]$	2.88^* $[2.70, 3.62]$	2.50^* $[2.29, 2.82]$	2.43^* $[2.01, 3.30]$
Edges	-0.29 $[-1.18, 0.79]$	0.99^* $[0.17, 2.09]$	1.81 $[-0.65, 3.69]$	1.18 $[-0.42, 2.96]$	1.07^* $[0.13, 1.98]$	1.98^* $[0.91, 4.01]$

Note: Estimates shown with 95% confidence intervals drawn from 10,000 bootstraps. Networks used in tests of H7 contain directed disclosure ties, rather than discussion partner ties. *Significant result.

The BTERGM used to test H7 uses the disclosure networks from rounds 2 through 10 as the network structure being predicted. Average opinion differences were calculated in identical fashion to that of RQ1, albeit on condition 2 cohorts. These matrices were entered into the model with a 1-round time lag (i.e., rounds 1 through 9; round 1 difference predicting round 2 disclosure ties, etc.). Finally, 2-stars and edge memory terms were included for operational consistency with the condition 1 hypothesis tests. The results of this model are presented in Table 10.

If people are less likely to disclose an opinion to their alter on an as-yet-to-be-discussed topic when they have encountered greater opinion differences on previously-discussed topics with that same alter, then a negative coefficient for time-lagged average opinion differences would be expected. Across the twelve condition 2 cohorts, five cohorts (2A, 2B, 2C, 2F, and 2L) show evidence of a significant negative effect. In these groups, people were significantly less likely to disclose their opinion with those they have previously experienced disagreement. In five of the other seven cohorts, the average difference of opinion (t-1) estimate was in the predicted direction but insignificant. Only in one cohort, 2J, does it appear as though participants tended to disclose their opinions more frequently to those with whom they encountered *greater* differences of opinion, although the confidence interval of this estimate overlaps 0. As a whole, these results provide mixed support of hypothesis 7.

The eighth hypothesis states that, much as issue importance was expected to moderate the relationship between differences of opinion and an ego's tie decision (H5), issue importance is also expected to moderate the relationship between a person's *anticipated* difference of opinion and their decision to disclose their opinion to their alter. Specifically, as issue importance increases, people should be more likely to disclose an opinion which is different from the expected opinion of their discussion partner. This analysis again uses the network of communication as determined by disclosure decisions and the projected difference of opinion from prior discussion rounds, rather than the distance between current-round opinions in the dyad. To construct the interaction parameter, I multiplied the rows of the average difference matrices at round t-1 with the issue importance for discussion round t to the corresponding participant. The results of these tests are presented in Table 11.

Hypothesis 8 posits that participants are more likely to discount previous differences of opinion and disclose their opinion on the current topic when the issue is of comparatively higher importance. That is, a positive coefficient is expected for the

Table 11

BTERGM Results - Hypothesis 8

Parameter	Cohort 2A	Cohort 2B	Cohort 2C	Cohort 2D	Cohort 2E	Cohort 2F
Importance x Difference	0.042 $[-0.021, 0.161]$	0.049 $[-0.005, 0.086]$	0.018 $[-0.035, 0.082]$	0.033 $[-0.005, 0.083]$	-0.042* $[-0.091, -0.008]$	-0.021 $[-0.082, 0.029]$
Avg. Issue Importance Time t	0.075 $[-0.043, 0.162]$	0.135* $[0.032, 0.254]$	0.017 $[-0.071, 0.134]$	0.034 $[-0.176, 0.134]$	0.174* $[0.024, 0.306]$	0.103* $[0.016, 0.198]$
Avg. Opinion Difference Time $t-1$	-1.06* $[-1.65, -0.64]$	-0.72* $[-0.97, -0.43]$	-0.51* $[-0.96, -0.07]$	-0.42* $[-0.89, -0.07]$	0.05 $[-0.21, 0.35]$	-0.13 $[-0.54, 0.29]$
2-stars	0.095 $[-0.053, 0.178]$	0.080 $[-0.070, 0.219]$	0.140* $[0.041, 0.252]$	0.038* $[0.003, 0.062]$	0.038 $[-0.024, 0.148]$	0.047 $[-0.062, 0.141]$
Edge Memory$_{(1)}$	2.90* $[2.60, 3.43]$	2.47* $[2.30, 2.76]$	2.27* $[2.12, 2.53]$	2.12* $[1.97, 2.35]$	2.59* $[2.50, 2.81]$	2.34* $[2.21, 2.54]$
Edges	1.05 $[-0.30, 3.38]$	-0.74 $[-2.84, 0.83]$	-0.19 $[-2.52, 1.53]$	0.15 $[-1.34, 3.18]$	-1.01 $[-2.74, 0.81]$	-0.49 $[-2.45, 1.32]$
	Cohort 2G	Cohort 2H	Cohort 2I	Cohort 2J	Cohort 2K	Cohort 2L
Importance x Difference	0.005 $[-0.027, 0.047]$	-0.017 $[-0.105, 0.079]$	0.032 $[-0.036, 0.085]$	0.039 $[-0.074, 0.113]$	0.062 $[-0.012, 0.154]$	> -0.001 $[-0.068, 0.080]$
Avg. Issue Importance Time t	0.088 $[-0.009, 0.192]$	-0.035 $[-0.209, 0.099]$	0.026 $[-0.153, 0.185]$	-0.190 $[-0.494, 0.122]$	-0.015 $[-0.282, 0.284]$	-0.057 $[-0.397, 0.305]$
Avg. Opinion Difference Time $t-1$	-0.38* $[-0.66, -0.04]$	0.04 $[-0.50, 0.64]$	-0.51 $[-1.12, 0.31]$	0.03 $[-0.92, 1.71]$	-0.39 $[-0.94, 0.32]$	-0.59 $[-1.46, 0.16]$
2-stars	0.232* $[0.119, 0.326]$	-0.003 $[-0.123, 0.121]$	-0.099 $[-0.449, 0.276]$	-0.023 $[-0.181, 0.029]$	-0.078 $[-0.218, 0.035]$	0.045 $[-0.122, 0.198]$
Edge Memory$_{(1)}$	2.24* $[2.16, 2.48]$	2.41* $[2.19, 2.81]$	2.81* $[2.70, 3.20]$	2.90* $[2.73, 3.70]$	2.50* $[2.30, 2.83]$	2.44* $[2.05, 3.34]$
Edges	-1.34 $[-3.01, 0.36]$	1.43 $[-0.18, 3.66]$	1.49 $[-1.21, 4.98]$	3.59 $[-1.18, 8.34]$	1.27 $[-2.61, 5.12]$	2.64 $[-1.18, 6.74]$

Note: Estimates shown with 95% confidence intervals drawn from 10,000 bootstraps. Networks used in tests of H8 contain directed disclosure ties, rather than discussion partner ties. *Significant result.

interaction term of importance and average opinion differences. Eight of the twelve condition 2 cohorts did evince such a positive interaction, although none of those estimates reached traditional levels of statistical significance (2A, 2B, 2C, 2D, 2G, 2I, 2J, and 2K). Of the remaining four cohorts with a negative interaction estimate, only one (2E) was significant. In this group, as both issue importance to ego and average differences of opinion between ego and alter increase, the disclosure tie is significantly *less* likely to occur in the round. That is, the average participant in this cohort was more guarded about disclosing their opinion to the alters they disagree with when that opinion concerns an important issue. On the whole, hypothesis 8 was not supported.

Hypothesis 9

To test the prediction that the generative role of selection homophily is lessened when people have the option to withhold their opinions compared to when they do not have that option (H9), I will need to compare the results from condition 1 cohorts (specifically, results from H1 and RQ1; see chapter 5) against identical models estimated among condition 2 cohorts. For this comparison, I return to the use of the relational tie affected by tie decisions at the end of the round, rather than the disclosure tie used to address H7 and H8.

First is the H9 equivalent of the test conducted in H1. As a reminder, this model specification predicts relational ties obtaining in each of the ten discussion rounds using current round opinion differences. Likewise, the "Disclosed Opinion" control is a dichotomous indicator of only whether the current round topic was disclosed from the alter. Note, however, that this latter measure does take on a slightly different meaning from the tests of H1, as disclosure can be directed (i.e., not necessarily reciprocated) in condition 2 cohorts. Finally, the same network controls of 2-stars and edge memory were included so that the results would remain comparable between conditions. Table

Table 12

BTERGM Results - Hypothesis 9, Current Round Only

Parameter	Cohort 2A	Cohort 2B	Cohort 2C	Cohort 2D	Cohort 2E	Cohort 2F
Opinion Difference	−0.003 [−0.031, 0.018]	−0.026* [−0.051, −0.003]	−0.039* [−0.065, −0.011]	−0.024* [−0.049, −0.003]	−0.019 [−0.038, 0.006]	−0.025* [−0.050, −0.008]
Disclosed Opinion	53.86* [53.72, 54.01]	54.14* [54.00, 54.29]	54.14* [53.97, 54.34]	54.15* [54.01, 54.32]	54.00* [53.83, 54.21]	53.95* [53.80, 54.10]
2-stars	0.069* [0.056, 0.080]	0.054* [0.046, 0.060]	0.064* [0.053, 0.074]	0.057* [0.047, 0.067]	0.046* [0.033, 0.058]	0.042* [0.025, 0.056]
Edge Memory$_{(1)}$	0.26* [0.18, 0.34]	0.33* [0.29, 0.37]	0.29* [0.24, 0.34]	0.33* [0.26, 0.40]	0.28* [0.21, 0.34]	0.30* [0.26, 0.35]
Edges	−27.33* [−27.45, −27.20]	−27.48* [−27.63, −27.32]	−27.51* [−27.73, −27.32]	−27.47* [−27.64, −27.32]	−27.30* [−27.53, −27.06]	−27.18* [−27.33, −26.98]
	Cohort 2G	Cohort 2H	Cohort 2I	Cohort 2J	Cohort 2K	Cohort 2L
Opinion Difference	−0.010 [−0.022, 0.003]	−0.035* [−0.073, −0.008]	−0.009 [−0.032, 0.011]	−0.041* [−0.089, −0.014]	−0.034* [−0.061, −0.013]	−0.029* [−0.048, −0.008]
Disclosed Opinion	53.95* [53.88, 54.02]	54.03* [53.88, 54.17]	53.98* [53.81, 54.18]	54.01* [53.88, 54.12]	53.64* [53.55, 53.76]	53.56* [53.44, 53.65]
2-stars	0.050* [0.037, 0.059]	0.077* [0.057, 0.103]	0.065* [0.047, 0.083]	0.100* [0.084, 0.131]	0.076* [0.055, 0.101]	0.059* [0.043, 0.072]
Edge Memory$_{(1)}$	0.28* [0.25, 0.31]	0.37* [0.30, 0.46]	0.31* [0.22, 0.40]	0.30* [0.21, 0.42]	0.27* [0.20, 0.34]	0.22* [0.16, 0.29]
Edges	−27.29* [−27.38, −27.15]	−27.42* [−27.61, −27.21]	−27.29* [−27.40, −27.19]	−27.50* [−27.75, −27.36]	−27.05* [−27.22, −26.88]	−26.91* [−26.98, −26.81]

Note: Estimates shown with 95% confidence intervals drawn from 10,000 bootstraps. *Significant result.

12 shows the results of this model specification on condition 2 cohorts.

As was the case with condition 1, greater opinion differences on the current topic, controlling for whether that opinion was disclosed and controlling for participants' tendency to produce dense networks, was a significant *negative* predictor of tie formation. Across twelve condition 2 cohorts, eight had a significant coefficient (2B, 2C, 2D, 2F, 2H, 2J, 2K, and 2L). The remaining four cohorts all had estimates which were in the predicted direction, but were insignificant.

That said, the real test of H9 is in comparing these results against those of H1 (see Table 3 in chapter 5). If the generative role of selection homophily is significantly different between conditions, then the parameter estimates for opinion differences in one condition should exceed the bounds of the 95% confidence intervals estimated among cohorts in the other condition. In comparing those results, it appears that all coefficients in the H1 results have at least one confidence interval in the H9 results which overlaps it. The inverse is also true – H9 coefficients are not significantly different from those in H1. At least as far as the current round is concerned, the ability to selectively disclose information to alters does not appear to lessen the effects of selection homophily on tie formation.

The second test of H9 – whether selective disclosure significantly reduces homophilous selection – draws on the modeling procedure used to test RQ1. That is, rather than considering only the current round of topics as meaningful to tie decision-making processes, this second test will look at averaged information about opinion differences and disclosure decisions over all prior rounds. Please see the Research Question 1 subsection in chapter 5 for a more detailed description of the averaging procedure and parameters used. Table 13 contains the results of the RQ1 equivalent test conducted on condition 2 cohorts.

As in condition 1, condition 2 cohorts generally show stronger preferences for forming ties with similar alters, particularly as opinion differences are averaged across prior rounds. Eight of twelve condition 2 cohorts evince a significant negative effect of average opinion differences on the tie obtaining (2A, 2B, 2C, 2D, 2E, 2G, 2I, and 2L). Similar to the RQ1 results, there were two cohorts which show a slight, but insignificant preference for forming ties with dissimilar alters (2F and 2J). However, the real test of H9 is once again comparing the results between conditions. With one exception, the coefficients in one test are contained within at least one confidence interval from the other test, and vice versa. The lone exception to this rule is cohort

Table 13

BTERGM Results - Hypothesis 9, Averaged Prior Discussion

Parameter	Cohort 2A	Cohort 2B	Cohort 2C	Cohort 2D	Cohort 2E	Cohort 2F
Avg. Opinion Difference	−1.59* [−2.30, −1.04]	−0.47* [−0.85, −0.14]	−0.56* [−0.91, −0.28]	−0.38* [−0.58, −0.16]	−0.45* [−0.78, −0.19]	0.10 [−0.16, 0.29]
# Disclosed Opinions	1.09* [0.62, 2.27]	0.37* [0.19, 2.93]	0.32* [0.14, 1.17]	0.48* [0.27, 2.70]	0.38* [0.23, 1.54]	1.37* [0.59, 4.57]
2-stars	−0.054 [−0.196, 0.075]	−0.052 [−0.108, 0.045]	−0.005 [−0.090, 0.089]	−0.074* [−0.119, −0.015]	−0.050 [−0.122, 0.090]	−0.116 [−0.222, 0.059]
Edge $\text{Memory}_{(1)}$	2.20* [1.14, 3.53]	2.04 [−0.12, 2.24]	1.98* [1.12, 2.32]	1.85 [−0.02, 2.13]	2.19* [1.02, 2.58]	1.44 [−1.00, 2.50]
Edges	2.93* [1.72, 5.36]	1.58 [−1.37, 2.31]	0.89 [−0.36, 1.36]	1.25 [−1.62, 1.95]	1.47 [−0.49, 2.46]	−0.52 [−4.01, 0.81]
	Cohort 2G	Cohort 2H	Cohort 2I	Cohort 2J	Cohort 2K	Cohort 2L
Avg. Opinion Difference	−0.77* [−1.10, −0.42]	−0.26 [−1.09, 0.16]	−0.53* [−0.81, −0.21]	0.01 [−0.39, 0.28]	−0.11 [−0.33, 0.16]	−0.64* [−1.38, −0.15]
# Disclosed Opinions	0.17 [−0.03, 1.26]	0.17* [0.04, 0.82]	0.47* [0.27, 1.46]	1.81* [0.65, 4.69]	6.72* [4.00, 47.44]	0.48* [0.31, 1.07]
2-stars	−0.113* [−0.260, −0.013]	−0.110 [−0.284, 0.036]	−0.055 [−0.495, 0.287]	−0.192* [−0.330, −0.109]	−0.229* [−0.296, −0.066]	−0.057 [−0.267, 0.136]
Edge $\text{Memory}_{(1)}$	2.50* [1.52, 2.87]	2.21* [1.47, 2.83]	2.13* [1.27, 2.60]	0.52 [−1.41, 1.48]	−2.83* [−23.22, −1.62]	1.79* [1.30, 2.83]
Edges	3.21* [1.75, 4.53]	1.73* [0.20, 3.01]	1.08 [−1.13, 3.13]	−0.40 [−3.67, 1.87]	−5.92* [−47.14, −3.46]	1.55 [−0.24, 4.05]

Note: Estimates shown with 95% confidence intervals drawn from 10,000 bootstraps. *Significant result.

2A which has a much larger negative coefficient for averaged opinion differences than any of the condition 1 cohorts, or even for that matter the other condition 2 cohorts.[26] Given that the prediction for hypothesis 9 was that condition 2 would *lessen*, not *strengthen* selectivity compared to condition 1, it is evident from these results that H9 is not supported.

Research Question 3

The final analysis concerns research question 3: "does selection in networks where selective disclosure is permitted still produce network-level partisan assortativity above chance?" Asking this research question relied on a number of assumptions regarding prior hypotheses. First, condition 1 had to produce network-level assortativity above chance. This was tested in hypothesis 2 (see chapter 5) and the results did not support this hypothesis, and in fact some cohorts showed significantly *lower* levels of assortativity than expected by chance. This was due, in large part, because of the tendency for participants to form many ties – as network density approaches 1, randomly-generated networks in the conditional uniform graph test are less and less likely to differ from the observed network in any meaningful way. Second, this question relied on support for hypothesis 9 – that selective disclosure would significantly reduce the generative role of selection compared to condition 1 in which participants always shared every opinion with their alters. This hypothesis was also not supported – participants in condition 2 were just as (and in one case, more so) selective as condition 1 participants.

That said, the tests conducted to investigate research question 3 largely mirror those used to test hypothesis 2. A modified conditional uniform graph test was conducted on each cohort, discussion round combination. This test applied the same number of vertices, the same distribution of the party identification measure, and the same number of edges (randomly distributed among nodes) to 1,000 randomly-generated networks. The statistic of interest, assortativity of party identification, is then calculated on each of these networks to draw a null distribution against which the observed network can be compared. Table 14 shows the results of these tests with the cell values indicating the proportion of simulated networks which had a higher assortativity value.

Among the 132 combinations of cohort and discussion round, at only 3 points in time did a cohort exceed state homophily (assortativity) levels expected by chance. Cohort 2H shows significantly greater assortativity than chance in rounds 6 and 7, before returning to the body of the null distribution by round 10. The other time assortativity significantly exceeds chance is in cohort 2A in discussion round 9 – the same cohort which showed drastically higher preferences for similar alters compared to the other cohorts in the second test of hypothesis 9. One cohort, 2L, measures significantly *less* party identity assortativity than the random networks from rounds 5 through 10. 2L is the smallest cohort in condition 2, and the smaller cohorts in hypothesis 2 (e.g., 1K and 1L) also showed this same significant result. Further investigation may be required to determine whether selection homophily varies as a function of the network size, or whether greater edge density (sociality) is more likely to obscure assortativity among smaller networks.

While the answer to RQ3 is "no" – networks in condition 2 do not show evidence of party identity assortativity above chance – this should not be construed to mean that selective disclosure results in less selection homophily (see H9). Rather, as discussed above, assortativity is confounded in these networks with edge density. Participants generally showed greater interest in forming any discussion ties at all rather than forming ties as selectively as possible. The implications of these findings,

Table 14

Conditional Uniform Graph Test Results - Research Question 3

Round	Cohort 2A	Cohort 2B	Cohort 2C	Cohort 2D	Cohort 2E	Cohort 2F
Random Assignment	.618	.154	.416	.902	.469	.731
1	.286	.643	.640	.905	.953†	.819
2	.561	.688	.478	.968†	.853	.815
3	.596	.637	.564	.892	.763	.787
4	.410	.514	.396	.510	.328	.551
5	.752	.842	.405	.415	.229	.553
6	.386	.856	.591	.458	.101	.355
7	.263	.702	.680	.212	.200	.220
8	.142	.695	.943	.491	.303	.363
9	.045*	.822	.951†	.288	.271	.202
10	.062	.810	.931	.254	.337	.182
	Cohort 2G	Cohort 2H	Cohort 2I	Cohort 2J	Cohort 2K	Cohort 2L
Random Assignment	.856	.822	.364	.923	.462	.423
1	.923	.813	.277	.842	.660	.634
2	.476	.377	.299	.802	.627	.689
3	.623	.320	.255	.633	.371	.795
4	.325	.202	.268	.860	.224	.904
5	.565	.258	.147	.854	.235	1.000†
6	.330	.036*	.148	.939	.201	1.000†
7	.382	.045*	.156	.945	.630	.998†
8	.467	.058	.112	.960†	.742	.999†
9	.580	.101	.383	.664	.741	.997†
10	.720	.273	.673	.251	.641	1.000†

Note: Cell values indicate the proportion of 1,000 simulated networks which had higher values of party identity assortativity than the observed network. $^{*}p < .05$. †Significantly *less* assortative than chance.

both theoretically and methodologically, are discussed in the next chapter.

Chapter 7: Discussion

Findings and Theoretical Contributions

The goals of this dissertation are threefold: 1) to isolate selection from other homophily mechanisms, 2) to explain individual variances in selectivity, and 3) to provide a framework with which interpersonal processes affect selection in dynamic discussion networks. To these ends, nine hypotheses and three research questions relating to selection homophily were proposed.

The first goal of isolating selection homophily was accomplished in tests of hypotheses 1 and 2, and in research questions 1 and 2. H1 offered the most straight-forward test of the assumptions of selection homophily – that people would form ties more frequently with someone they agree with. These tests used absolute difference on a single issue position for each of the ten discussion rounds in the study to predict ties obtaining at the end of the round (i.e., "add" or "maintain"), conditional on whether the topic was actually discussed in the dyad, participants' tendency to form many ties (2-stars), and whether the tie was present in the prior discussion round. Consistent with the hypothesized *negative* relationship between differences of opinion and tie formation, all twelve cohorts had a negative coefficient for this term. However, only four of the twelve reached conventional levels of statistical significance. RQ1 then asked whether people consider information learned about alters from prior discussions – in addition to the current topic of discussion – to inform their decision about the status of a tie. To this end, absolute differences across all previously-discussed topics were averaged – this average was recalculated at each round when the dyad had a tie in the network. Results from this test indicate support for selection homophily: nine of twelve cohorts had significant coefficients in the predicted direction and two additional cohorts showed (insignificant) similarity preferences. Together, these results provide all-but-definitive support for the notion that people prefer to select politically similar alters more frequently than politically dissimilar alters.

However, one key assumption in the homophily literature is that dyadic political selection should "scale up" to the network-level in the form of party identity assortativity (Lazarsfeld & Merton, 1954; McPherson et al., 2001). The theory behind this "scaling", microdeterminism, regards the seeming mathematical certainty with which the greater likelihood of ties forming among politically similar alters should lead to greater correlation of a political characteristic (i.e., party identity, although this has been operationalized as ideology as well) across all connected dyads in the network. H2 and RQ2, both assessed using the same analytic procedure, posited that the networks would be assortative above chance at some point over ten rounds. With only a few, short-lived exceptions, the networks were not assortative above chance. This, I argue, is likely because participants in the study first preferred to form a lot of ties with one another (i.e., sociality was the primary consideration in tie decisions), and similarity of opinions was considered secondarily. This resulted in much higher network density than I expected to find, and thus the simulated networks in these tests were severely constrained.

The second goal of this dissertation, to explain individual variation in selectivity, was accomplished in tests of hypotheses 5 and 6. Specifically, it was hypothesized that subjective issue importance (H5) and affective polarization (H6) would each moderate the effect of opinion differences on tie decisions. Both hypothesized interactions were expected to be *negative*, meaning that as importance/affective polarization increase, the negative relationship between larger differences of opinion and the likelihood of the associative tie decision is *magnified*. Hypothesis 5 was not supported in the data – just one of twelve cohorts showed evidence of a significant interaction in the predicted direction. One other cohort also had a significant interaction between subjective importance and opinion differences, but the interaction term was *positive*, suggesting that as issue importance increases, people are more likely to form ties with politically *dis*similar alters.

The tests of the interaction between affective polarization and opinion differences on tie decisions (H6) were only somewhat more successful at identifying individual variations in selectivity. In two of twelve cohorts, a significant negative interaction was found. This suggests that, at least in those groups, people who more positively evaluate political in-group (i.e., like-partisan) members compared to out-group members are *more* selective than people who evaluate in- and out-groups more evenly. Among the other ten cohorts, non-significant findings showed a split between positive and negative interaction coefficients. Taken together, no definitive evidence was found in support of issue publics (Krosnick, 1990; Krosnick et al., 1993) or affective polarization (and perhaps by extension, social identity theory; Tajfel & Turner, 1979) explanations for why two people might be differentially selective. Further research is needed to explain individual differences in selectivity, whether they may be political or apolitical in origin.

The final goal of this dissertation was to begin to adapt this methodological framework to determine what, if any, role interpersonal theories of communication have in explaining networked interactions around politics. To this end, I began with two tests of some principles which govern *why* people might opt to be politically selective. The first test (hypothesis 3) investigated whether people could safely assume that if they form ties with others based on similarity of previously discussed opinions, they will be more likely to encounter similarity in future interactions. This desire to predict the outcome of future interactions – and subsequent avoidance of the interaction if dissimilarity is expected or if outcomes are less certain – is a core principle of uncertainty reduction theory (Berger & Calabrese, 1975). H3 was tested in two sets of models: the first set used differences of opinions on non-disclosed issues from the same ten topics that were discussed (i.e., if the "A" version was discussed, differences on the "B" version was used for this test; see Table 1). The second test used differences of opinion on the 10 issues from the five withheld topics: terrorism, foreign policy, healthcare, education, and the environment.

The former test was largely successful – associative tie decisions were significantly related to differences of opinion on the ten withheld public opinion questions from the ten discussed topics in seven of twelve cohorts tested. Additionally, four of the five remaining cohorts had coefficients that were in the predicted (negative) direction. This suggests that if participants were to discuss issues related to topics they have already discussed and made selective decisions on, then they will likely encounter agreement on those issues. The second test associating tie formation with differences of opinion on completely withheld topics was unsuccessful. Three of twelve cohorts showed a significant *positive* relationship between tie formation and average differences of opinion on these five topics. Together, these two findings suggest that people are correct in using selective tie decision-making to form discussion ties which will be more likely to encounter agreement in the future, but this predictive capacity has limits – similarity on related issues within broader topic categories that have been discussed already is safe to assume, but people will be less likely to encounter agreement from selective decision-making if the future interaction involves discussion of a totally new topic.

Next, I turned to the interpersonal process of selective disclosure (Cowan & Baldassarri, 2018; MacKuen, 1990). These tests required a second quasi-experimental condition in which participants were allowed to decide who, from among their list of alters, they would like to share their opinion on the current topic with. Hypotheses 7 and 8 concern these selective disclosure decisions and used networks which operationalized disclosure ties, rather than the discussion relationships used in prior tests. First, H7 predicted that people would be more likely to disclose their opinion to a politically similar alter – determined by averaging opinion differences from prior discussions – compared to a politically dissimilar alter. Results indicated mixed support for this hypothesis, with five of twelve condition 2 cohorts showing significant evidence of the negative relationship between differences of opinion and subsequent opinion disclosure. Among the non-significant findings, two cohorts showed a slightly greater propensity to share their opinions with politically dissimilar alters. Hypothesis 8 posited that a person's subjective importance attributed to the issue about to be discussed would moderate the relationship between prior differences of opinion and disclosure decisions. The expected interaction was hypothesized to be positive, indicating that people would be less concerned with prior differences of opinion when the new opinion about to be disclosed is relatively important to them. This hypothesis was not supported – eight cohorts showed a positive, but insignificant interaction, while one cohort showed a significant *negative* interaction. Together, these results suggest that prior differences of opinion are weighed when deciding whether to disclose an opinion to an alter, but that the importance of the issue being discussed does not affect the weight of those differences. In this way, dyadic opinion disclosure decisions on specific topics operate in a similar manner to more general political discussion tie decisions.

The last tests (hypothesis 9 and research question 3) were conducted to determine 1) whether selectivity is reduced in networks which permitted selective disclosure compared to networks which did not include this process, and 2) whether such networks evinced state homophily (assortativity) above chance. The skepticism that selection homophily would operate to the same degree in networks where selective disclosure operates as in networks where selective disclosure is not operating stems from a logical extension of H7 results: as disclosure tends to occur more often when two people have expressed more similar opinions on prior topics of discussion, then opinions that are likely to encounter disagreement are less likely to be shared. This changes the information environment to one in which agreeable opinions are more prevalent among dyads. Thus, selectivity may result in more connections between politically-dissimilar alters in these circumstances than if dissimilar opinions were more often shared. Two tests were conducted of hypothesis 9, each mirroring the parameter specifications of tests of H1 and RQ1 (respectively). The results were broadly similar between conditions – just one cohort showed a *greater* degree of selectivity in the differences-averaged test (RQ1 equivalent). In other words, selective disclosure does not reduce selection homophily. Finally, RQ3 was intended to assess whether network-level assortativity could exceed chance levels in networks with selective disclosure. While the results of these tests indicate that significant party identity assortativity is unlikely and not sustainable in these networks, the conclusion that selective disclosure is the root cause should be eschewed. This testing procedure suffered from the same shortcoming that plagued tests of H2 and RQ2 – participants' tendency to form really dense networks may have obscured any assortativity that could exist.

All told, the mixed results, and in some cases results which were significant against the predicted direction, were surprising. That dyadic selection homophily was largely supported comports with much of the theoretical work on homophily (broadly) and less so with certain arguments made in the literature that selection homophily does not occur (e.g., Lazer et al., 2010; Sinclair, 2012). However, that party identity assortativity was not an emergent property of the network is unexpected. Research in this area has long relied on the quasi-mathematical certainty with which microdeterminism should link dyadic selection with broader network-level observations of correlated political identities or ideologies among all connected pairs. There may be a number of reasons for the discordant findings of this study.

The first explanation is that, while dyadic selection was identifiable in this study, the selectivity observed was not sufficiently strong to produce homophily as it is conventionally measured in observational studies. This argument would seem to support those who claim that selection's contribution to homophily in real-world relationships is small-to-nonexistent (e.g., Lazer et al., 2010; Sinclair, 2012; Song, 2015). The effects of selection homophily in this study are difficult to contextualize in this respect; coefficients, or any exponentiated transformation of them, in ERGM family results should not be interpreted as an effect size as they are confounded with residual variances which are idiosyncratic to both the network and the model specification (Duxbury, 2021). For that same reason, results across cohorts could not be aggregated into a single model with one result.[27] That said, one can convert the log-odds of a tie obtaining into more interpretable odds by using an exponential function to alter the coefficients. By this measure, among members of the most selective cohort in the tests of hypothesis 1, each 1-unit increase in difference of opinions (range 0-6) on the current round's issue means that the tie is on average 95.60% as likely to obtain in the network. A 4.40% decrease in the odds of a tie obtaining, spread across such a small range of opinion differences is by no means large. This is approximately in-line with a recent study by Aral et al. (2009), which found that the contribution of the influence mechanism to observed dyadic similarity is in fact quite small. However, I am hesitant to conclude that this means selection homophily does not substantively contribute to observable network-level assortativity without further investigating other possible explanations for these findings.

Another possible explanation for these surprising results is that participants were sociable first and politically selective second; this was substantiated with the descriptive statistics of the networks presented in chapter 4. That is, dyadic selectivity was evidenced in the BTERGM results because sociality, or the tendency for people to have many ties, was controlled for with the addition of a two-stars parameter in the specification. Indeed, when this endogenous feature is excluded from the model, the model is a poor fit for the observed data. However, in the CUG tests and descriptive statistics assessing network-level party assortativity, such density could not be accounted for, and so state homophily was likely obfuscated in these results. This sociality phenomenon could be the result of a number of phenomena, many of them particular to the time and method of data collection.

First, because this study took place online and participants interacted with each other anonymously, it is possible that participants saw few “costs” associated with adding new ties or maintaining existing ties, regardless of the size or political composition of their ego network. The instruction provided at the beginning of the discussion round phase – that tie decisions determine chat phase interactions – was included to convey to participants that their decisions were consequential, and that they ought to treat these interactions as they would in-person interactions around politics. This instruction did not tell participants they ought to be selective, nor was it ever repeated during the discussion rounds that followed. Further, it is possible that participants view a one-time, short, and anonymous online chat differently than they would an in-person discussion of politics – that is, they may have been less inclined to be selective and more inclined to be sociable if any disagreement they anticipate in the chat phase is only temporary. An in-person replication of this study is needed to address whether the online nature of participant interactions substantively affected the network structures. Relatedly, the instructions could be altered to remove any indication that participants may have as many alters as they would like, or in the extreme, the number of alters per person could be constrained in the study design in accordance with cognitive limits on sociality (e.g., Dunbar, 1992). Doing so could shift the interpersonal goals of participants from sociality to selectivity in such a way that assortativity is more strongly evidenced in the results. That said, one should be careful in implementing such changes, as incentivizing selectivity above what participants would normally implement in their everyday interactions runs counter to the internal validity of this study design.

Two other phenomena could also explain participants' sociality in the present study. As I mentioned in a previous chapter, this study was conducted in late 2020 and early 2021, when much of the United States was still in lockdown from the COVID-19 pandemic. The majority of U.S. adults had not received a vaccine yet. Offices and schools were closed, forcing many to work from home. Bars, sports venues, movie theaters, and many restaurants were also closed or operating in very limited capacities. And so the ability of people to socialize in most in-person contexts was severely constrained. Compared to other online studies conducted among MTurk participants, which often involve short surveys or tasks like image or text categorization, this study offered people a unique chance to interact with other MTurk participants. While this study was conducted after one of the most contentious elections in U.S. history and most cohorts were collected after the deadly events of the January 6th protests at the U.S. Capitol, it is possible that the relative isolation that participants had felt over the prior months, perhaps coupled with a desire for unity after experiencing traumatic political disunity, led participants to be more sociable in this study than they would have been had data collection occurred under different circumstances. Related to a desire for unity, it is also possible that sociality and even tolerance for differing political opinions are socially normative behaviors. That is, people may feel pressured to have many connections with others, or to have discussion connections which cross party lines. And so when tie decisions are directly observed in this study, a Hawthorne effect, or participants' tendency to behave in accordance with these pressures as a result of being observed, may be responsible for the overwhelming sociality and comparatively weak selectivity of participants. This discrepancy may not manifest in unobserved political discussion networks. While the former phenomenon could be addressed with a replication study after the pandemic closures have ended and people are able to socialize outside of online spaces, the latter phenomenon would be much more difficult to address with the current study design. Measuring political selectivity discretely while also constraining the information environment to political opinions in order to isolate selection from other generative mechanisms may require vastly more complex methods than this framework offers.

A further reason why discrepant findings between the dyadic- and network-level might exist is that specific issue opinions were used in the tests of the former, while party identity – a more abstract political characteristic which was not shared between participants – was used for the latter. This methodological decision was made to both allow for the discussion rounds to vary over time as political discussions do in the real world in response to the salient issues of the day, and also to provide a single metric at the network level which corresponds to conventional operationalizations of political assortativity in much of the homophily literature. However, this decision also means that in order for participants to form ties which are homophilous with respect to party identity, they have to form an abstract perception of their alter's identity from several specific opinions on a variety of issues. If this perception is vague or inaccurate, then selective decision-making will not necessarily result in ties which are similar with respect to party identity, but may still be associated with similarity on specific issue opinions. Some of the constituent issues may be less often correlated with party identity, although evidence suggests that policy preferences are often correlated with political party (Carsey & Layman, 2006; Layman & Carsey, 2002). Two further explanations could also account for why people have either vague or inaccurate perceptions of their alters' party identities. First, it is possible that the accuracy of these perceptions depends, in part, on subjective variance in political sophistication. That is, people who know more about the American political party system and their respective policy platforms may be better equipped to place an alter on a party identity spectrum from learning their opinions on different issues than someone who knows or cares less about politics. Perhaps if participants had been allowed to explain or support their opinions in a sentence or two, their alters may have been better able to pinpoint their party identity. While the methodological decision to constrain communication to the sharing of responses on a public opinion questionnaire was made to further isolate political selection, it may have contributed to the mixed results here. I will return to this in the next section.

Second, the decision to include political independents in this study may have made the process of ascribing a party identity to alters more challenging for participants. Some people may identify as independents because they have either moderate or varied opinions on different issues which do not neatly conform to one political party or another. Others may identify as independents, but have opinions which more closely align to one side of the political spectrum; for example, many Libertarians identify as political independents, but often have views of social issues which align with Democrats and views of economic issues which align with Republicans (Boaz & Kirby, 2007). To assess whether independents in this study had a significantly less cohesive set of policy preferences compared to Democrats and Republicans, I ran a separate post hoc test fitting all 30 issue positions to a single factor in an exploratory factor analysis. While the results indicate that independents had opinions which were significanly less cohesive compared to Democratic participants, this single factor loading fit equally well between independent participants and Republican participants.[28] At any rate, further study is needed to determine whether participants form accurate perceptions of their alters' political identities.

Finally, some of the methodological decisions may also explain the mixed results between dyads and the network as a whole. Specifically two decisions, when considered together, may have resulted in more associative tie decisions in the study compared to disassociative tie decisions. The first is the decision to allow only 20% of ties to be randomly selected to update in a given round. While this was included in this study to both constrain the amount of time it takes participants to interact in each round and to mimic social "viscosity" found in real-world networks (Harrell et al., 2018; Nishi et al., 2015; Rand et al., 2011), the relatively low rate of updating may have left participants feeling that they needed to first add many ties to get a sense of the landscape of opinions before they could be politically selective. This, coupled with the decision to limit discussion rounds to 10 different topics with no advanced warning that not all topics would be discussed, may have meant that participants thought they would have more time to be selective later on in the study. The clearest evidence of this phenomenon among the data presented here is in Figure 6, depicting changes in the edge density of networks over ten discussion rounds. While density steadily increased across all cohorts in the study (i.e., high sociality), this trend levels off in later rounds at levels which are still substantially below full connectivity (1) in the network. Future iterations of this study should explore different rates of tie changes and different numbers of discussion rounds in order to determine whether this had a substantive impact on tie decision-making. To the extent that questions were left unanswered by this dissertation, I am confident that this study framework could be applied and adapted accordingly to provide more useful insights in future work.

Strengths and Limitations of the Study

One of the chief strengths of the design of the current proposal is that the amount of information any participant has about others in the network is limited. As I have mentioned previously, structural mechanisms of homophily are an important determinant of similarity among interactors, but they are often overlooked when researchers attempt to disentangle the root causes of homophily in a network. Structural homophily occurs through two, neither mutually inclusive nor mutually exclusive, processes. First, political homophily may be the result of the distribution (or "availability") of viewpoints (Blau, 1977). When party identity is skewed in a population – that is, when there are majority and minority representations of different identities – it is comparatively easier for members of the majority party to encounter like-minded individuals with whom to discuss political matters. Second, structural homophily may occur when people are associated with one another through some other means – such as similarity in neighborhoods, workplaces, or age groups (Feld, 1982). To the extent that political ideology correlates with these other factors, people will have homophilous relationships in a partisan dimension, even if the root cause of their relationships is apolitical.

Research which fails to account for structural homophily may be over- or understating the extent to which other mechanisms of homophily – such as selection – play a role in the formation of the network. Using a conditional uniform graph test which simulates networks with the same number of vertices, the same distribution of party identification, and the same edge density as the observed networks, I can ascertain how much of the observed assortativity can be attributed to the availability component of structural homophily (and consequently, what portion can be attributed to selection).[29] Further, by constraining the information about potential alters to a player identifier and their political opinions, it can be ensured that participants in both conditions are only making their tie decisions using that information. In other words, participants cannot select discussion partners on the basis of race, age, geographic, or any other structural source of homophily simply because that information is not available to them when they are making that decision.

By a similar token, this study rules out the effects of the social influence mechanism. Participants are asked their opinions regarding each of the 15 topics before they are placed in a network and those opinions are not permitted to change during or after discussion of the issues. Likewise, their responses to the party identification question – used for determining assortativity in the network – are kept confidential, and so would not be swayed by participants' attempts to show that they are more similar to their alters than they are in actuality. Even if it is the case that opinions are permitted to change or that party identification is shared with others, it is unlikely that participants know each other as close friends or family members,[30] and so the participants' responses to the opinion and party identity survey questions are less likely to be influenced by their alters (Bello & Rolfe, 2014). With both influence and structural mechanisms controlled for, any state homophily (assortativity) found in the networks – or generative role of dyadic opinion differences in the formation of network ties – after ten discussion rounds is the sole result of selection of ideologically similar alters.

Another strength of this approach is that by first demonstrating an internally-valid study design which isolates selection occurring in dynamic discussion networks (condition 1), further extensions of this design can begin to add different theoretically-relevant processes to continue to expand on our understanding of selection homophily. Importantly, comparisons can be made between the outcomes of the framework of the study as presented in this dissertation and a corresponding study with the additional process to determine the unique impact of that process on selectivity. This technique is used in the present study with the second quasi-experimental condition: participants are allowed to decide whether or not to disclose their opinion to their alters. By comparing the results of the cohorts in each condition, I investigated how topic avoidance – an interpersonal process which in prior research has had only limited application in networked contexts – constrains the social information available to decision-makers, and thus their selective decisions.

That said, the focus of this dissertation on providing an internally-valid study design means that many of the ways in which participants interacted with one another were artificial, and thus limit the external validity of the findings. One of the most obvious ways that interactions in this study differ from real-world interactions is the way that communication among a dyad was operationalized – as the sharing of answers to a public opinion questionnaire. Participants were not permitted to elaborate on their opinions, or to give reasons as to why they hold that position. For example, consider the statement used for the abortion, version B measure: "Employers should provide employees with healthcare plans that cover contraception or birth control at no cost." One may generally agree with this statement when applied to public employers (e.g., the federal government), but not when it comes to private companies (e.g., Hobby Lobby). Or devout Catholics may disagree with this statement because of sincerely-held religious beliefs, even if the opposing opinion would be more consistent with their political party identity. That participants are not afforded the opportunity to further explain their opinions is an intentional part of the study design – variability in political sophistication, education, wordiness, or even familiarity with typing on a computer keyboard could be associated with features of an explanation or reason for an opinion that might be preferred by a person's discussion partners. Selection on political similarity may have been obscured by selection on one's ability to explain their opinion, regardless of what that opinion is, or it may have been difficult to parse these competing explanations for tie formation. Political conversations are much more nuanced, asymmetric, and detailed than the political communication which occurred in this study and future work which may not need to place such a large emphasis on internal validity can begin to integrate features of interactions that will make the study more naturalistic.

Relatedly, information was transmitted and received between participants with perfect accuracy; in other words, there was no error involved in one's ability to communicate their opinion to their discussion partners, nor was error involved in the perception of the meaning of the opinion on the part of the receiving discussion partner or in recalling that information at a later point in time. Receiving individuals were still tasked with interpreting the information they learned about others, and also with forming an abstract attribution of a political identity (Heider, 1958) out of the sum of information. The attribution process helps one to form a prediction about opinions on yet-to-be-discussed topics (Berger & Calabrese, 1975). On a similar note, because issue opinions are an abstraction away from party identity, perhaps discussion topics that more closely relate to party identity, such as who participants supported in the previous national election, would have helped participants form more accurate attributions and by extension form networks which are more assortative on party identity than those observed in the study.

That said, the information that participants had about one another was simple in form, and thus easier to compare and contrast with one's own responses to the same questions. In a similar vein, participants were always shown a summary of the discussed topics in the dyad prior to making a tie decision. This aspect of the design was likewise intentional – it helped ensure that selectivity was not dependent on an unmeasured characteristic of individuals: memory for the supplied information in prior discussion rounds. However, real-world political conversations do not often include a 100% accurate and easily-interpreted ledger of opinion discussed in the dyad, and so more work could be done to make this study framework more closely mirror an error-prone conversation.

Other design decisions concerning the networked side of interaction are likewise concerned with internal validity over external validity. For example, the decision to randomly assign discussion partners (20% of possible connections) at the start of the discussion phase was reached to ensure both that 1) participants would start the first round with some information about others in the cohort, and 2) the network would not be more homophilous than random chance, given the constraints of availability in the cohort. Real-world political discussion ties sometimes form as a constituent component of broadly social ties, such as friendships, coworkers, or via shared acquaintances (Sinclair, 2012), and so the randomness involved in the design is not representative of how discussion networks are first formed. This shortcoming is explained by a desire to constrain the effects of structural homophily, which accounts for those apolitical sources of political homophily. A similar design decision was made with regard to the random assignment of tie updates: only 20% of all possible ties were selected at random to update. While constraining the number of ties that are allowed to update over time in order to mimic social "viscosity" is not uncommon in network experiments (Harrell et al., 2018; Nishi et al., 2015; Rand et al., 2011), normally people have much more subjective control over the viscosity of their networks. For example, some people may be more gregarious, interested in political matters, or communicative of their political convictions than others. Further studies are needed to determine if either of these design decisions have an effect on the overall results.

Two possible explanations for the greater than expected edge density (or sociality) in the networks – participants' clear pattern of choosing the associative tie decision with greater frequency – could be addressed in future studies. First, because this study was conducted on the internet only,[31] it is possible that the "risks" involved with encountering disagreement in a short, anonymous extemporaneous discussion of political matters were insufficient to elicit selectivity. Recall that participants were instructed at the start of the discussion phase: "At the end of the study, you will have the opportunity to join a chat room to discuss political matters in more detail with your social network. Your decisions about who you include in your social network will determine who you talk to directly at the end of the study. **Please consider other participants' political opinions as they are shared and try to make tie decisions as you would in real-life situations.**" While this one-time instruction was thought to be sufficient to convey a sense that tie decisions were consequential, it is possible that participants did not view selection of politically dissimilar alters in a short online experiment as risking negative interaction outcomes. The implication this has is that interpersonal theories which concern this careful consideration of possible outcomes (e.g., URT; Berger & Calabrese, 1975) have limited application when interaction decisions move online.

Relatedly, this study is very different from many of the studies on Amazon's MTurk system. "HITs" often involve very short participation, such as completing a survey or categorizing pictures or text for machine learning algorithms, and rarely allow MTurk workers to interact with one another. The novelty of this type of interactive design could mean that people were generally more pro-social on the platform.[32] Whether these explanations could be fixed with in-person data collection, or a stronger or repeated induction message, are important questions that future replications could address.

Finally, the MTurk sample used for this study was hardly a representative sample of the United States. Participants were considerably more Democratic leaning, male, college-educated, and younger than the population. This is not entirely surprising, given prior demographic surveys of MTurk workers (Huff & Tingley, 2015; Levay et al., 2016). The analyses, particularly of H2, RQ2, and RQ3, took into account the distribution of party identity in the cohorts in order to address concerns related to structural availability. That said, had I known that participants would so overwhelmingly choose associative tie decisions, I would have been more concerned by this at the outset as a more politically diverse cohort may have been more resistant to the density constraints placed on the conditional uniform graph tests. MTurk was selected as the participant pool, in part, as a matter of convenience – the Breadboard software integrates with the platform (McKnight & Christakis, 2019). This obviates the need to recruit many concurrent participants ahead of a scheduled start time through some other platform or participant pool. However, the results presented here do not generalize well to the broader American population. Given this dissertation's focus on providing an internally valid framework, and certain time and fiscal constraints that come with completing a dissertation, I thought this is a worthy tradeoff. That said, future studies in this paradigm will need to reconsider participant selection.

Implications

The implications that this study has for theory and research at each of the interpersonal and network levels will be somewhat limited due to the mixed support for hypotheses. That said, in my view, the largest implication this dissertation will have for future work is at the intersection of levels.

In particular, the discordant findings between dyadic selection homophily (supported) and network-level assortativity (not supported), suggests to me that the reliance on the assumptions of microdeterminism in the homophily literature may be misguided. Dyadic selection can be identified as a generative process absent significant network-level assortativity. This conclusion has interesting parallels with the social network literature's warnings about "macrodeterministic" assumptions, or that because state homophily is found to describe a network, it must mean that process homophily (i.e., selection) occurred to make the network this way. Greater care and attention, both in theorizing about and studying, the complex interplay between macro and micro scales is clearly required in political homophily research.

In political communication research specifically, there still exists a need for definitional and operational assimilation. My hope is that, by focusing on operationalizing political discussion ties as a separate, but often constituent relationship within broader, multiplex social ties, further research on the generative mechanisms of political homophily can make clearer distinctions between which processes should and should not be applicable to selective decision-making. Likewise, I expect that the macro- and microdeterminist perspectives will need to make clear whether homophilous selection in the dyadic discussion of political opinions can reasonably be associated with state homophily of party identity in an observed network. To be fair, operational definitions of party identity or ideological assortativity are readily applied to a variety of research methods, including survey measures (Klofstad et al., 2009) or with large observational data sets (Barberá, 2015; Barberá et al., 2015; Bond & Sweitzer, in press). Further, the expectation that party identity would be associated with specific policy preferences is not unfounded either (Carsey & Layman, 2006; Layman & Carsey, 2002). However, further research is needed into the attributions of a political identity on the part of individuals to their discussion alters in order to assess how well these two perspectives can be integrated into a single representation of selection homophily.

While my intention with this dissertation was to answer a call made by Eveland, Morey, and Hutchens (2011), among others, for social networks researchers to "... [place] a greater emphasis on individuals functioning as communicators in relationships" (p. 1082), the conclusions of this study add to this chorus as well. The framework presented in this dissertation can be used to explore any number of applications of interpersonal or small group communicative processes, even beyond the scope of political discussion contexts. Moreover, this framework can be used to integrate the many levels of communication theory and research, from psychological, to interpersonal, to small group, and to networked phenomena. It is my hope that this study will serve as a foundation for more integrative research to follow.

Future Research

As mentioned above, the methodological framework of this study is readily adapted to assess the role of a variety of interpersonal processes in shaping homophilous tie decisions. This research paradigm has three planned extensions of the current study, but this is by no means an exhaustive list of potential uses of the framework or set of theories contained in this dissertation. The first extension will be a simple replication of this study which will use a more representative sample and will be conducted in an in-person setting so that a new induction – instructing participants that they will engage in a face-to-face discussion with one of their network alters at the end of the study – can be tested. It is my hope that this may sufficiently increase the potential costs of interaction sufficiently so as to reduce edge density to a more manageable level for the hypothesis tests regarding assortativity.

While this dissertation focused on isolating the selection mechanism and explicating how it varies as a function of subjective characteristics or a fundamental change to the interpersonal communication process, it is nevertheless important to further investigate *why* people are selective. The next two planned extensions of this paradigm concern uncertainty reduction theory (Berger & Gudykunst, 1991; Berger & Calabrese, 1975) as one applicable avenue for this line of research. Relational uncertainty is thought to explain why people prefer connections with similar alters – perceptions of similarity reduce the cognitive stress brought about by a desire to predict the outcomes of future interactions. One of the ways uncertainty has been operationalized in prior studies of URT is through attributional confidence (Clatterbuck, 1979), or the assessed confidence one has in their ability to predict what their discussion partner thinks about an issue. One URT extension of this study could ask participants to both make an attribution of their partner's opinion on a future topic, and to rate their confidence in this assessment. Not only would this allow for the investigation of attributions and their accuracy in political discussion, but it could also provide further insight into why some people are more selective than others (i.e., perhaps attributional confidence varies systematically).

A later extension to uncertainty reduction theory posited that shared relationships are another source of perceptions of similarity in a dyad (axiom 8, Berger & Gudykunst, 1991). For example, suppose Sam and Nasrin don't know each other, but they meet through a mutual friend Huan. If they have both discussed politics with Huan before and they have each agreed with Huan on most issues, then they will be more confident that they are politically similar to each other than if they didn't have a mutual friend who has similar political opinions. In this way, axiom 8 of uncertainty reduction theory draws from balance theory (Heider, 1958, 1979) to expand from dyadic to triadic communication. The former extension utilizing URT could also have a corresponding second quasi-experimental condition in which participants are permitted to see the ties that exist between their alters in the graph on the left-hand side of the Breadboard user interface. This examination of selectivity is particularly exciting to me, as it offers a succinct integration of interpersonal and networked communication.

Conclusion

Political homophily, or the tendency for political discussion ties to form more frequently between like-partisans than between people with differing political identities, is a well-studied phenomenon in the political communication and social networks literatures. Homophilous network structures have profound effects on the flow of political information and on participatory democracy. However, few studies have been able to isolate the mechanisms which are thought to produce such network structures. Communication theories at multiple scales offer valuable insight about the complex dynamics of networked political interactions, and so integrative frameworks are required to bring these perspectives together.

This dissertation advances the concept of political selectivity, or the degree to which one's decisions about the status of ties in a political discussion network favor discussion partners who one perceives to be similar to themselves. A five-phase, two-condition quasi-experiment was designed to isolate the selection mechanism of homophily from structural and influence generative processes, to identify possible causes of subjective variance in selectivity, and to investigate the role of selective disclosure in shaping the tie decisions of networked participants.

Subjects ($n = 366$) were recruited into 24 cohorts. In condition 1, participants shared their opinions with each of their alters; in condition 2, participants were permitted to decide from among their alters who they would like to disclose their opinion to. Results broadly support the selection homophily hypotheses that people are more likely to form political discussion ties with others who hold similar opinions to themselves. However, further findings were more nuanced. Selection of similar discussion partners did not, despite the conventional wisdom, scale to the network-level in the form of political identity assortativity. In condition 1, selection homophily was found to produce relationships which were significantly more similar regarding withheld opinions on related issues that had been discussed in the dyad. However, such similarities do not extend to new topics. Neither issue importance nor affective polarization were found to significantly interact with opinion differences in predicting tie decisions. In condition 2, averaged similarity on previously-discussed topics was found to predict disclosure of the current opinion. However, the generative role of selection homophily was not found to significantly differ between networks with selective disclosure and networks in which all opinions were shared with network alters. These findings bring new insight to the study of generative mechanisms and point to a growing need to integrate theory and practice across interpersonal and social network disciplines.

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Footnotes

[1] To their credit, the authors later state that disagreement should be "communicated effectively" (Huckfeldt et al., 2004, p. 4), implying that the discrepant viewpoints must be shared between discussants.

[2] Additional terms are used in the literature, including "heterogeneity" and "dissimilarity". In my view, these are both interchangeable with "difference".

[3] Balance theory (Heider, 1958, 1979) refers to a psychological phenomenon in which members of a triadic relationship achieve cognitive consistency, or "balance", in their affectively valenced attitudes towards one another. Balance is achieved when the product of these valenced attitudes equates to a positive result – when either all three members have a positive relationship, or two edges are negatively-valenced and one of them is positive (i.e., "the enemy of my enemy is my friend"). In networked terms, this tends to result in greater local density, or clustering, in the network (Cartwright & Harary, 1979). In other words, if i is friends with both j and k, it is likely that j and k are friends with one another as well (a balanced triad).

[4] "Assortativity" may also refer to similarity of a network feature between two dyads, such as similarity in degree (Newman, 2002).

[5] Although both party identity and ideology are used in homophily research, the remainder of this dissertation will focus on party identity as it is both the more widely adopted measure, and because it is more readily applicable to group communication processes cited later in this paper.

[6] While the focus of this dissertation is on political opinions, influence is often also employed to examine similarity in political behaviors between networked people (Bond et al., 2012; McClurg, 2003).

[7] One notable exception to this static network approach is work by Aral et al. (2009) which used a dynamic matched sample estimation framework to distinguish influence from "homophily", finding that previous approaches tended to overestimate influence effects by 300-700%. Critically, though, the authors conflate selection homophily and structural homophily.

[8] One recent paper which, to me, comes closest to accomplishing this task – albeit in a very constrained information environment – is Huber & Malhotra's (2017) work on political selection on dating websites. Specifically, the authors were able to account for similarity on a wide range of socio-economic characteristics, such as age and race. Notably, though, relationships formed on dating websites typically serve an apolitical purpose, and thus may be less likely to evince selection on political characteristics than political discussion network ties.

[9] Note: the goals of this dissertation do not include identifying precisely which of the following theorize reasons *why* people are selective is the best or strongest explanation. Rather, my focus is on isolating the selection homophily mechanism from structural and influence sources, and identifying how it varies over time, whether it dyadic selection scales to the network-level, and whether it varies as a function of personal characteristics or communicative processes.

[10] Again, it is helpful to distinguish between social and political discussion networks. If a tie is severed in the latter, it does not necessarily mean that the same tie is severed in the broader social context. Rather, the alters no longer engage in discussion about political topics. It is not uncommon for people to avoid political discussion while retaining some other form of social relationship (Cowan & Baldassarri, 2018; Settle & Carlson, 2019).

[11] This describes the influence mechanism much more so than it does selection.

[12] This is a kind of inverse argument to the one for used in observational studies: assortativity (state homophily) is used as a network-level measure for the selection (process homophily) which precedes data collection. Instead, I intend to observe dyadic selection (H1 & RQ1) and determine whether it follows that the network produced from this process is assortative.

[13] Assuming that one's depiction of their discussion partner's position is accurate; as some studies have pointed out, the accuracy of a person's evaluations of their alters is not always perfect (Goel et al., 2010).

[14] While these perspectives draw the same conclusions – that people will tend to withhold opinions when they expect to encounter disagreement – they have different implications for the operationalization of a topic avoidance decision. Because the rest of this study focuses on dyadic processes, I elected to use the interpersonal perspective when operationalizing these decisions.

[15] Relatedly, spiral of silence theory (Noelle-Neumann, 1974, 1993) posits that there are certain members of a so-called "vocal minority", who voice their opinion in spite of the likelihood that they will encounter disagreement. Noelle-Neumann offers a few explanations, including that these people are social outcasts or wealthy intelligentsia who have nothing to fear by speaking out. Issue importance may provide a more reasonable avenue through which people who don't fit that description might still voice their opinion in spite of disagreement.

[16] As of Breadboard version 2.3.1 (McKnight & Christakis, 2019), dropped participants do not free up one of the 35 'HITs' requested

[17] The color change in the waiting room phase appears only to the administrator – node colors on the participant side remained fixed at yellow unless a tie decision was being considered (purple) or the participant chose either the green or

orange chatrooms in the chatroom phase.

[18] These colors were selected both to avoid the association with a particular political party (e.g., red with Republican) and to provide enough contrast for colorblind participants to be able to distinguish participants.

[19] Note: subjects under the age of 18 were ineligible to participate

[20] These colors were chosen to avoid the stereotypical red and blue dichotomy that colloquially represents the Democrat and Republican parties.

[21] Available at https://breadboard2.asc.ohio-state.edu/?page_id=9 and https://breadboard2.asc.ohio-state.edu/?page_id=55.

[22] Unfortunately, these external factors were outside of my control. It is unknown to what extent they shaped the results of this study – at a minimum, that healthcare was rated as the most important issue in this study is not surprising.

[23] Additional analyses were run substituting *ideology* for *party identity* and the results were substantively similar. These results can be made available upon request.

[24] I ran these CUG tests again with the number of nodes used instead of edge density to form the randomly-generated networks, and the results were substantively similar.

[25] In real-world interactions, people may also use the dispersion of shared opinions to develop a sense of the accuracy of their prediction – larger dispersion may increase relational uncertainty as a function of doubt about one's attributions of their alter's opinions (Clatterbuck, 1979). Additionally, the likelihood of disagreement (even if the average is close to one's own opinion) may be higher. Because this may be somewhat conflated with dissimilarity, and because this hypothesis test is the first extension of an already complex study, I focus here on averages only. However, this may be an interesting avenue for a future extension of the study.

[26] To understand why this might be the case, it may help to look over the network graph for cohort 2A in Appendix A (Figure 21). There are no Republicans in this group, 5 independents, and 1 weak Democrat. The remaining 7 participants are all strong Democrats and it becomes clear beginning in round 6 that these participants have formed a tight-knit "core" of the network. The independents tended to occupy peripheral network positions after that point. This tight interconnectedness among like-partisans likely resulted from homophilous selection, as this test of H9 shows.

[27] Some similar research has used meta-analytic techniques to aggregate results across many networks. For example, Song (2015) examined the generative processes of political discussion networks among members of student interest groups at a university. In that paper, the author aggregated ERGMs across 20 groups with 15 to 30 members each. Importantly, each ERGM was fit with a tailor-made combination of network endogenous and exogenous parameters, rather than with a universal set of features as was used here to ease interpretation. While this approach may be appropriate for further investigation of the data, I did not feel comfortable at the time of writing to assume that the aforementioned interpretation problems posed by the residual variances in each model (see Duxbury, 2021) were sufficiently minimal to rely on this result for this dissertation.

[28] Overall root mean squared error of approximation (RMSEA): .119, 95% CI [.113, .124]; Democrats: .114 [.106, .122]; Independents: .127 [.116, .140]; Republicans: .131 [.121, .144].

[29] This also has the added benefit of correcting for the unrepresentative distribution of party identity in convenience samples, like MTurk (Huff & Tingley, 2015; Levay et al., 2016).

[30] Some notable exceptions to this statement may exist, such as if friends or a married couple join the MTurk cohort at the same time. By keeping interactions anonymous in the software, it is hoped that even if two participants know each other outside of the context of the study, that they would still be unable to figure out if they are connected to each other in the study. It is thus unlikely that there would be any appreciable effect on any of the tested hypotheses or research questions.

[31] Because of pandemic restrictions at the time of data collection, planned in-person studies that could complement the online data collection could not take place. Future replication using an in-person sample in which the induction is that real, "face-to-face" discussion will occur with someone from participants' networks at the end of the study may be a more powerful induction to ensure people are as selective as they want to be.

[32] Anecdotally, I noticed many participants in the chat room phase discussing how interesting or fun it was to interact with everyone else. Some even mentioned seeking out politically dissimilar people because they wanted to see what people on MTurk think about different issues.

Appendix A: Network Graphs

The following network graphs were constructed using the participants in each cohort who remained active until at least the chat phase of the study (“bots”, or dropped participants were removed). The color of vertices corresponds to each participants’ political party identity on the 7-point scale from “strong Democrat” to “strong Republican”. The Fruchterman-Reingold (1991) layout algorithm was used to place vertices in graph space. At “Time 0” in the graphs – representing random assignment at the start of the study – this algorithm used a random ring starting position. For all subsequent graphs (e.g., “Time 1”, “Time 2”, etc.), the prior calculated layout was provided to seed the new algorithm. This means that changes in a single participant’s position in the graph space over time is a function of changes in their relative network position.

Vertex names may be duplicated in the network graphs of different cohorts. This is a function of the random name generation and should not be construed to mean that the same participant appeared in multiple cohorts. Breadboard’s MTurk worker ID screening feature was used to ensure that no participants from prior iterations could participate in future iterations of the study.

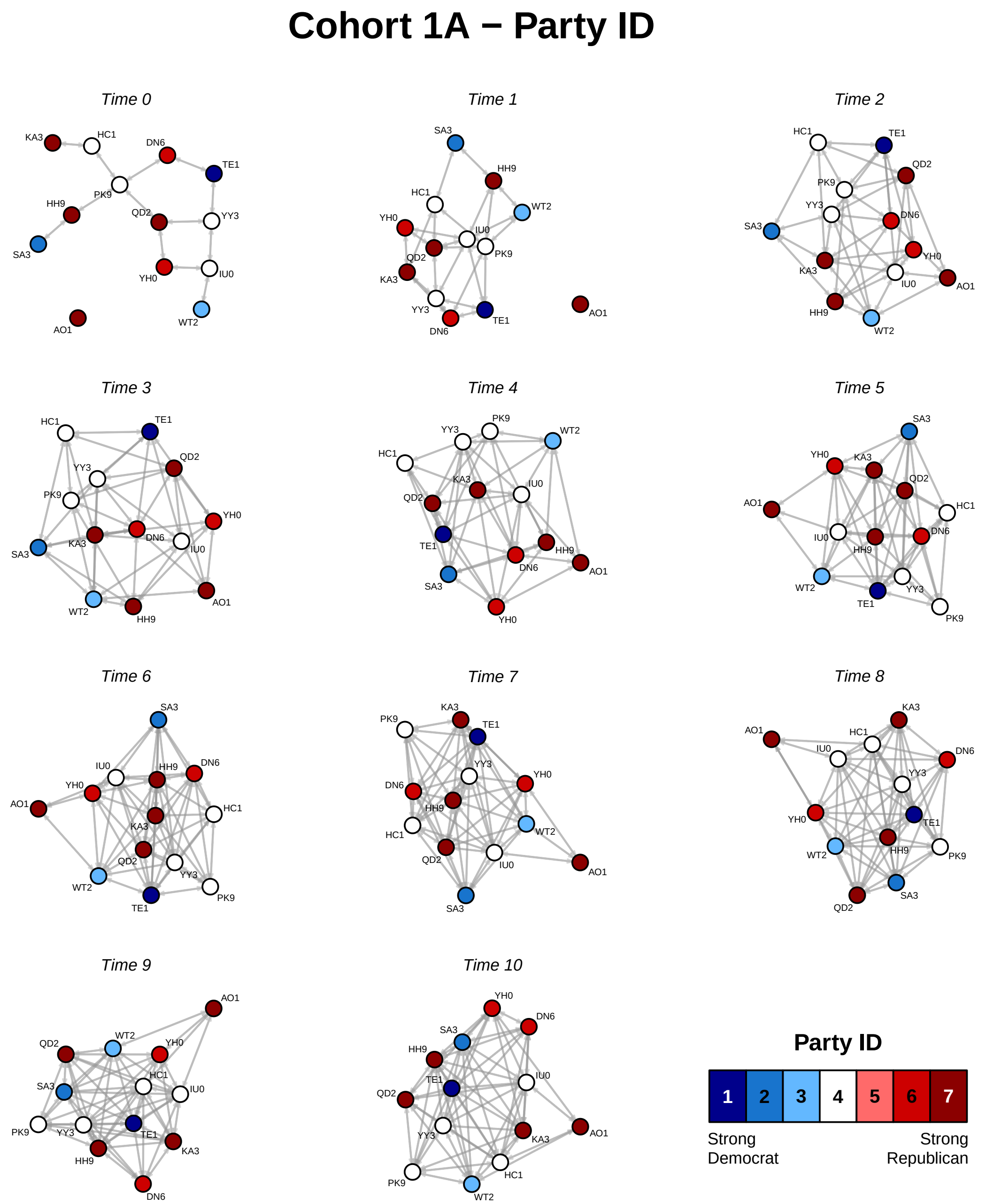

Figure 9. Network graphs from round 0 (random assignment) to round 10 of cohort 1A. Vertex colors indicate the participant's party identity.

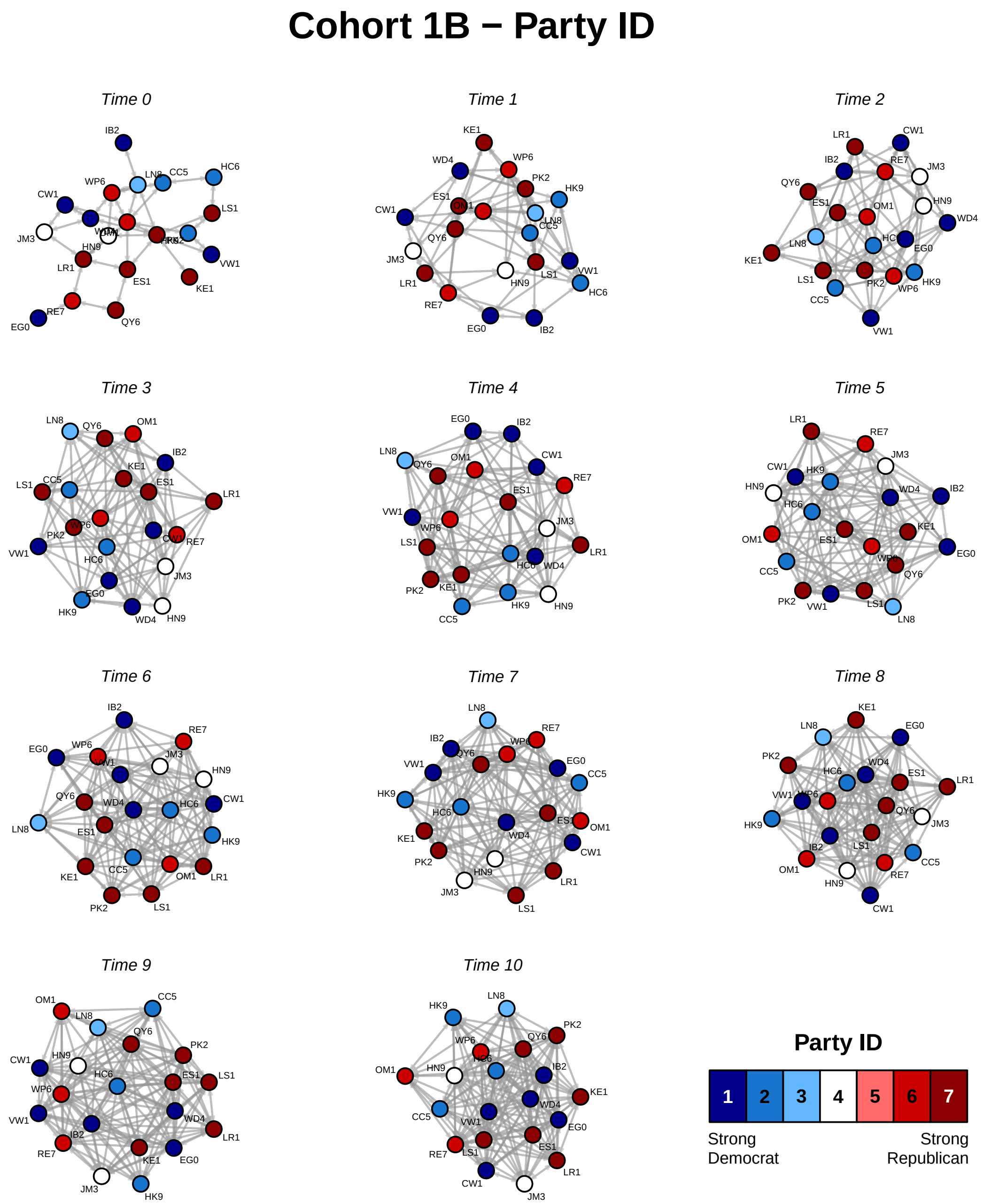

Figure 10. Network graphs from round 0 (random assignment) to round 10 of cohort 1B. Vertex colors indicate the participant's party identity.

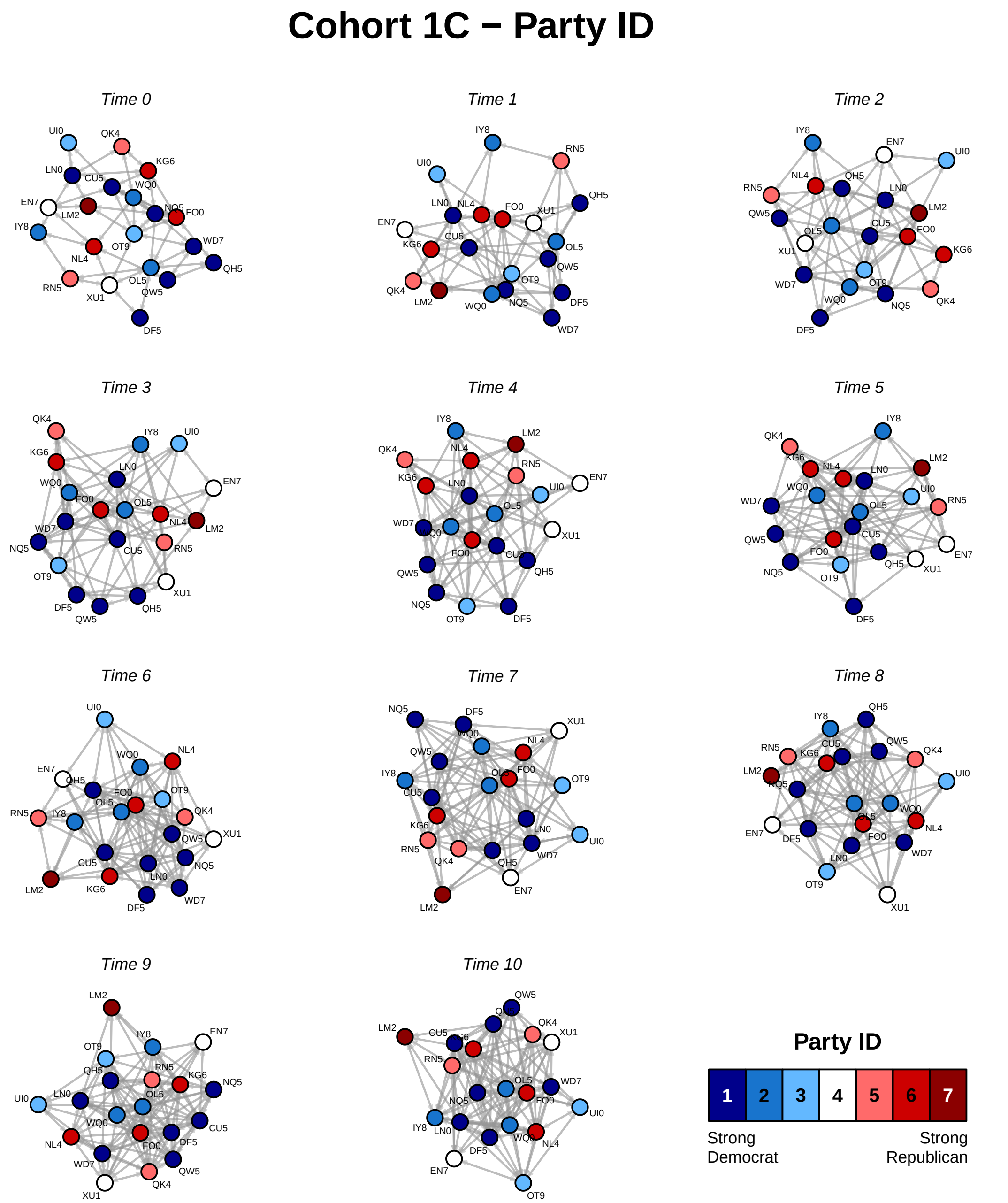

Figure 11. Network graphs from round 0 (random assignment) to round 10 of cohort 1C. Vertex colors indicate the participant's party identity.

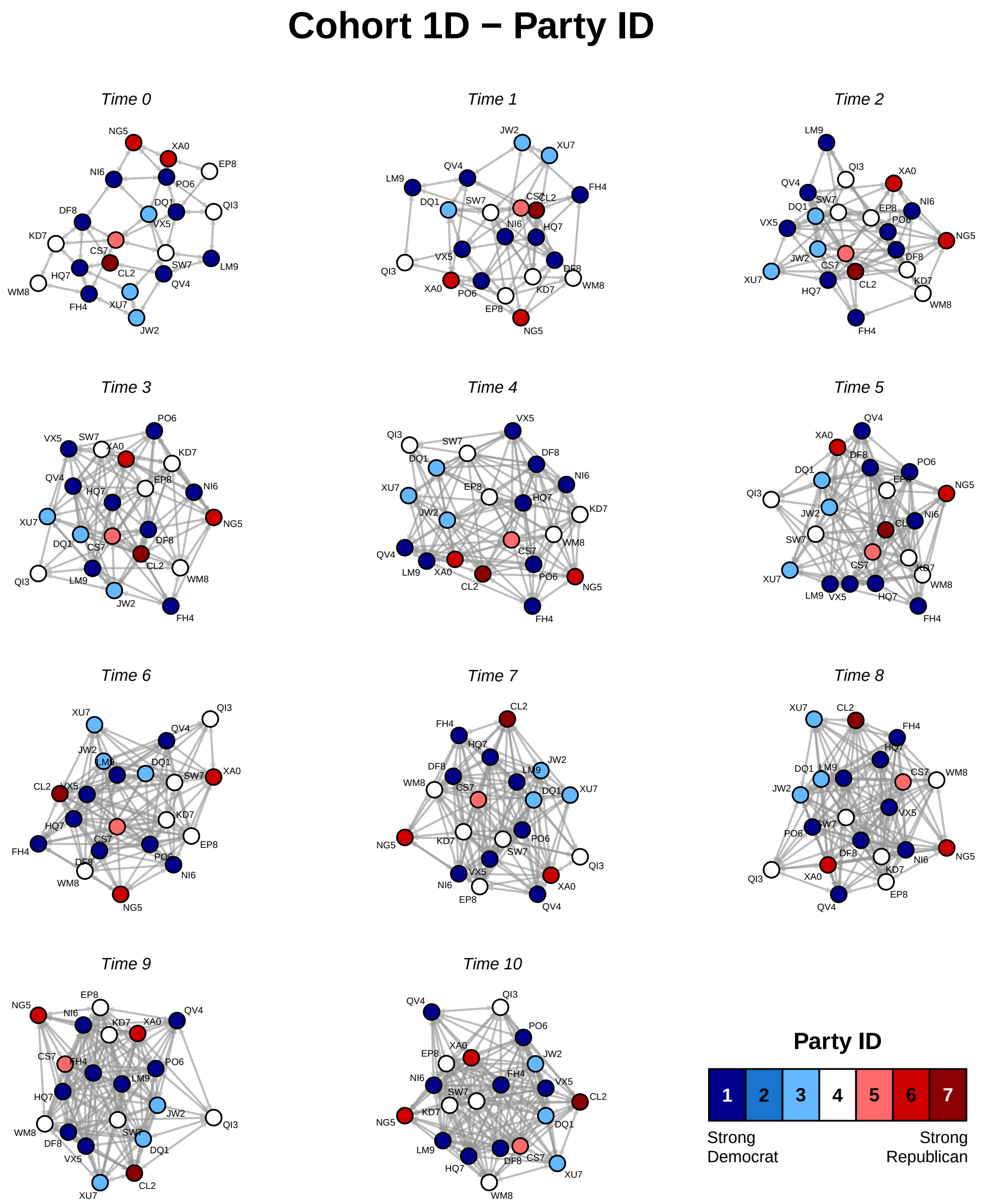

Figure 12. Network graphs from round 0 (random assignment) to round 10 of cohort 1D. Vertex colors indicate the participant's party identity.

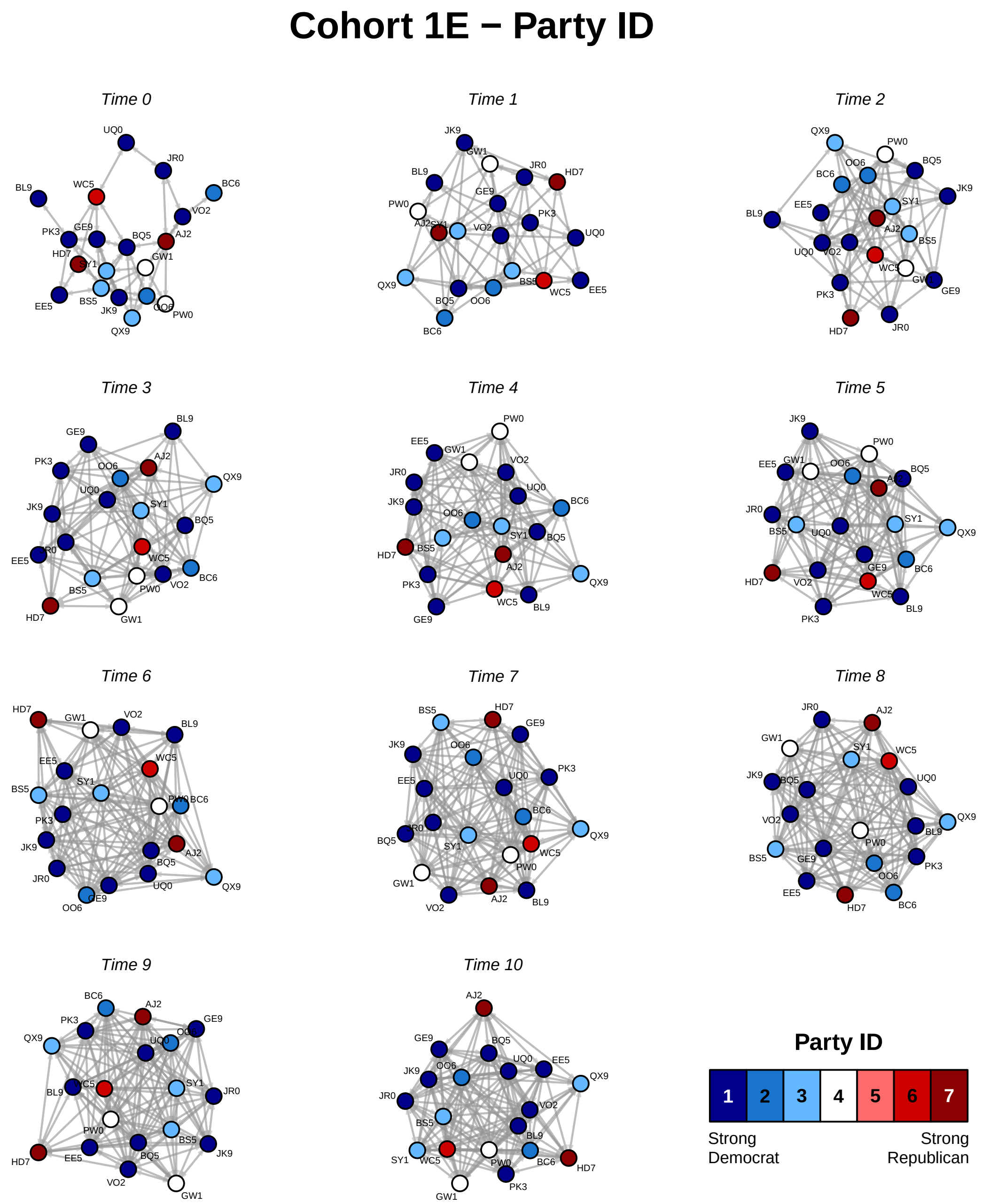

Figure 13. Network graphs from round 0 (random assignment) to round 10 of cohort 1E. Vertex colors indicate the participant's party identity.

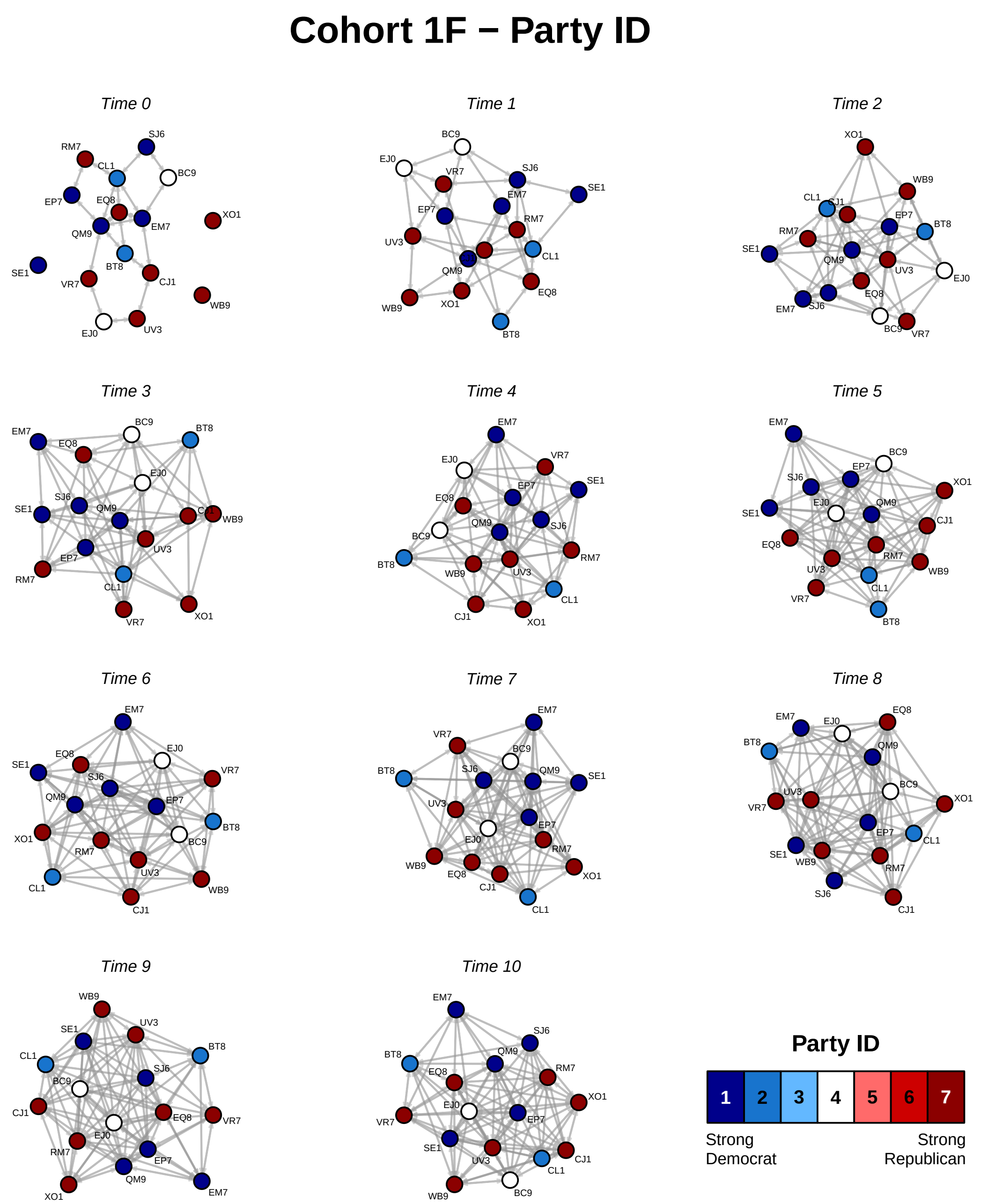

Figure 14. Network graphs from round 0 (random assignment) to round 10 of cohort 1F. Vertex colors indicate the participant's party identity.

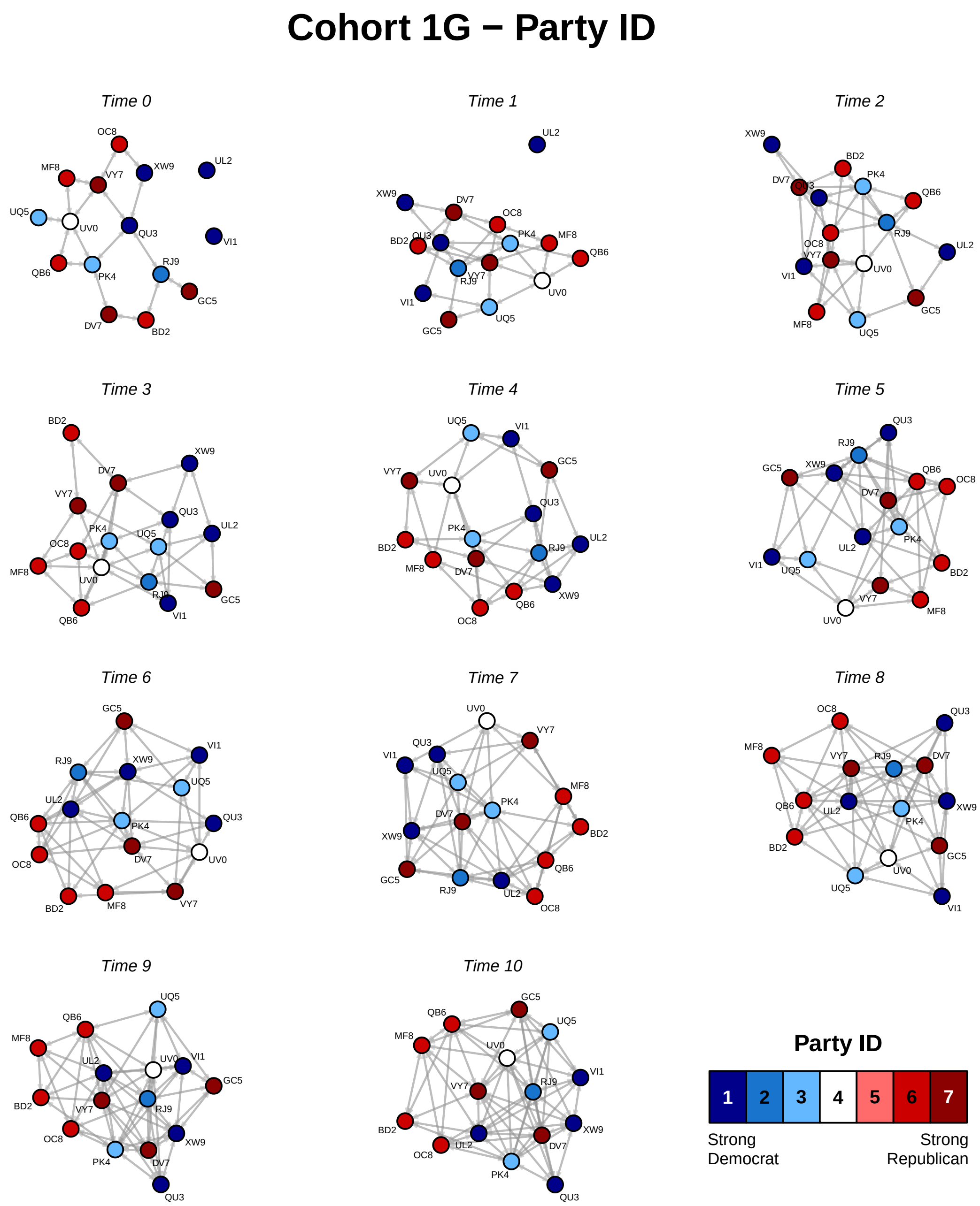

Figure 15. Network graphs from round 0 (random assignment) to round 10 of cohort 1G. Vertex colors indicate the participant's party identity.

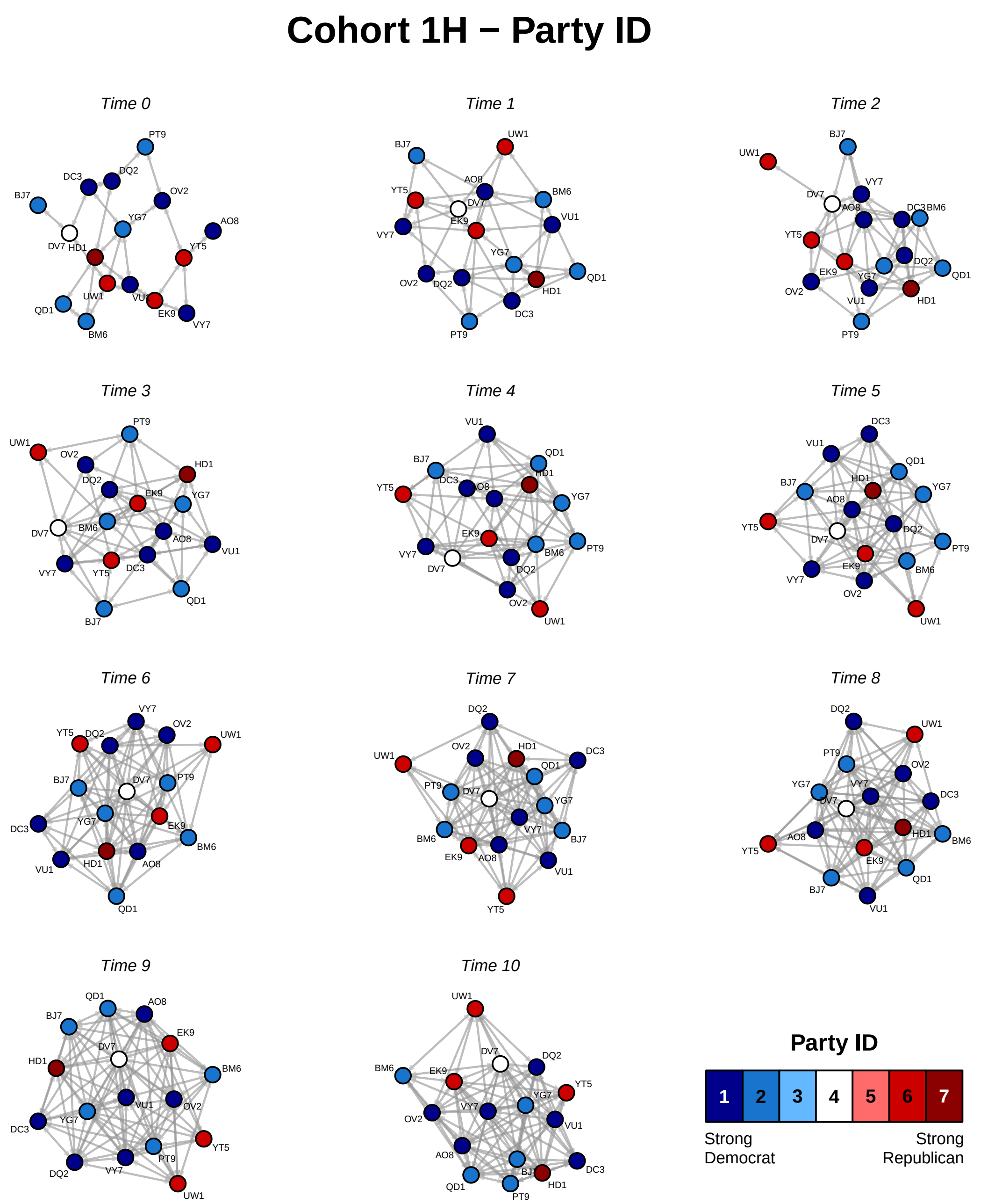

Figure 16. Network graphs from round 0 (random assignment) to round 10 of cohort 1H. Vertex colors indicate the participant's party identity.

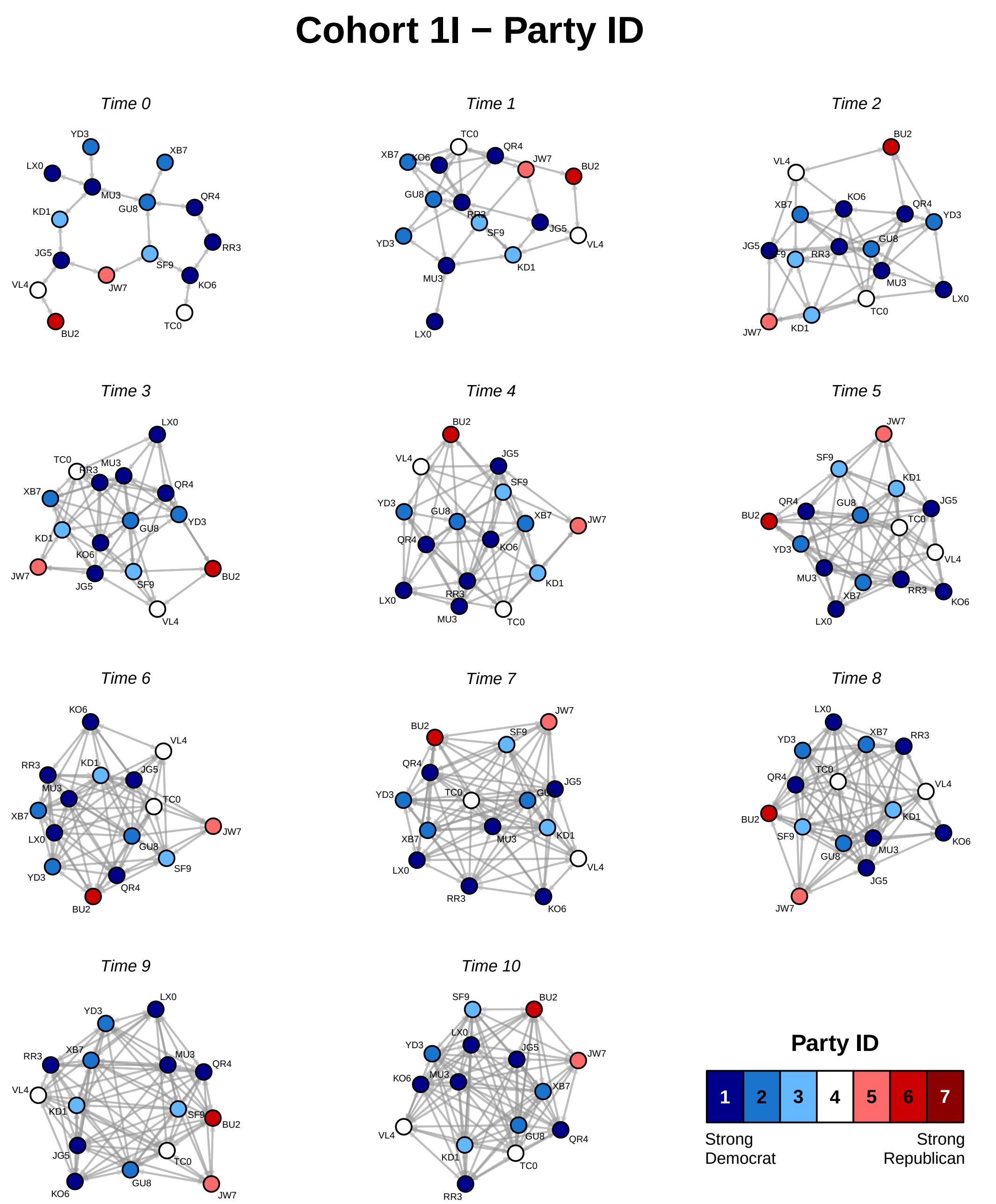

Figure 17. Network graphs from round 0 (random assignment) to round 10 of cohort 1I. Vertex colors indicate the participant's party identity.

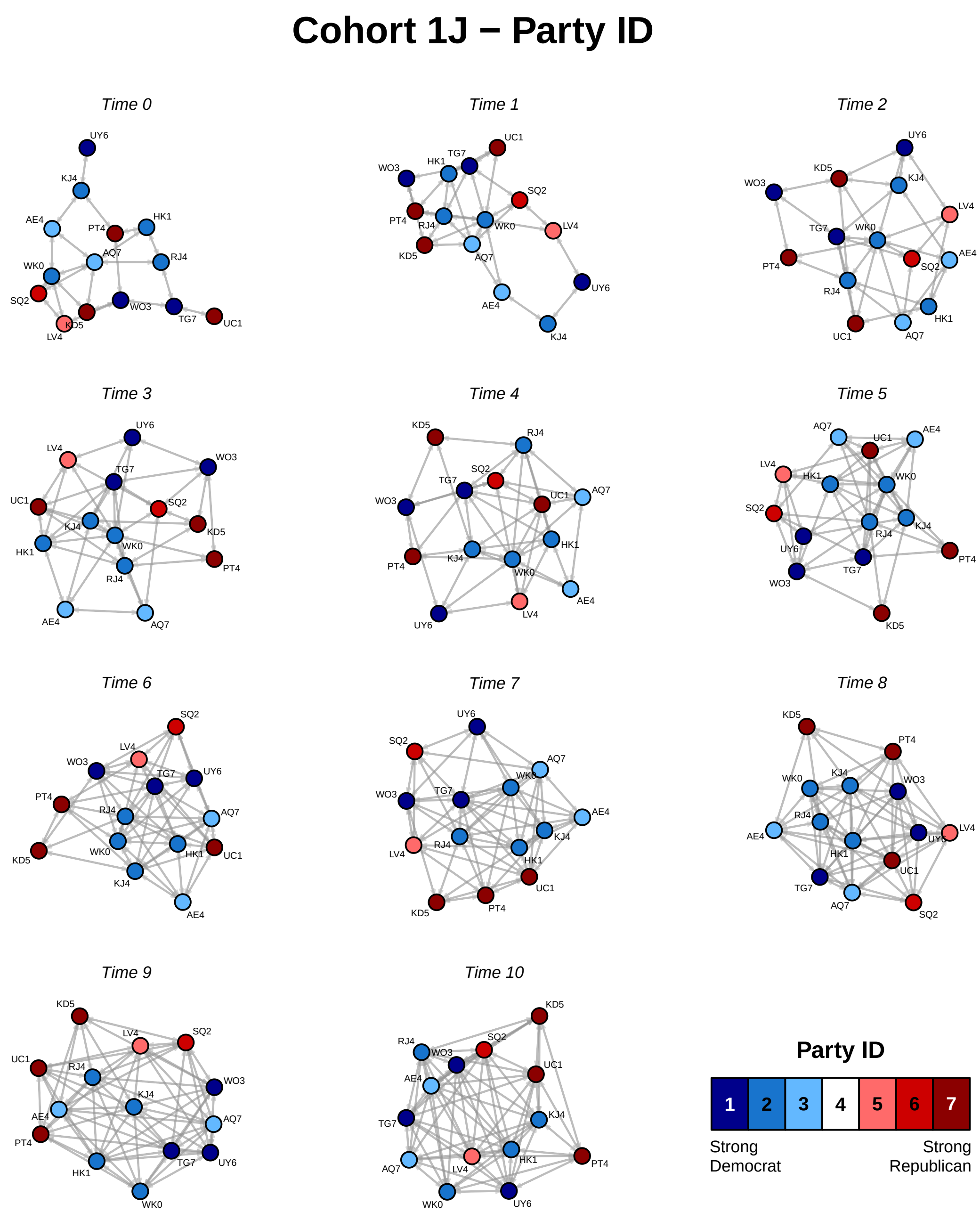

Figure 18. Network graphs from round 0 (random assignment) to round 10 of cohort 1J. Vertex colors indicate the participant's party identity.

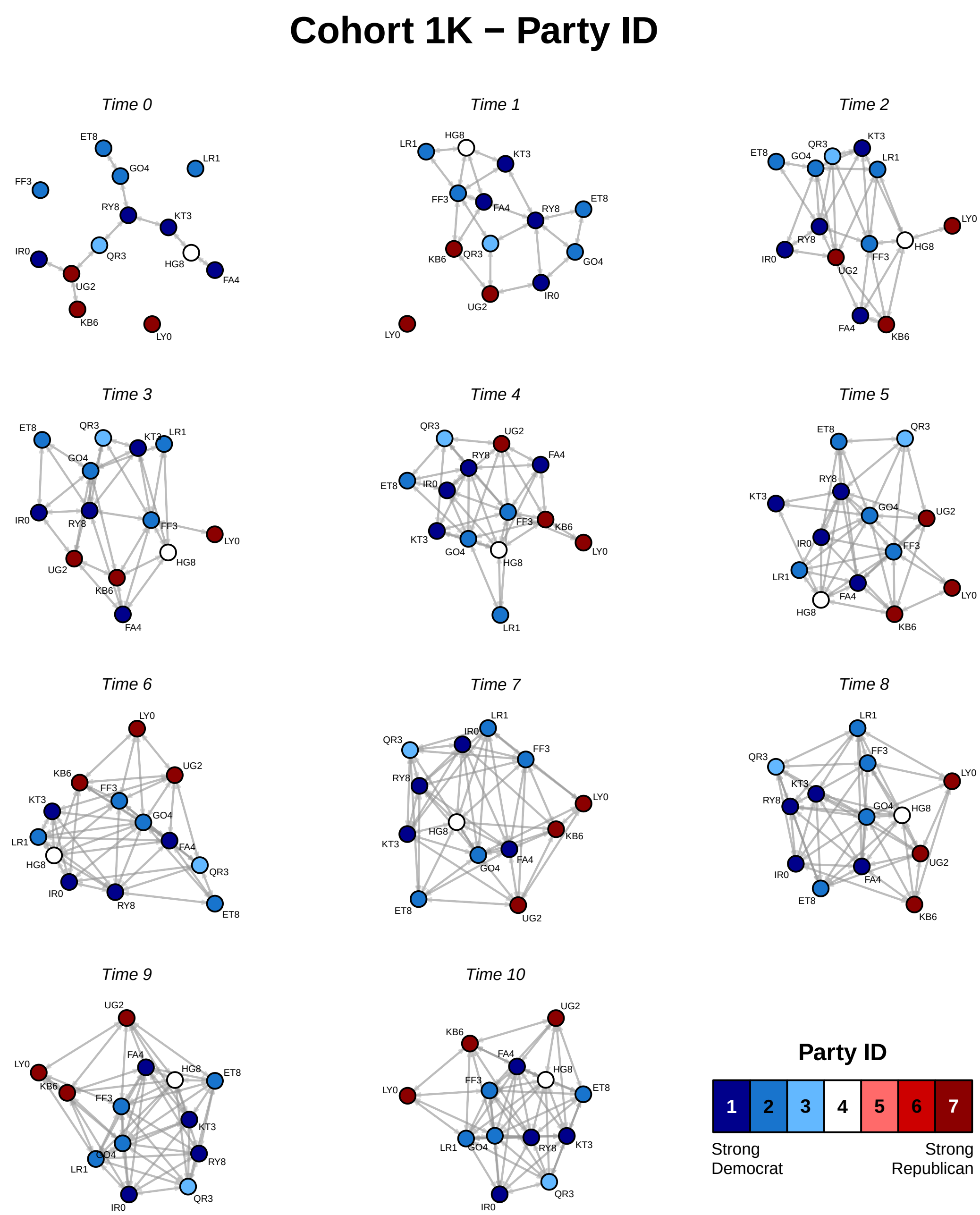

Figure 19. Network graphs from round 0 (random assignment) to round 10 of cohort 1K. Vertex colors indicate the participant's party identity.

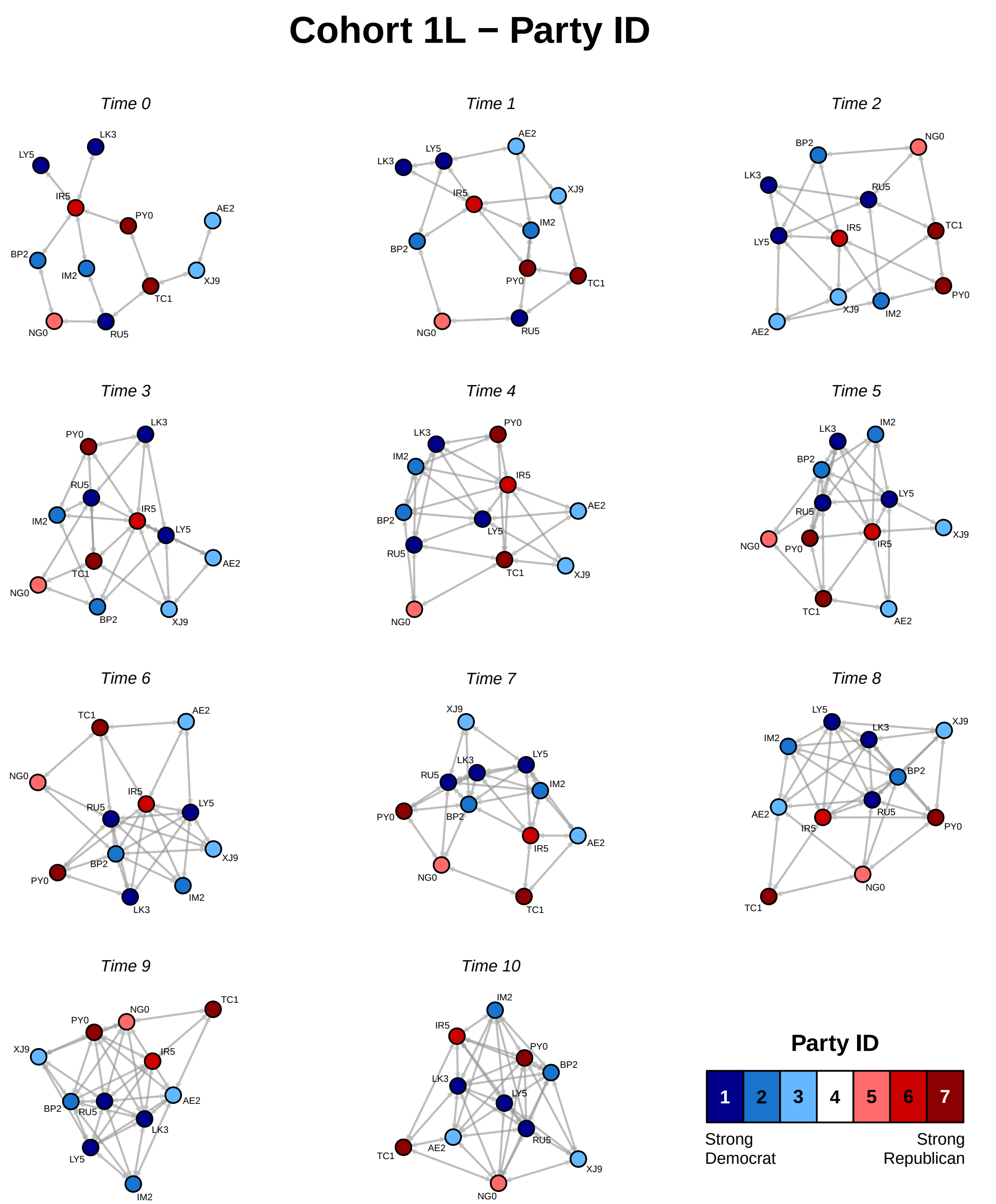

Figure 20. Network graphs from round 0 (random assignment) to round 10 of cohort 1L. Vertex colors indicate the participant's party identity.

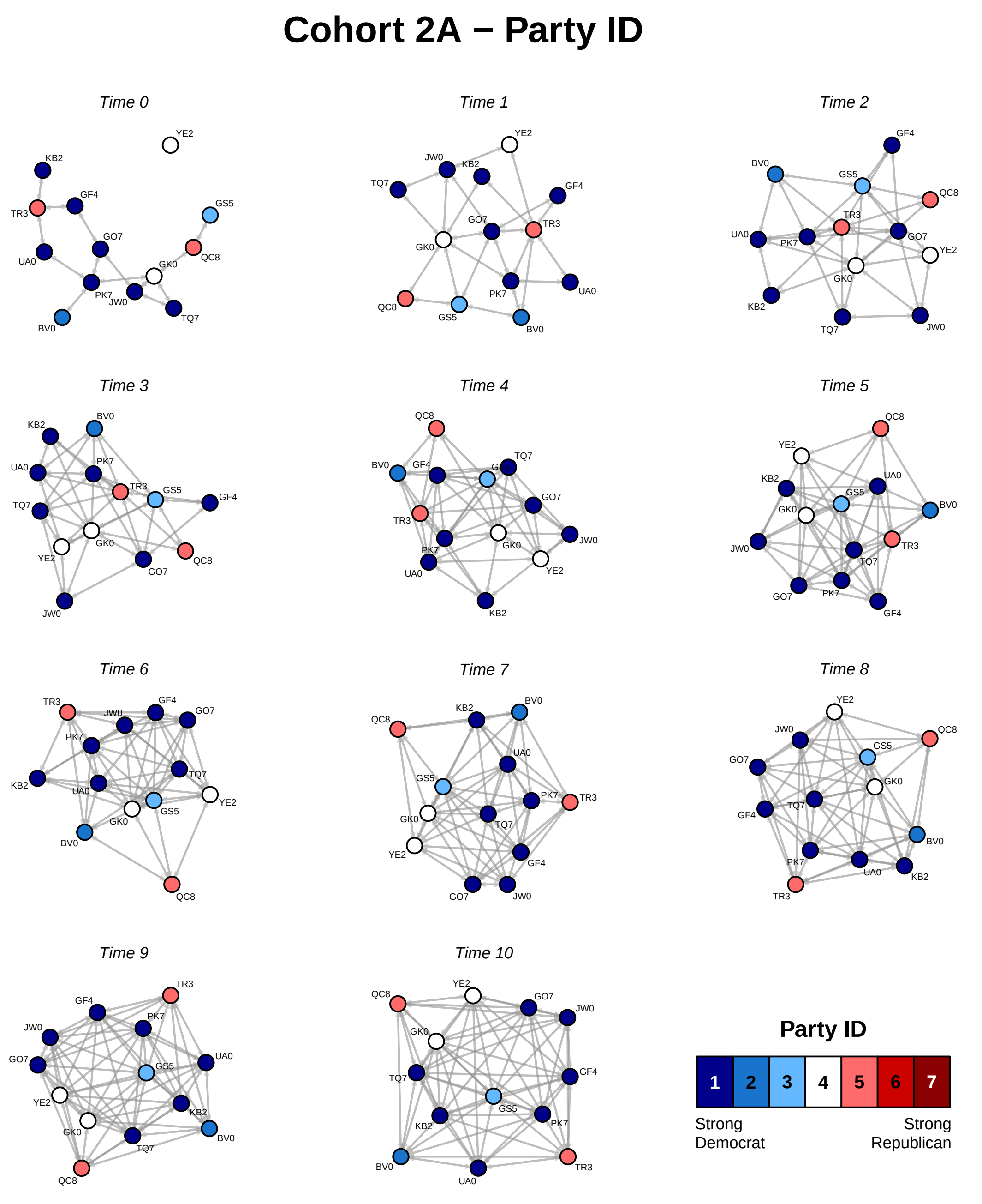

Figure 21. Network graphs from round 0 (random assignment) to round 10 of cohort 2A. Vertex colors indicate the participant's party identity.

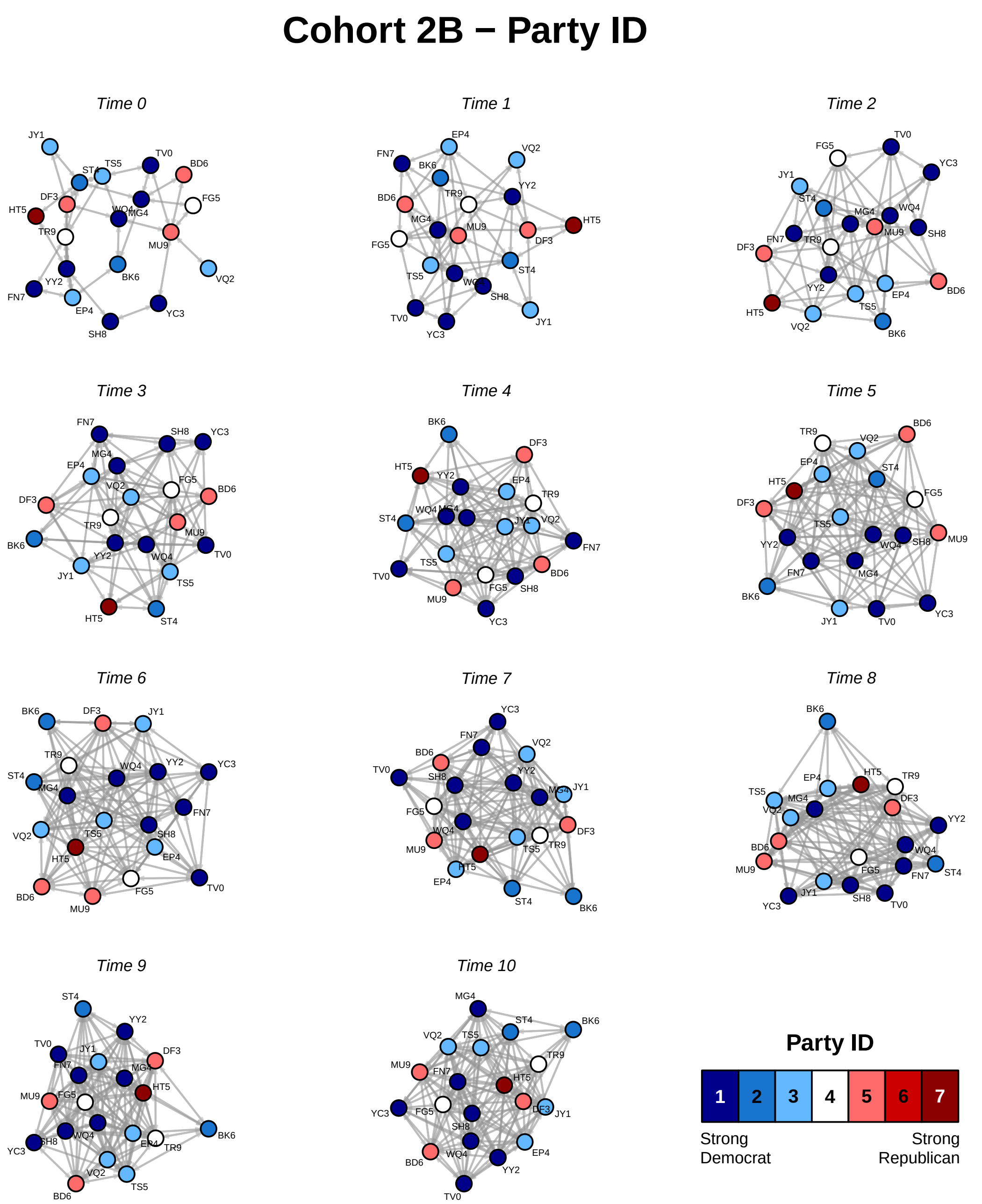

Figure 22. Network graphs from round 0 (random assignment) to round 10 of cohort 2B. Vertex colors indicate the participant's party identity.

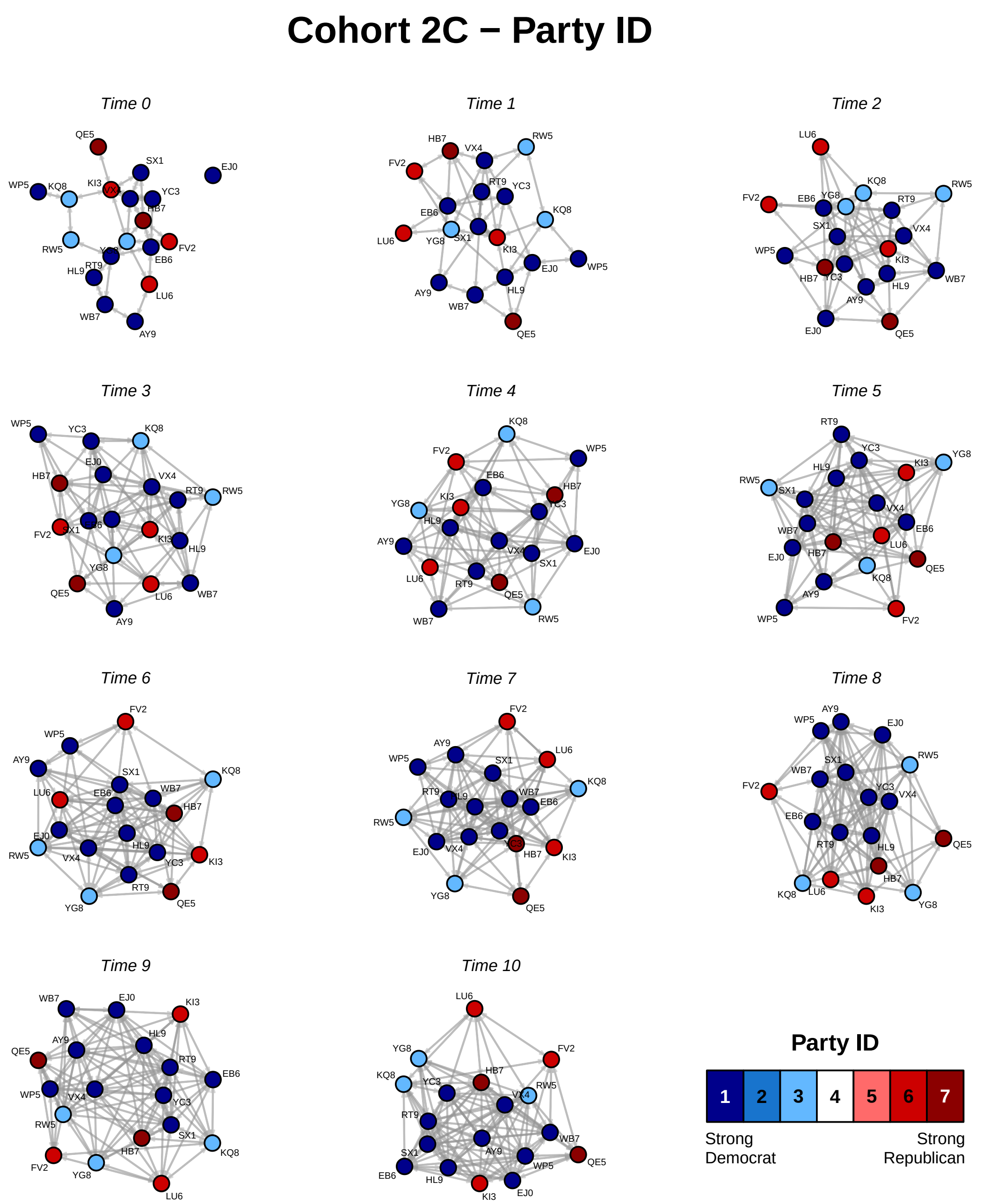

Figure 23. Network graphs from round 0 (random assignment) to round 10 of cohort 2C. Vertex colors indicate the participant's party identity.

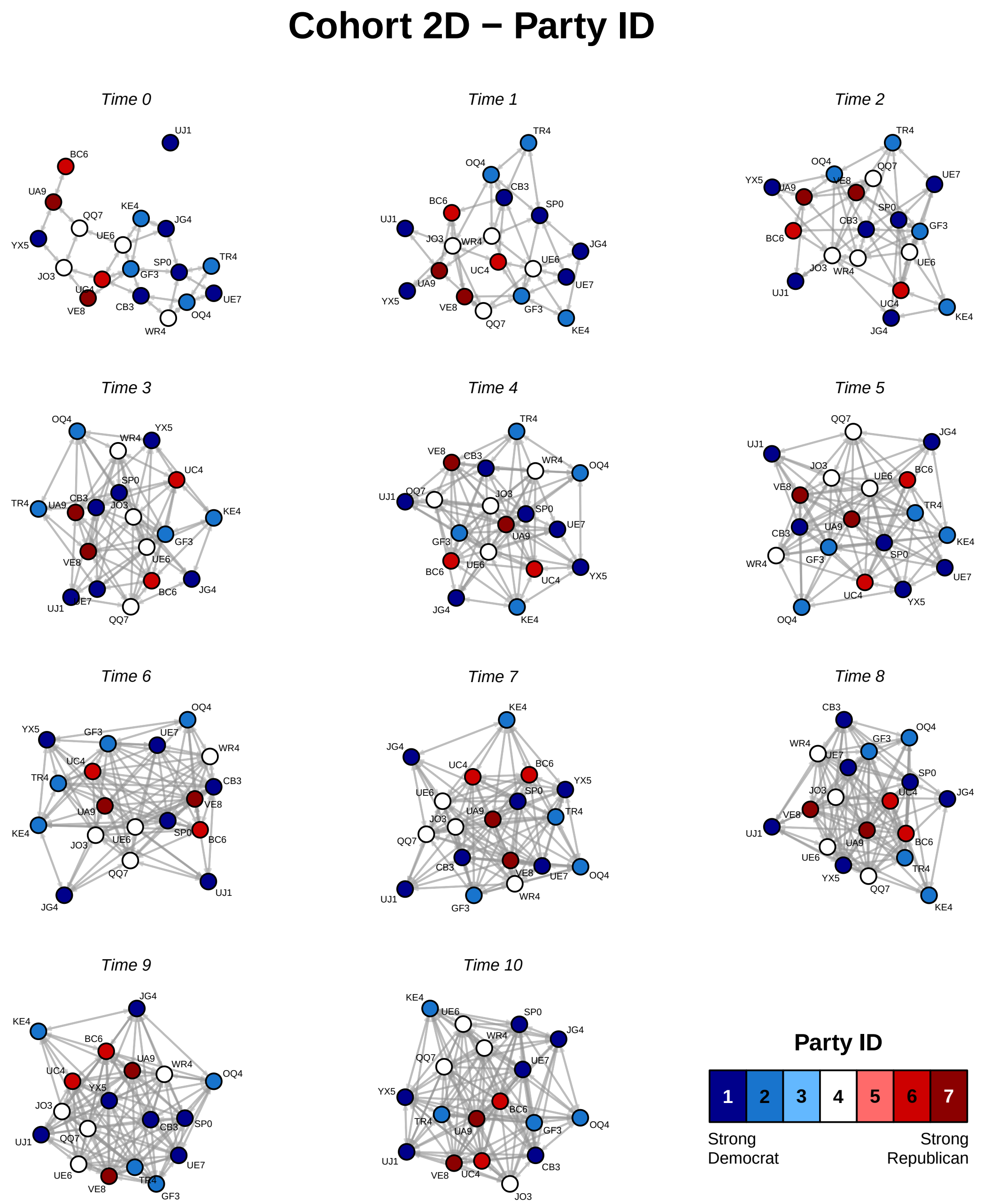

Figure 24. Network graphs from round 0 (random assignment) to round 10 of cohort 2D. Vertex colors indicate the participant's party identity.

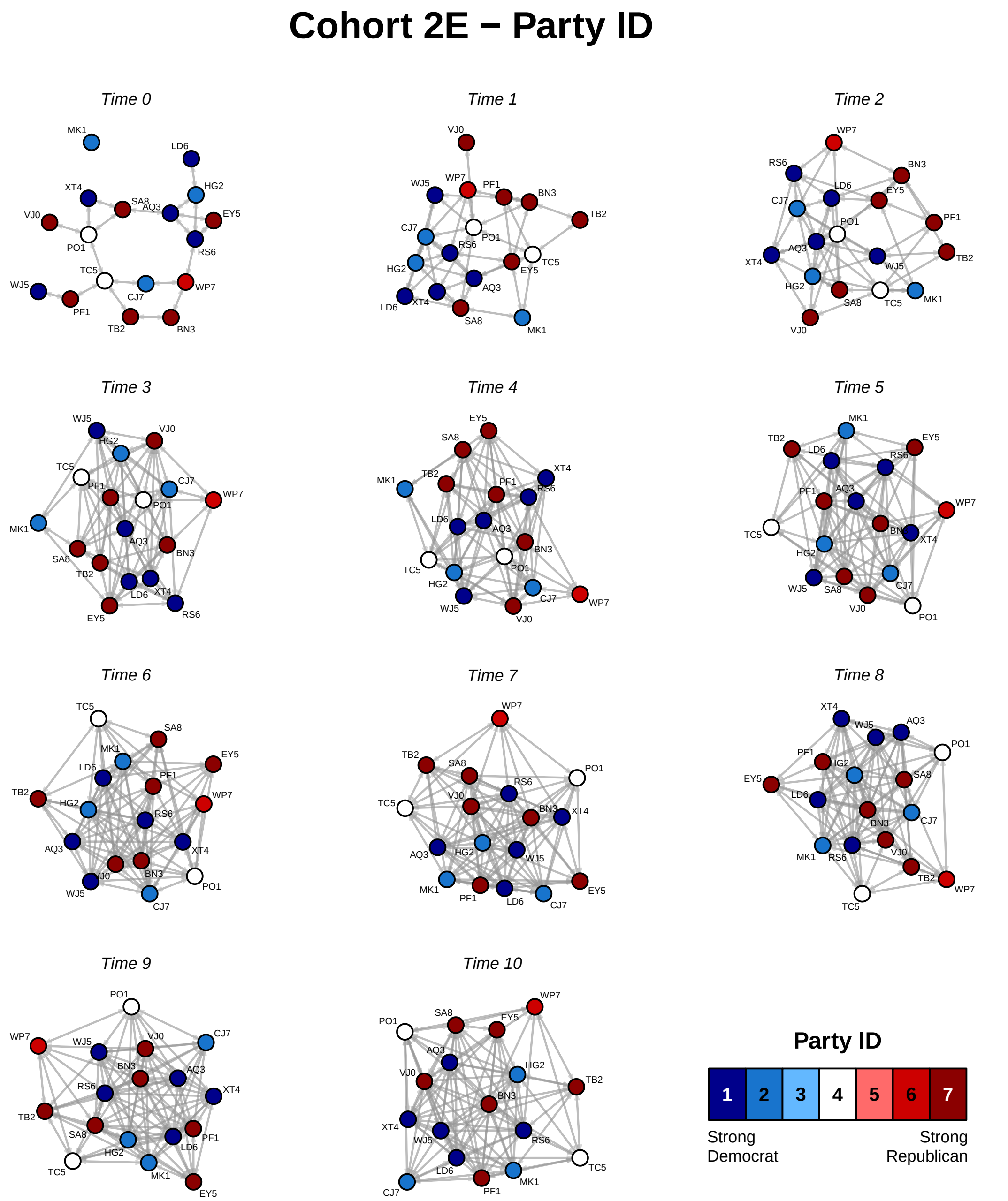

Figure 25. Network graphs from round 0 (random assignment) to round 10 of cohort 2E. Vertex colors indicate the participant's party identity.

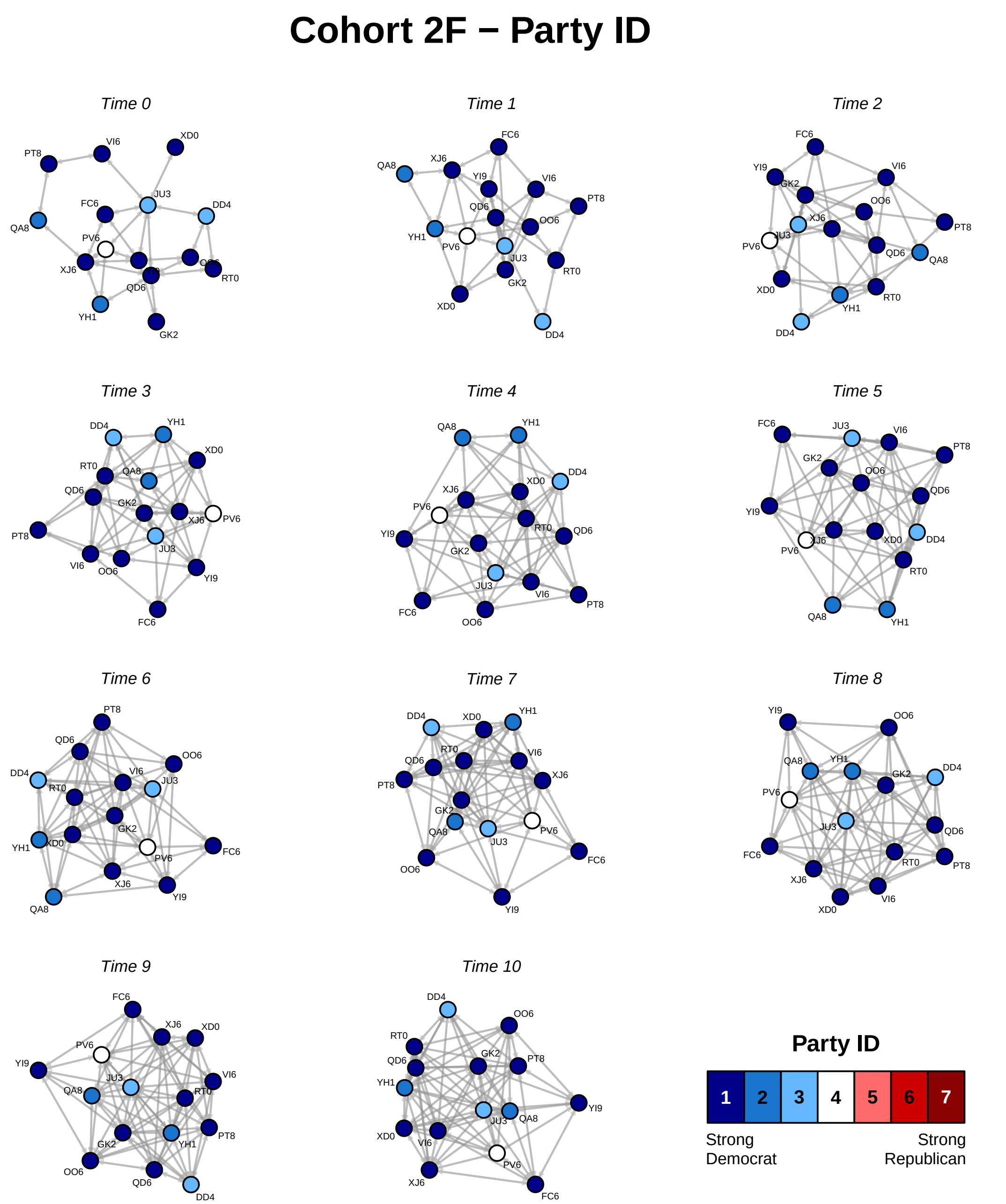

Figure 26. Network graphs from round 0 (random assignment) to round 10 of cohort 2F. Vertex colors indicate the participant's party identity.

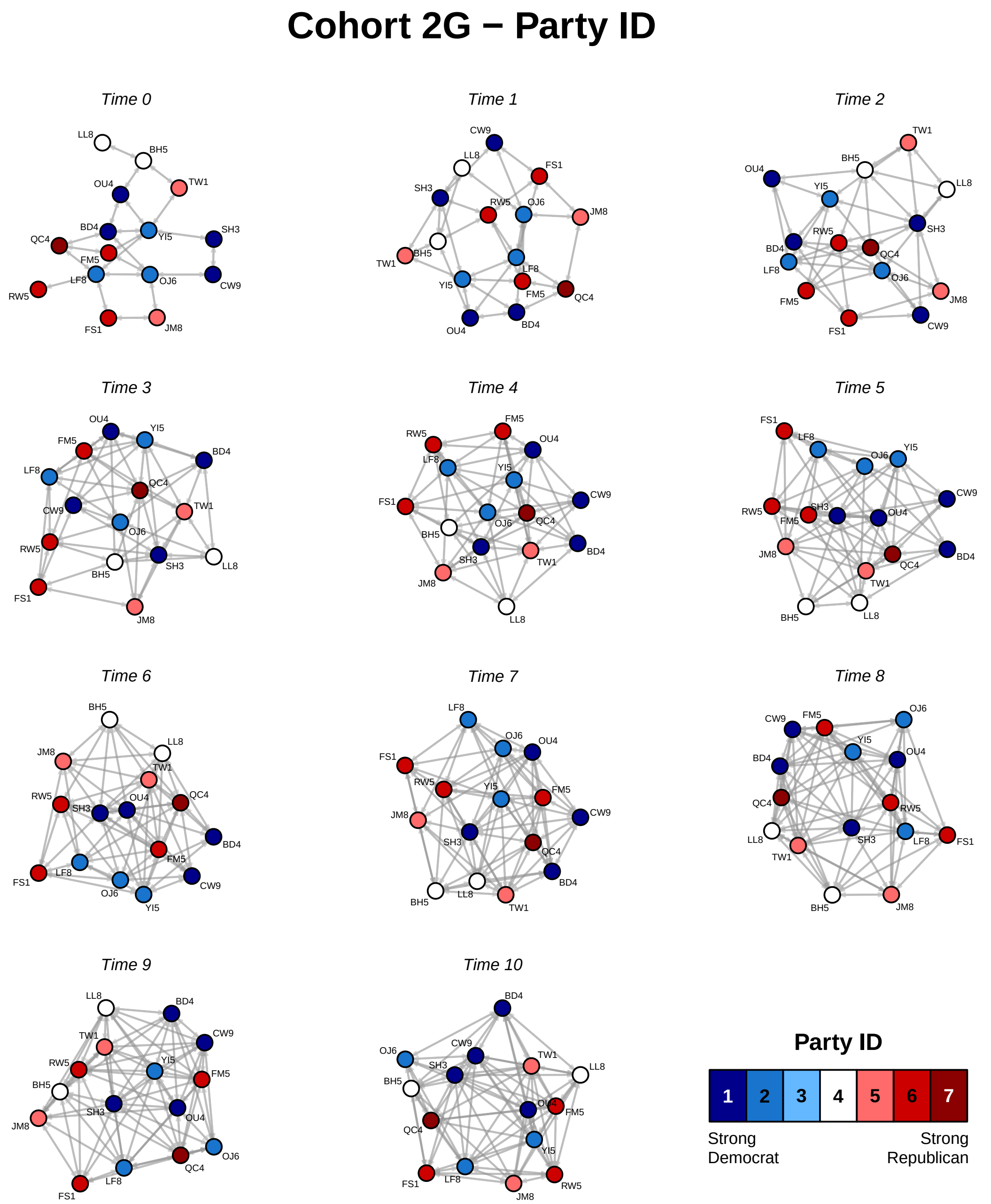

Figure 27. Network graphs from round 0 (random assignment) to round 10 of cohort 2G. Vertex colors indicate the participant's party identity.

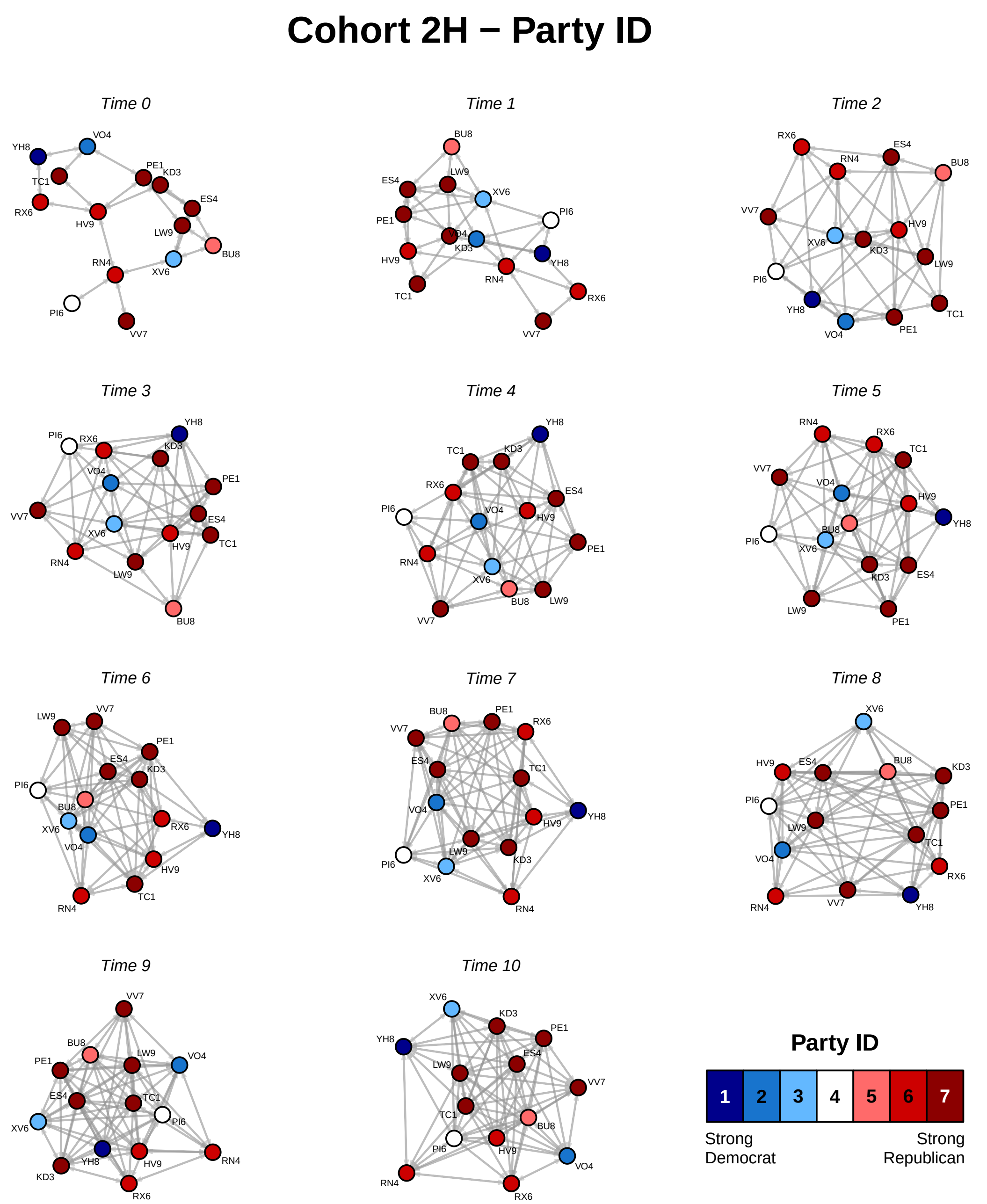

Figure 28. Network graphs from round 0 (random assignment) to round 10 of cohort 2H. Vertex colors indicate the participant's party identity.

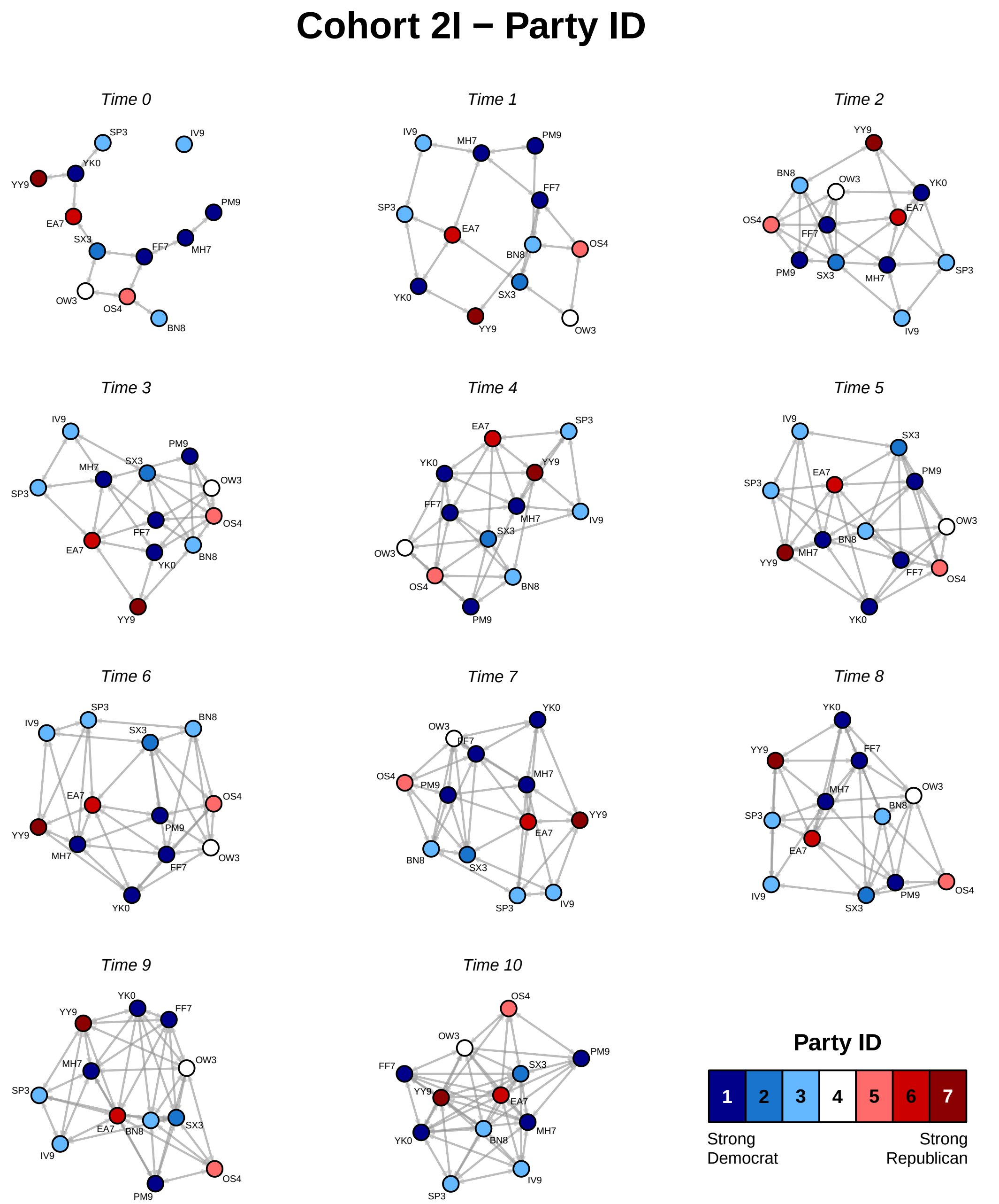

Figure 29. Network graphs from round 0 (random assignment) to round 10 of cohort 2I. Vertex colors indicate the participant's party identity.

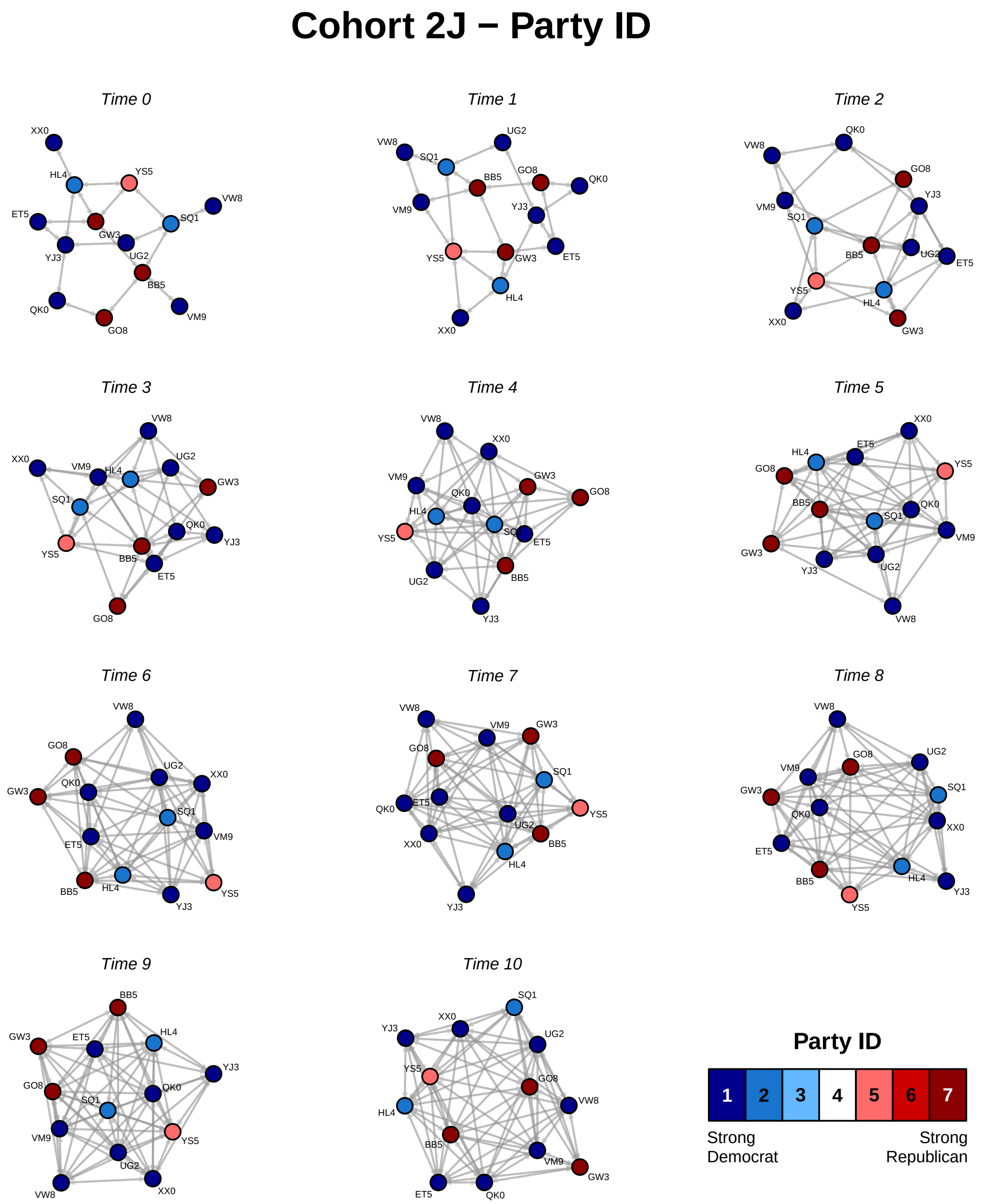

Figure 30. Network graphs from round 0 (random assignment) to round 10 of cohort 2J. Vertex colors indicate the participant's party identity.

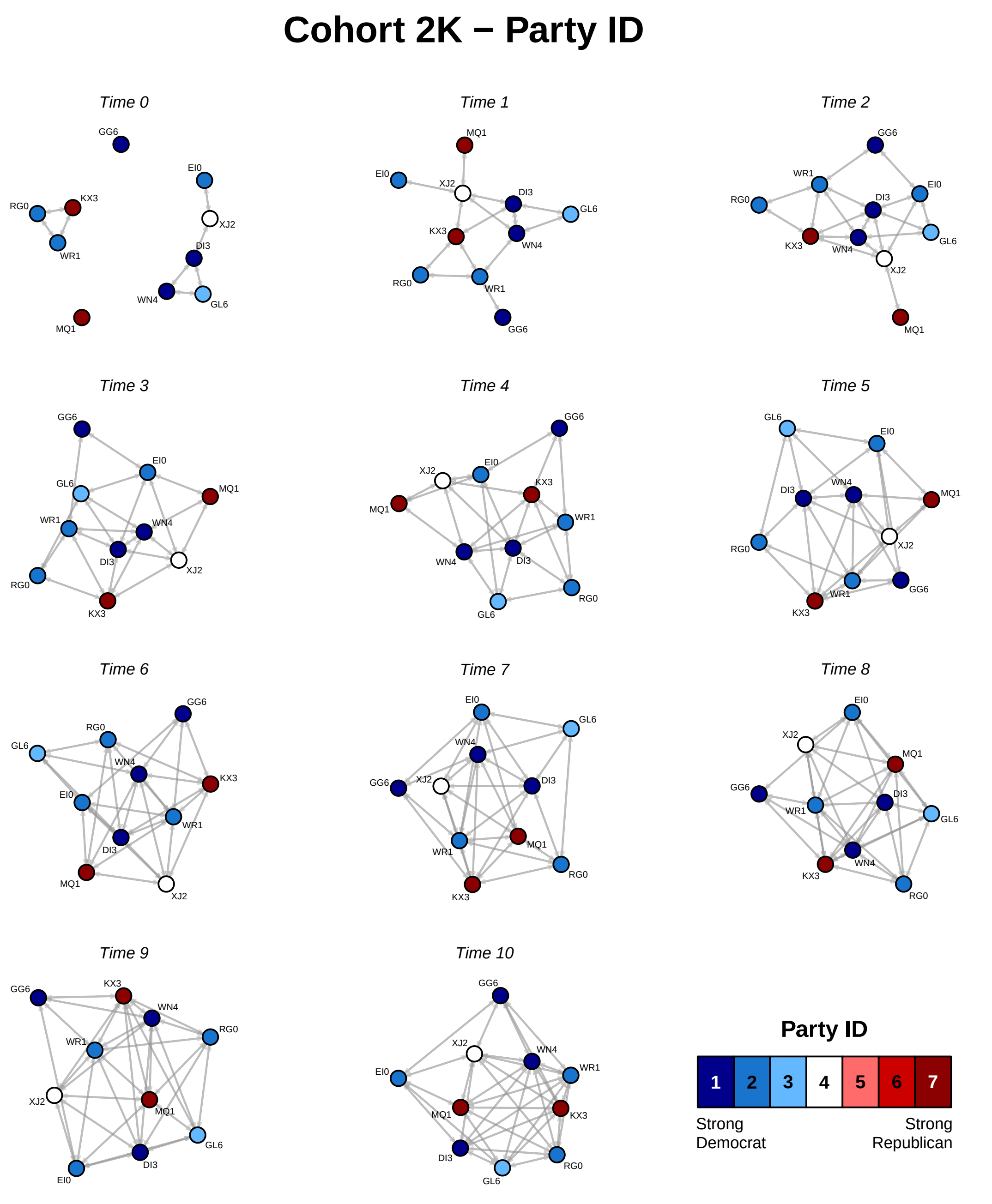

Figure 31. Network graphs from round 0 (random assignment) to round 10 of cohort 2K. Vertex colors indicate the participant's party identity.

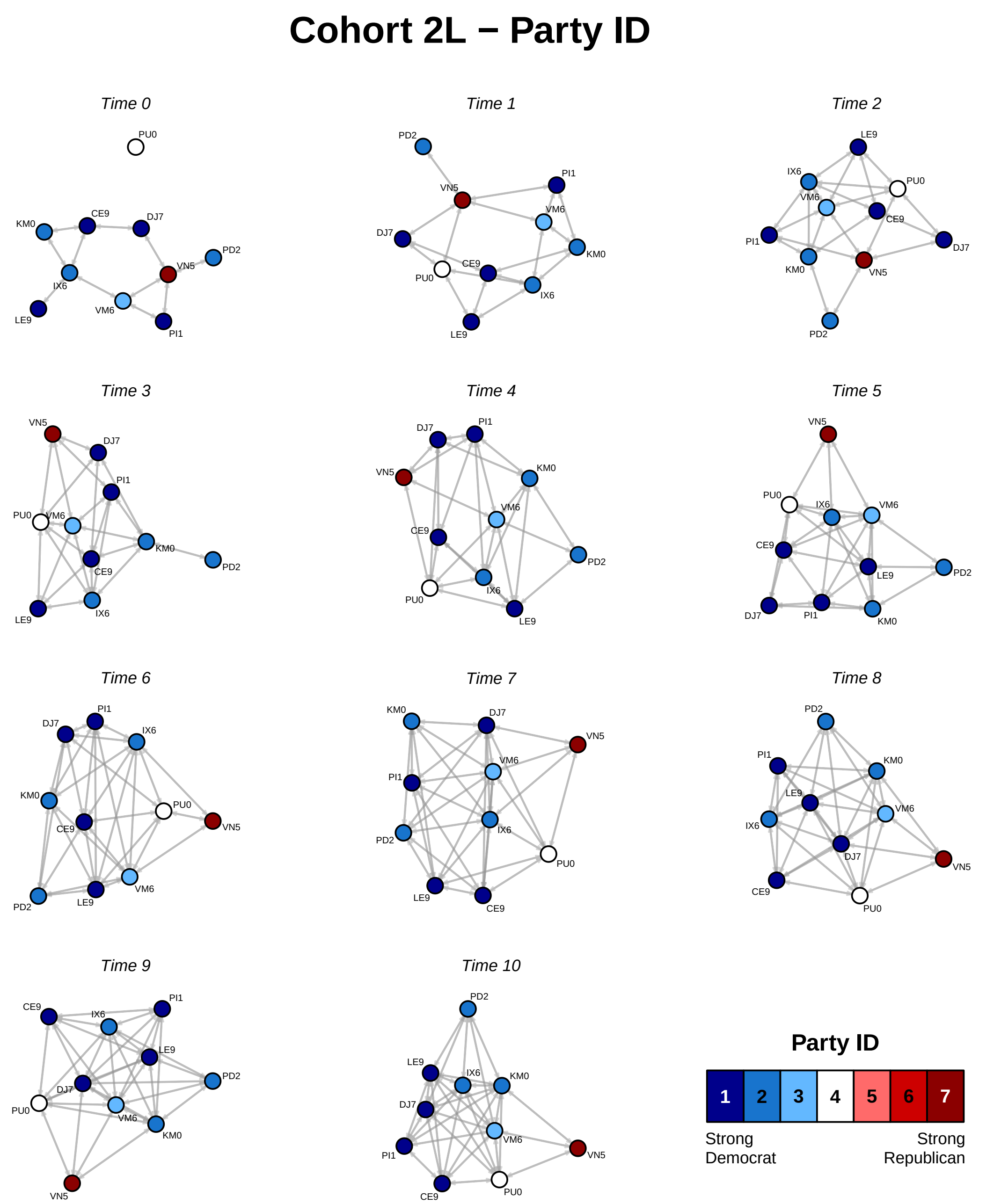

Figure 32. Network graphs from round 0 (random assignment) to round 10 of cohort 2L. Vertex colors indicate the participant's party identity.

Appendix B: Conditional Uniform Graph Test Results

The following figures contain pseudo null distributions of the transitivity statistic generated by conditional uniform graph tests conducted on each cohort network. Specific examples were selected to highlight significant differences between the transitivity in the observed networks (red lines) and the randomly-generated networks which conditioned on the number of edges. This should not be interpreted as an exhaustive collection of all of the significant findings in this procedure. Rather, to conserve space, only a portion of the results are shown here. The purpose of conducting the conditional uniform graph test prior to hypothesis testing was to determine whether conventional approaches to significance testing could be used without violating IID assumptions. That each cohort had at least one round where the transitivity differed significantly from the randomly-generated networks suggests that a network analytic approach is required.

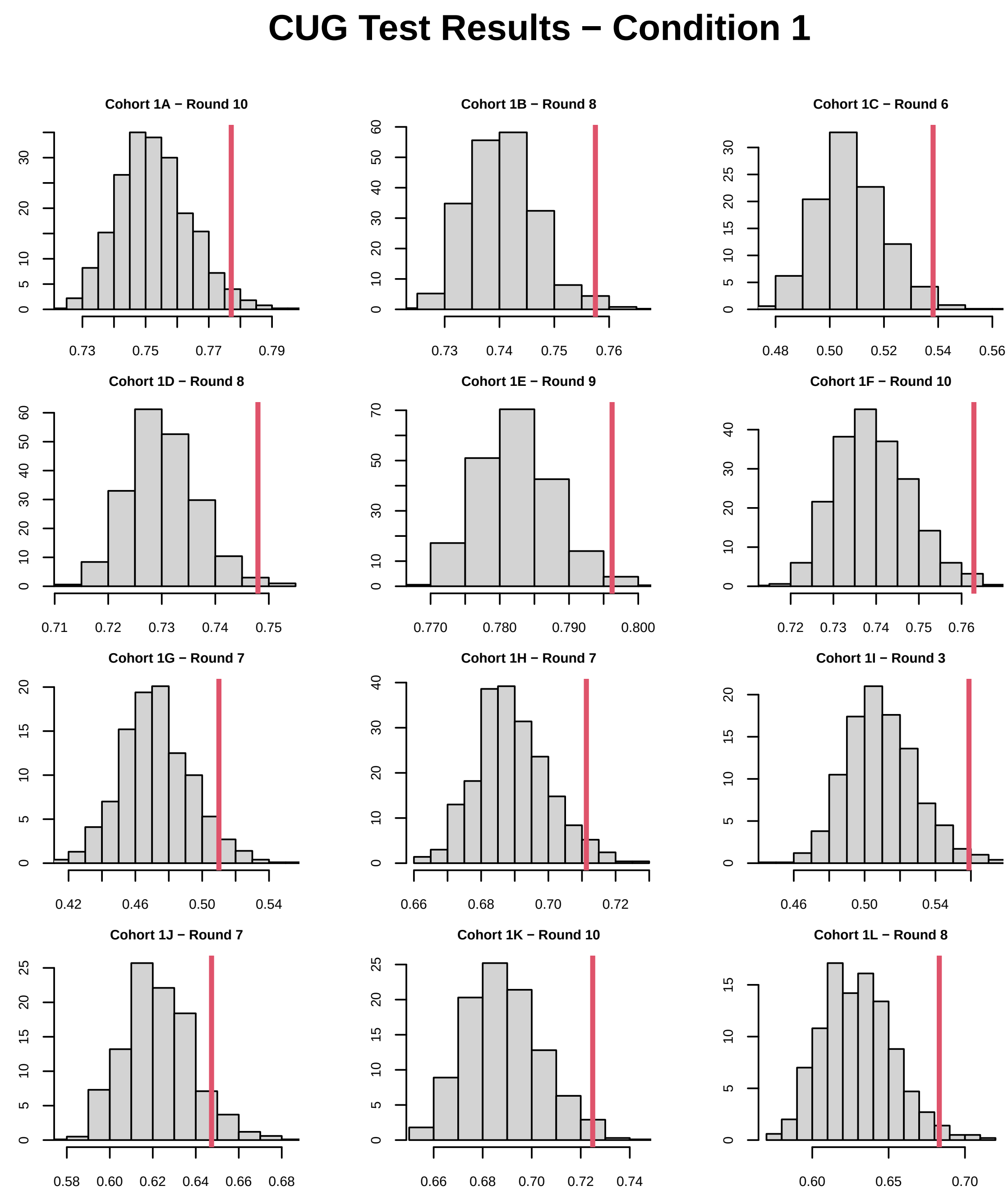

Figure 33. Conditional uniform graph test results, condition 1 cohorts. Transitivity was used as the test statistic and the randomly-generated networks conditioned on the number of edges in the observed network. The histogram depicts the distribution of transitivity in the random networks, while the red line indicates the transitivity value of the observed network.

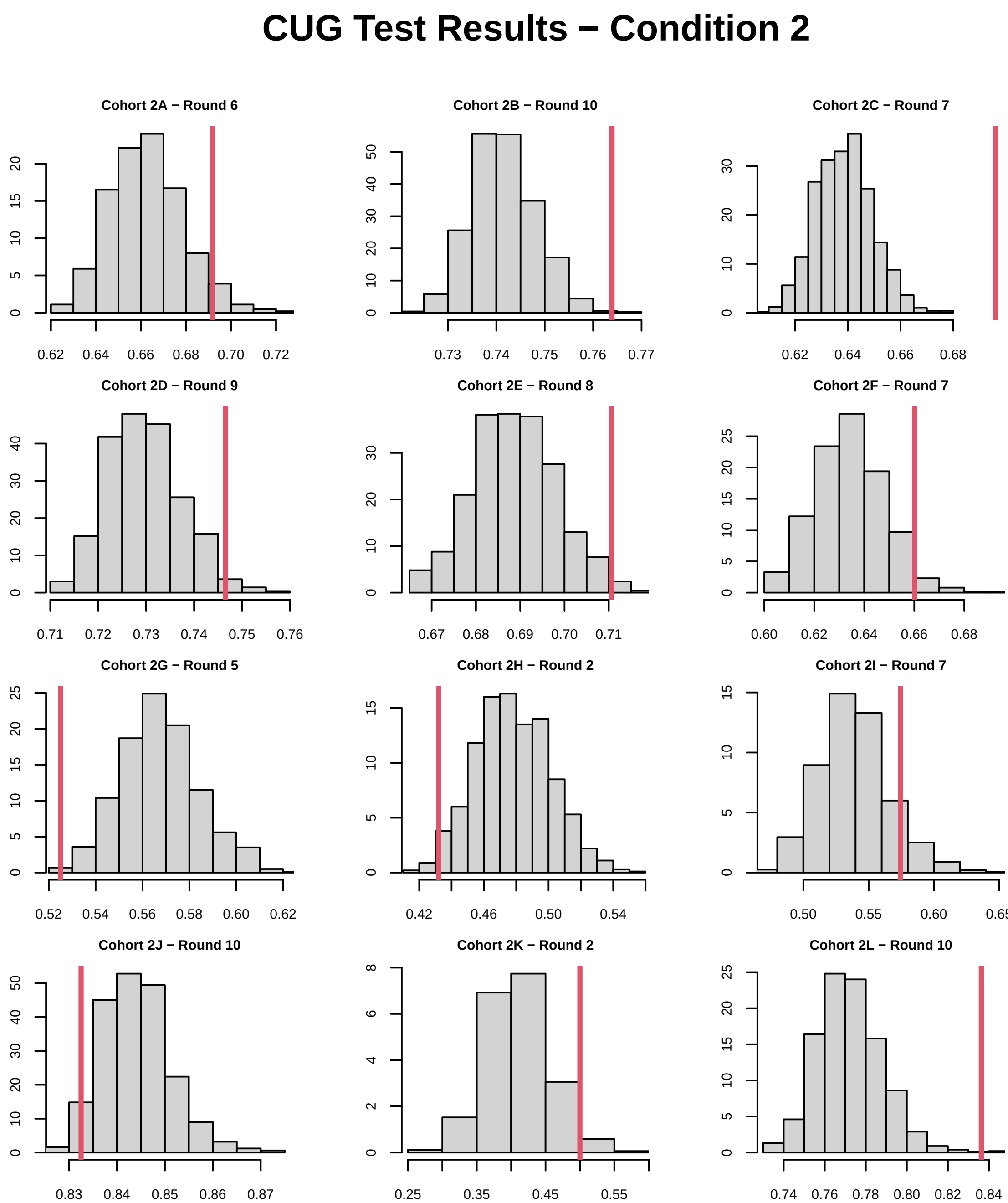

Figure 34. Conditional uniform graph test results, condition 2 cohorts. Transitivity was used as the test statistic and the randomly-generated networks conditioned on the number of edges in the observed network. The histogram depicts the distribution of transitivity in the random networks, while the red line indicates the transitivity value of the observed network.

Appendix C: BTERGM Goodness of Fit - Condition 1 (H1)

The network statistics used to determine BTERGM model fit include dyad-wise and edge-wise shared partners, degree (total), indegree, geodesic distances (shortest path) and walktrap modularity. Solid lines represent the observed networks.

In order to conserve space, I opted to include only the goodness of fit graphs for the core hypothesis of condition 1 - hypothesis 1. Additional goodness of fit graphs are available for the other hypotheses of condition 1 at https://github.com/Matt-Sweitzer/Dissertation/tree/main/Results.

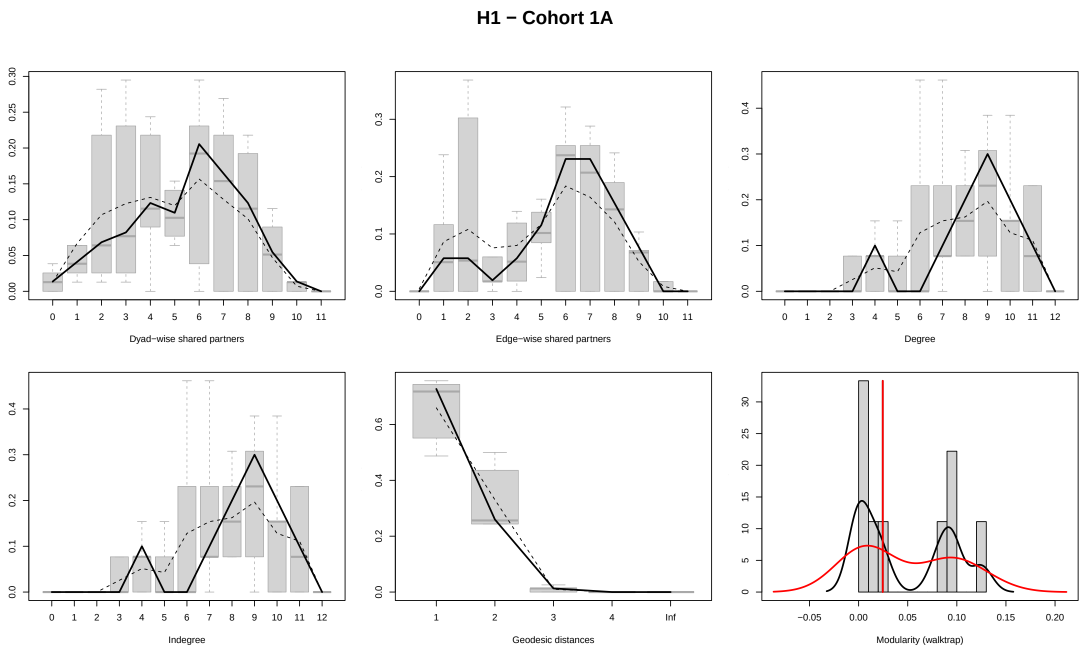

Figure 35. BTERGM model fit statistics of the test of H1 using cohort 1A.

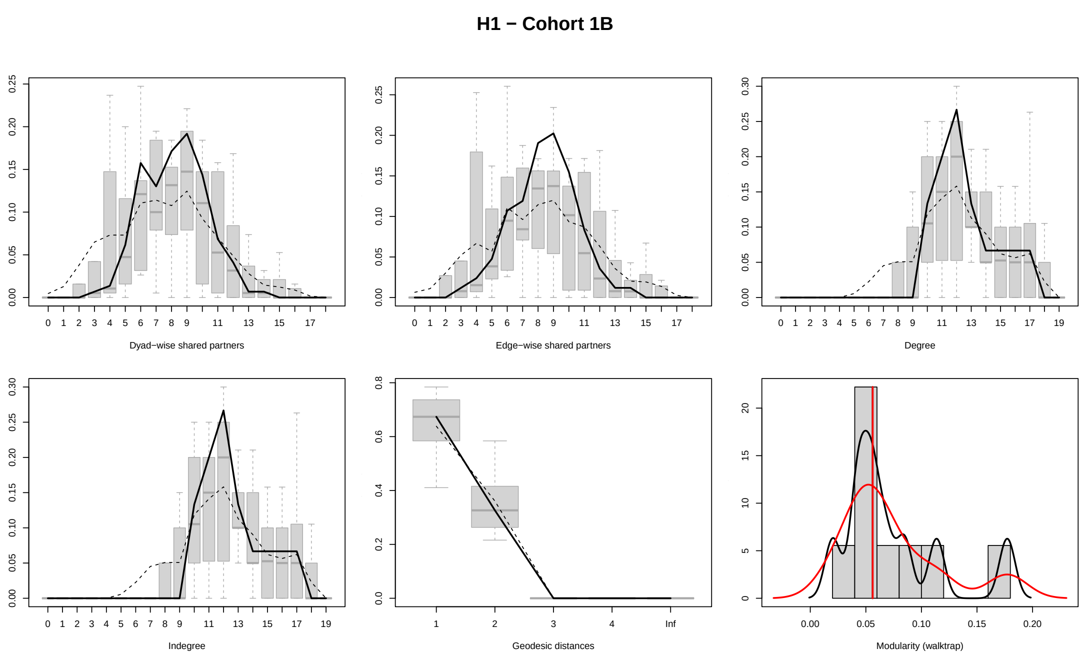

Figure 36. BTERGM model fit statistics of the test of H1 using cohort 1B.

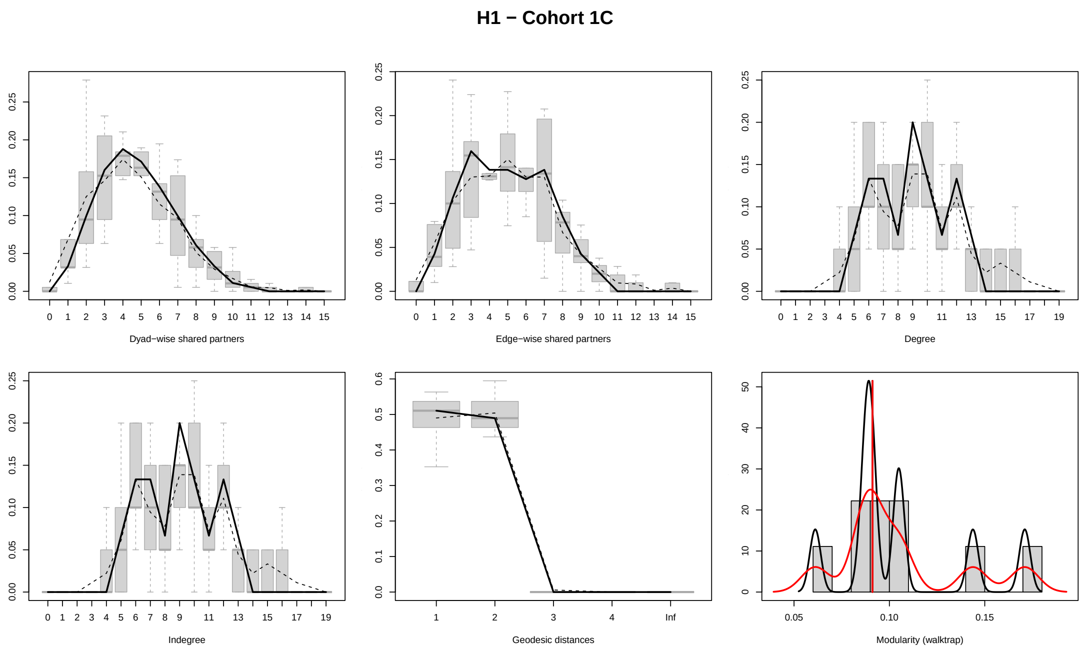

Figure 37. BTERGM model fit statistics of the test of H1 using cohort 1C.

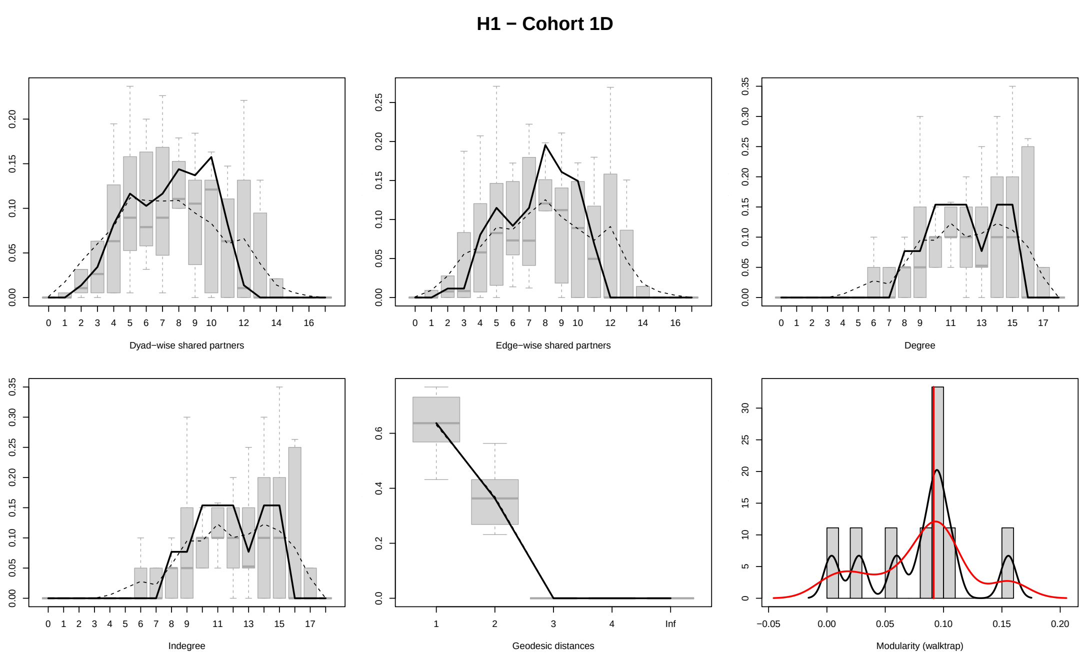

Figure 38. BTERGM model fit statistics of the test of H1 using cohort 1D.

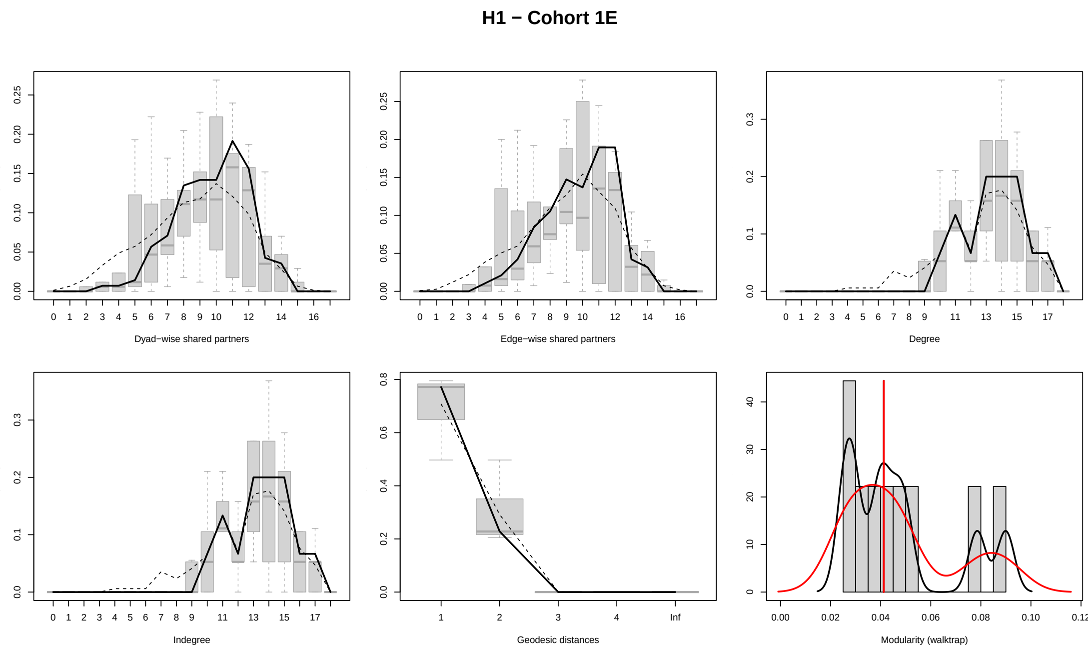

Figure 39. BTERGM model fit statistics of the test of H1 using cohort 1E.

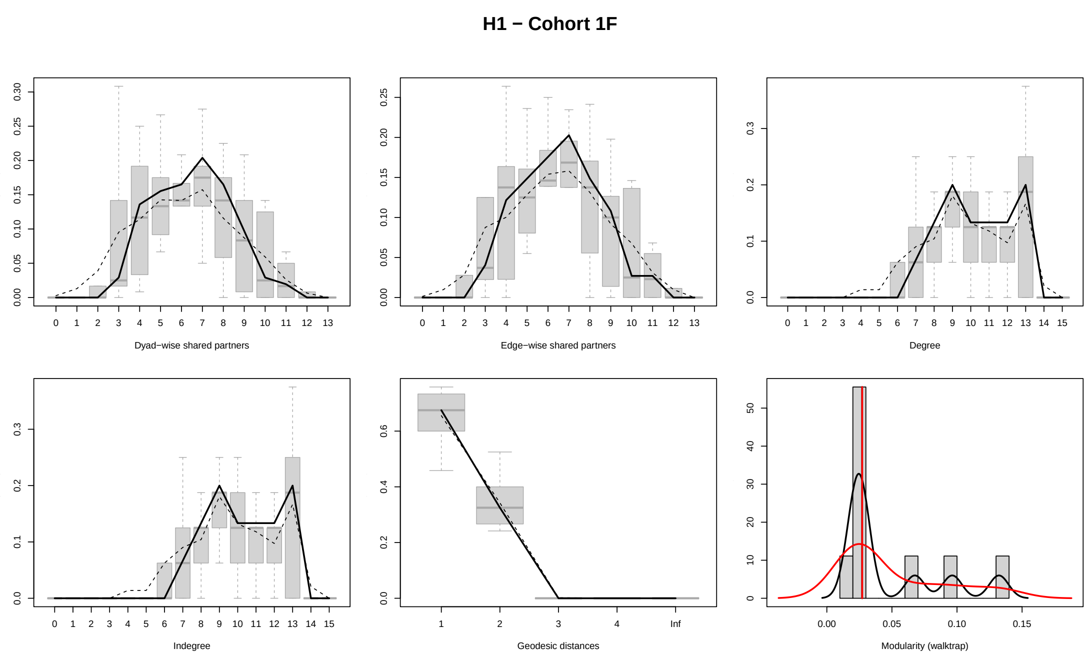

Figure 40. BTERGM model fit statistics of the test of H1 using cohort 1F.

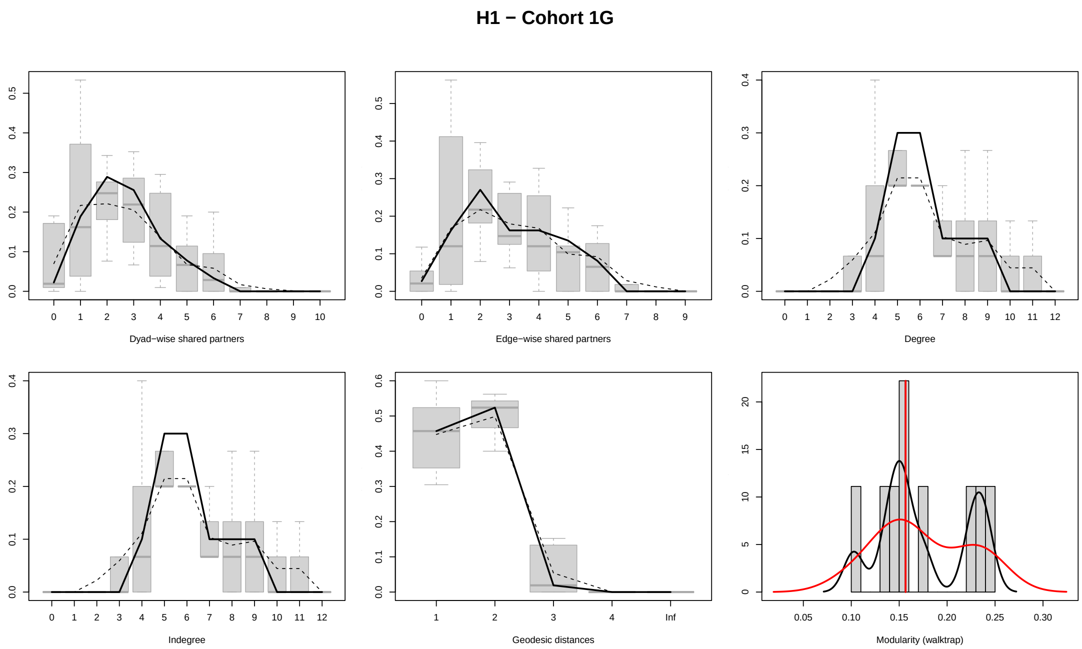

Figure 41. BTERGM model fit statistics of the test of H1 using cohort 1G.

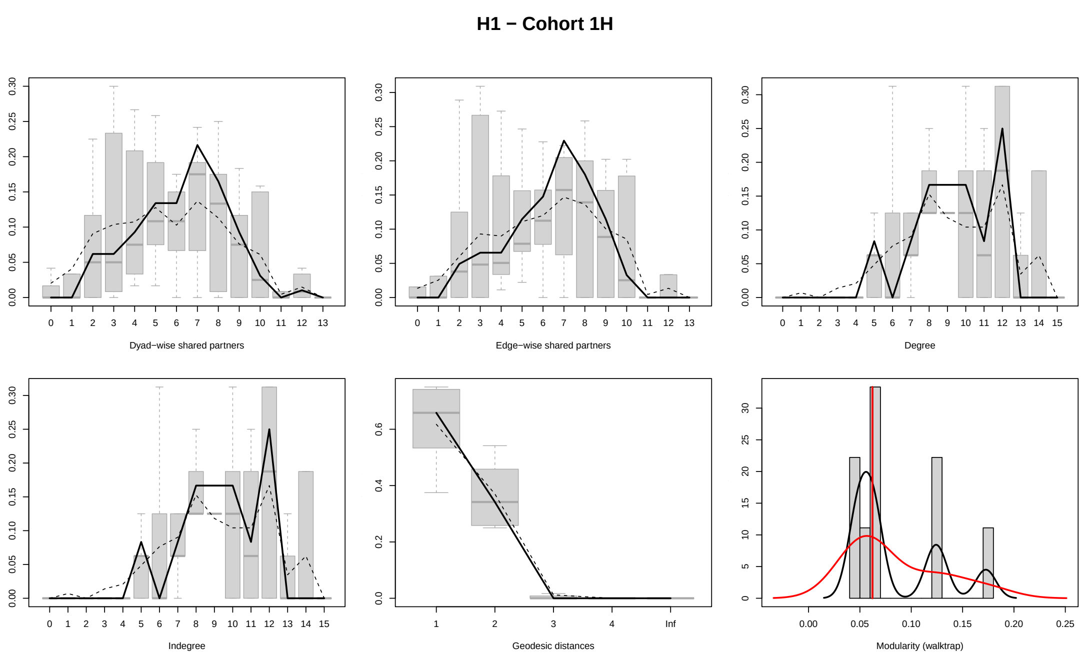

Figure 42. BTERGM model fit statistics of the test of H1 using cohort 1H.

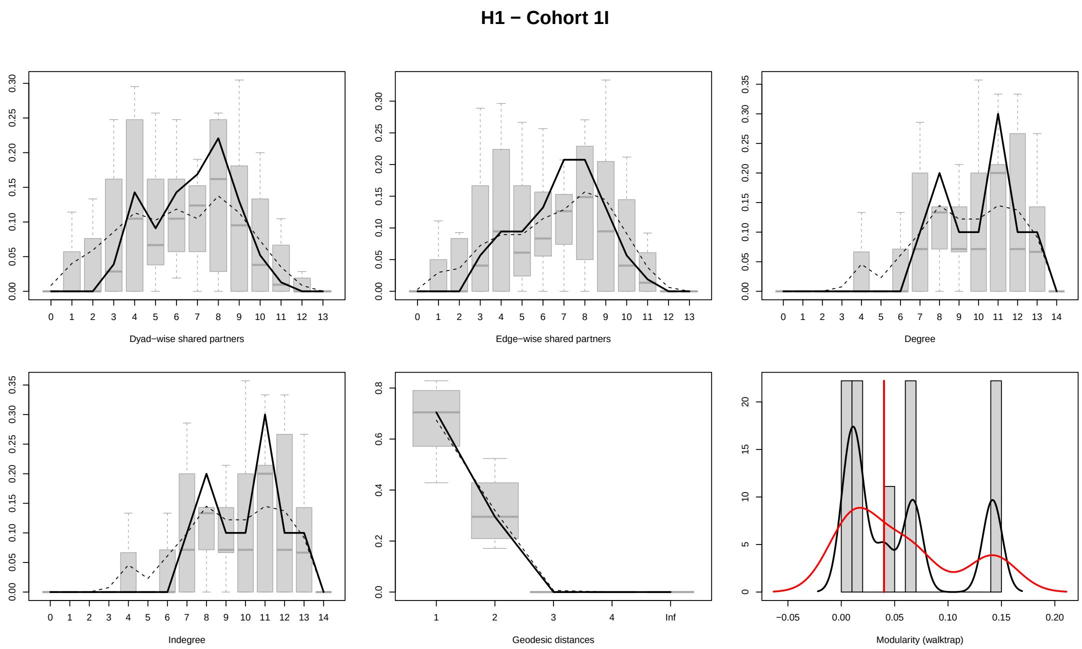

Figure 43. BTERGM model fit statistics of the test of H1 using cohort 1I.

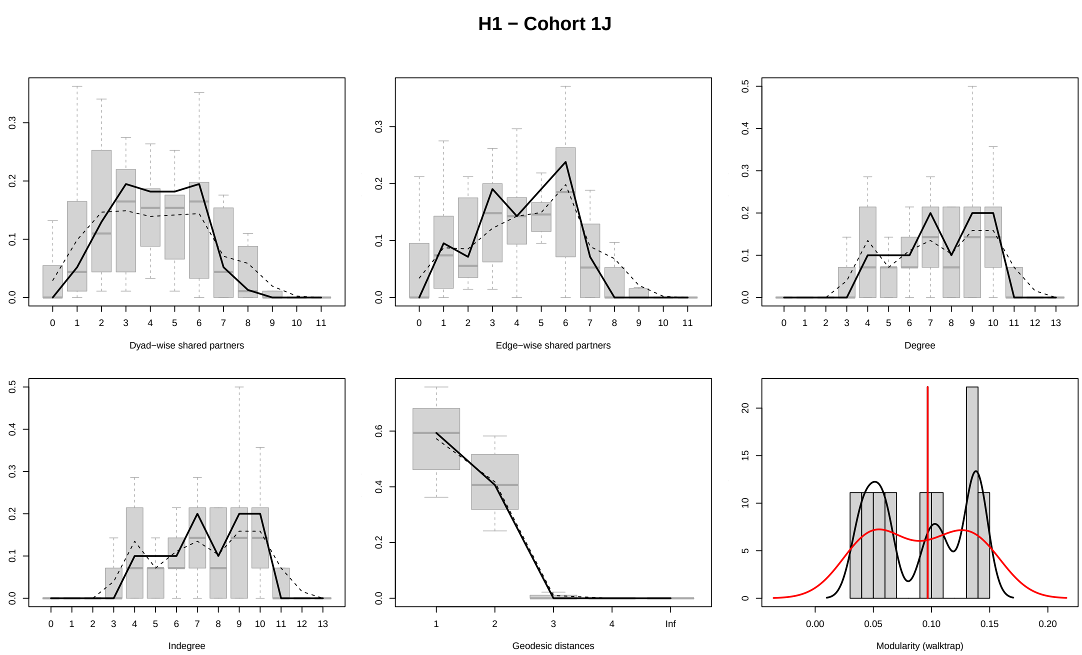

Figure 44. BTERGM model fit statistics of the test of H1 using cohort 1J.

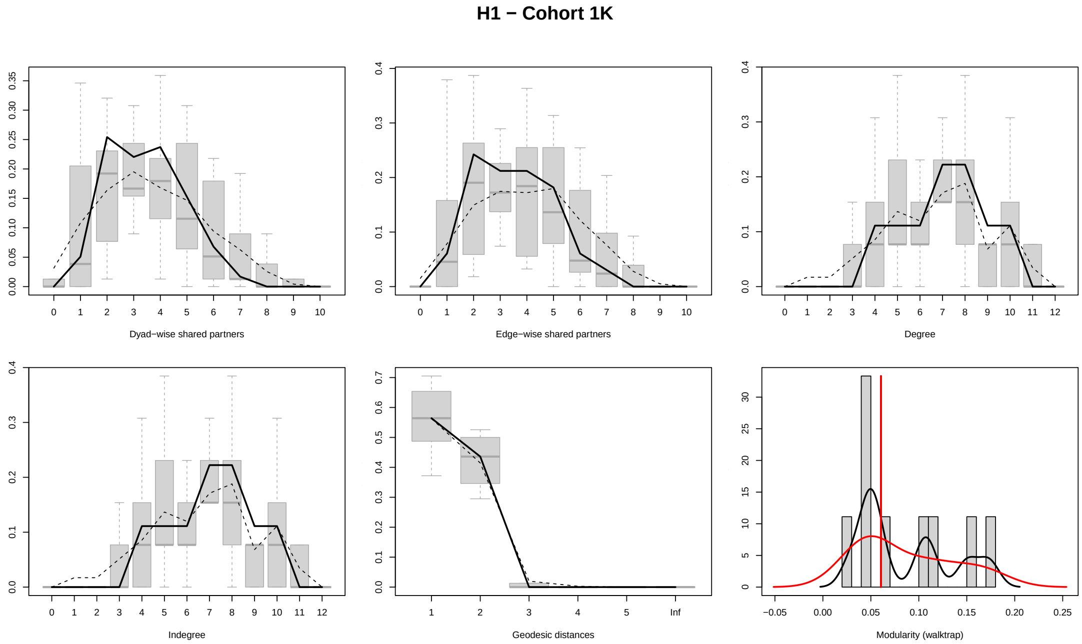

Figure 45. BTERGM model fit statistics of the test of H1 using cohort 1K.

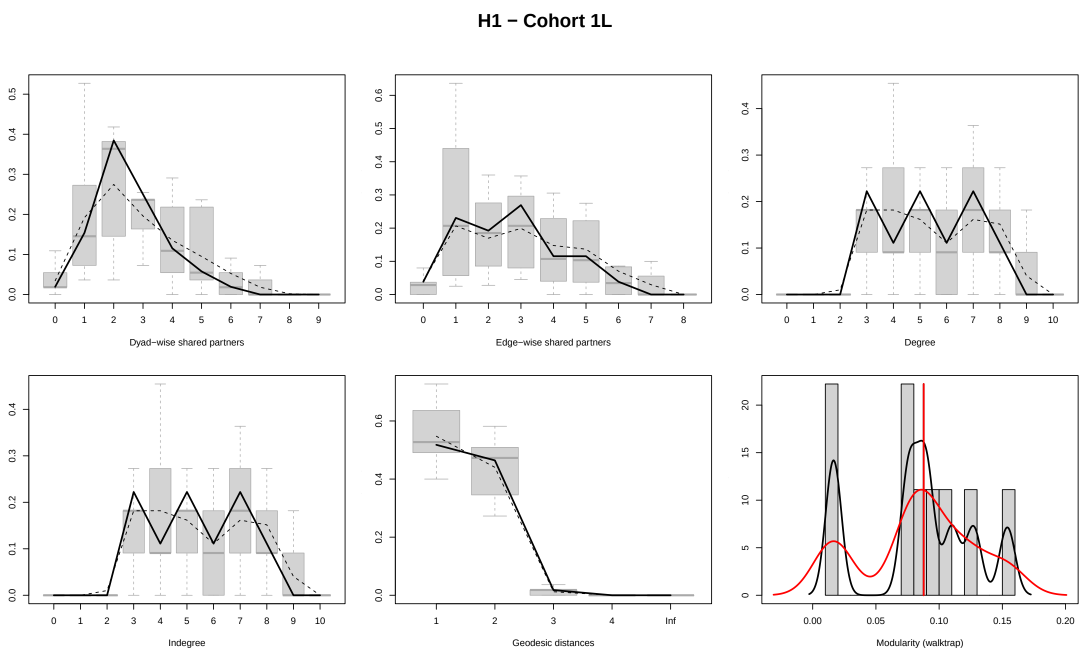

Figure 46. BTERGM model fit statistics of the test of H1 using cohort 1L.

Appendix D: BTERGM Goodness of Fit - Condition 2 (H9)

The network statistics used to determine BTERGM model fit include dyad-wise and edge-wise shared partners, degree (total), indegree, geodesic distances (shortest path) and walktrap modularity. Solid lines represent the observed networks.

In order to conserve space, I opted to include only the goodness of fit graphs for the core hypothesis of condition 2 - hypothesis 9 (the first tests using current-round differences of opinion). Additional goodness of fit graphs are available for the other hypotheses of condition 2 at
https://github.com/Matt-Sweitzer/Dissertation/tree/main/Results.

H9 − Cohort 2A

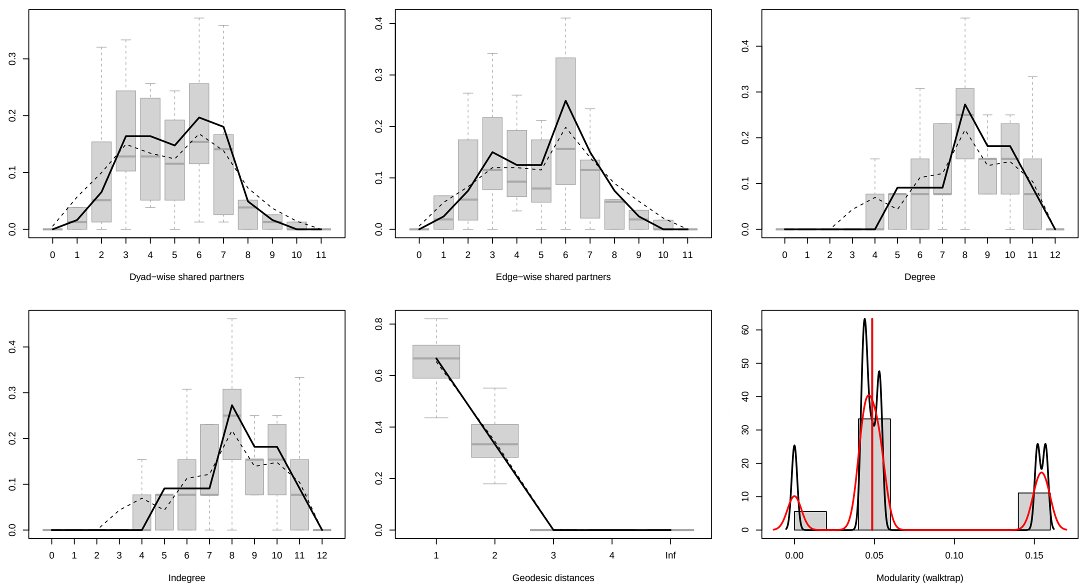

Figure 47. BTERGM model fit statistics of the test of H9 using cohort 2A.

H9 − Cohort 2B

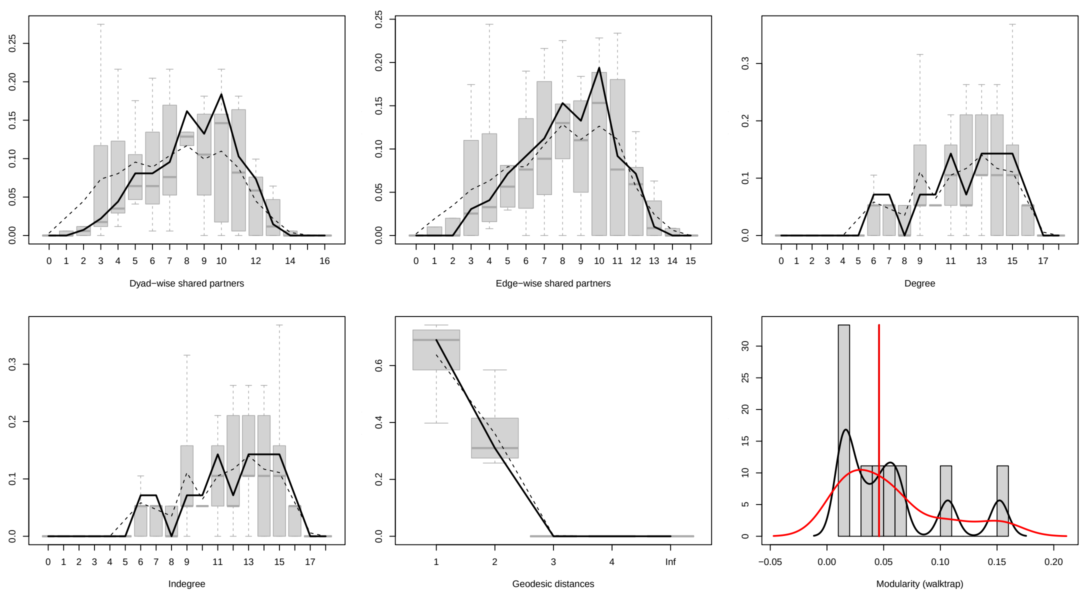

Figure 48. BTERGM model fit statistics of the test of H9 using cohort 2B.

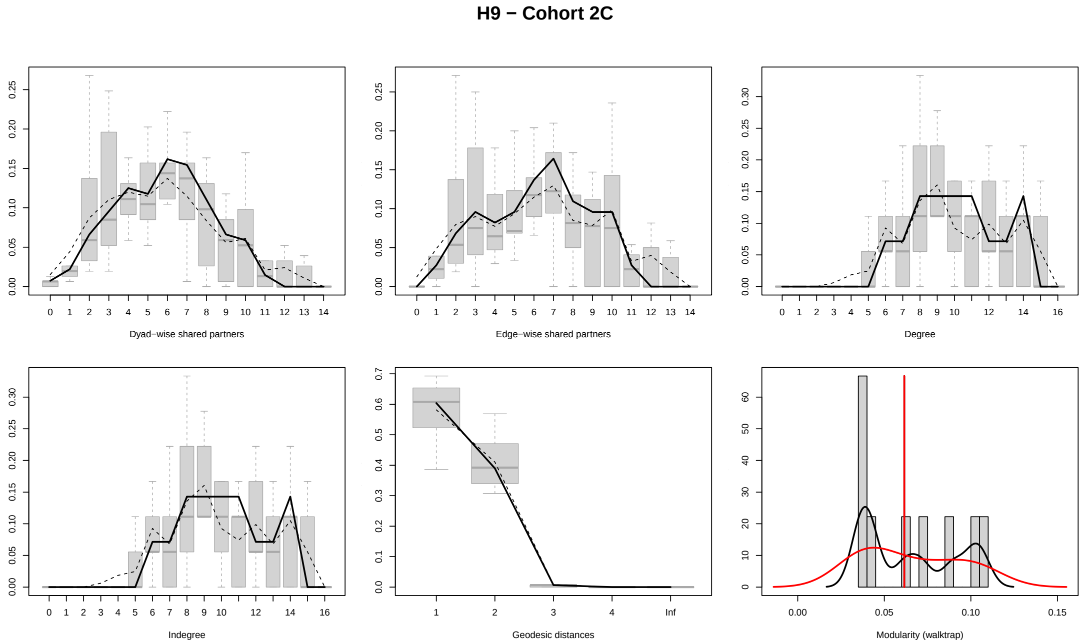

Figure 49. BTERGM model fit statistics of the test of H9 using cohort 2C.

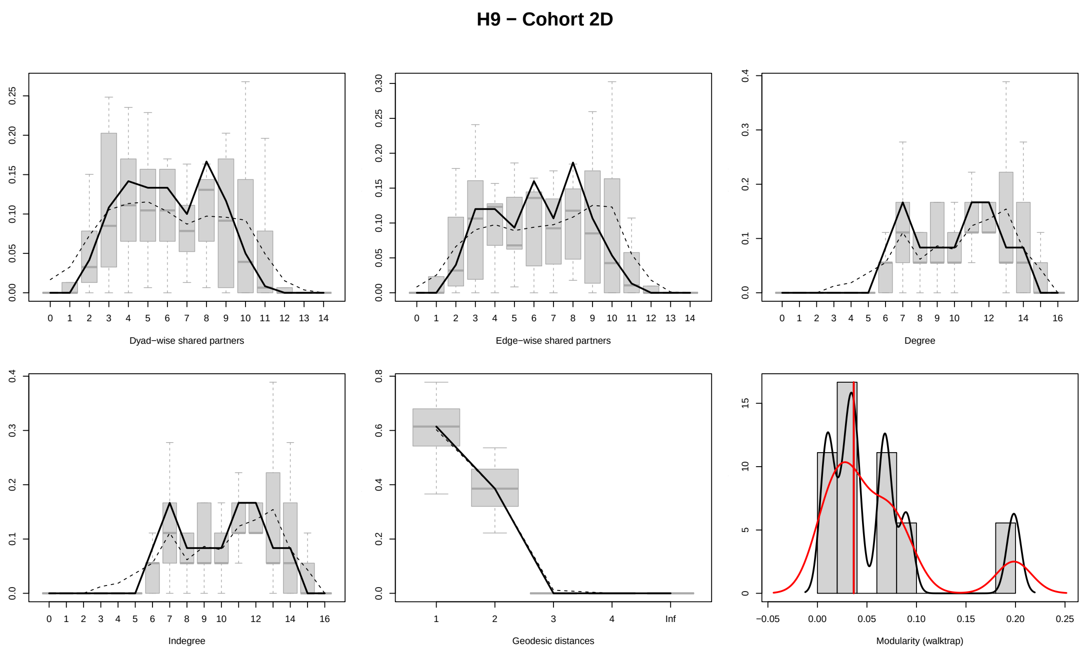

Figure 50. BTERGM model fit statistics of the test of H9 using cohort 2D.

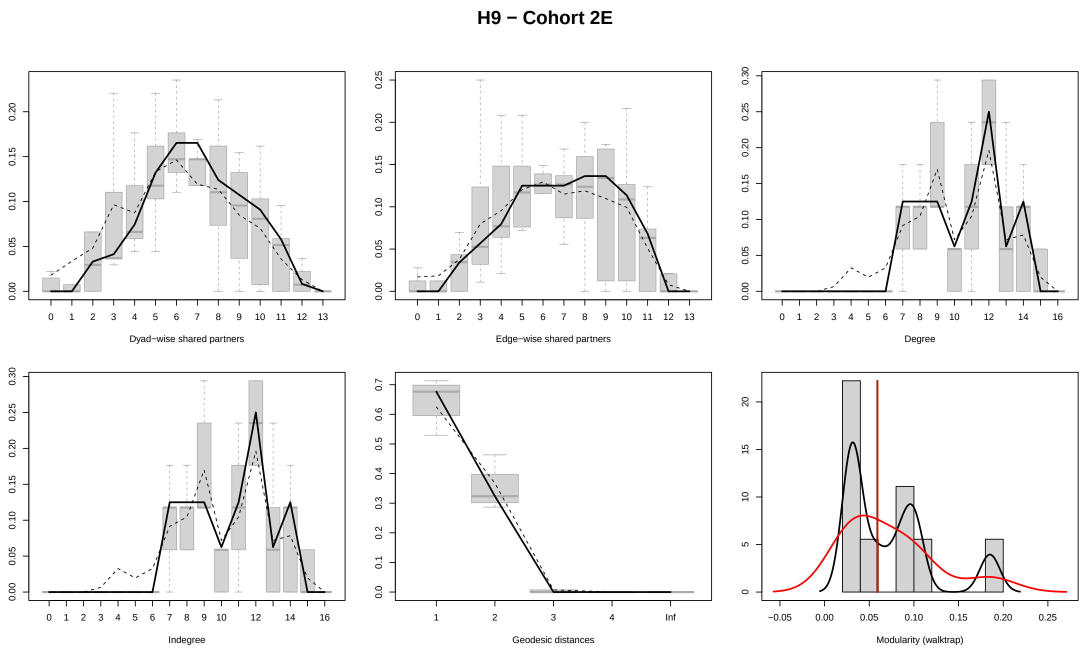

Figure 51. BTERGM model fit statistics of the test of H9 using cohort 2E.

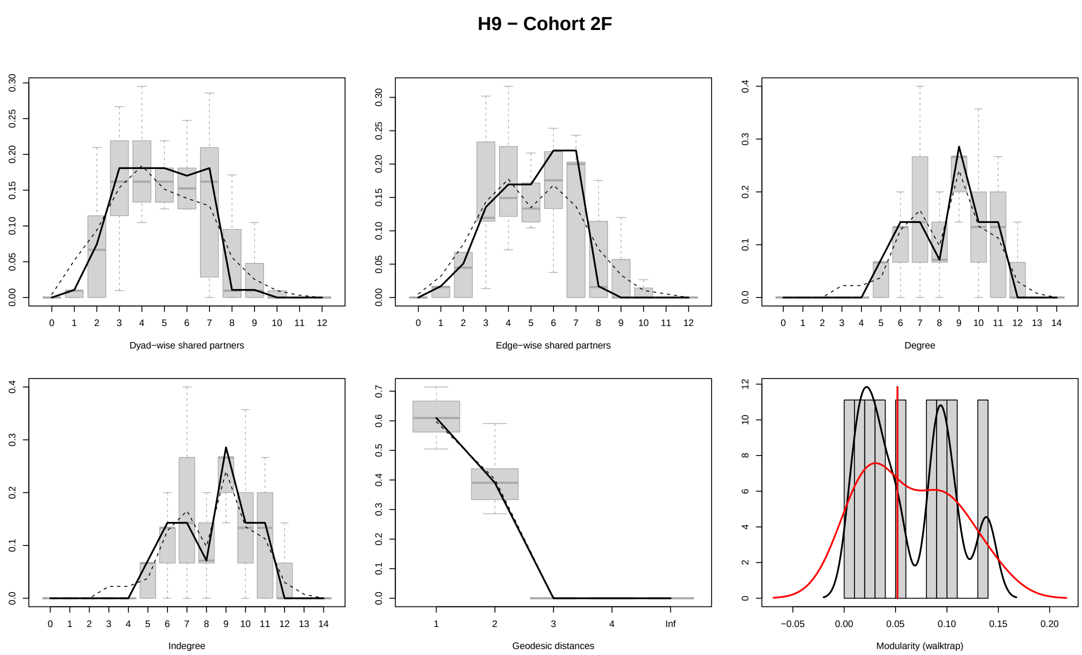

Figure 52. BTERGM model fit statistics of the test of H9 using cohort 2F.

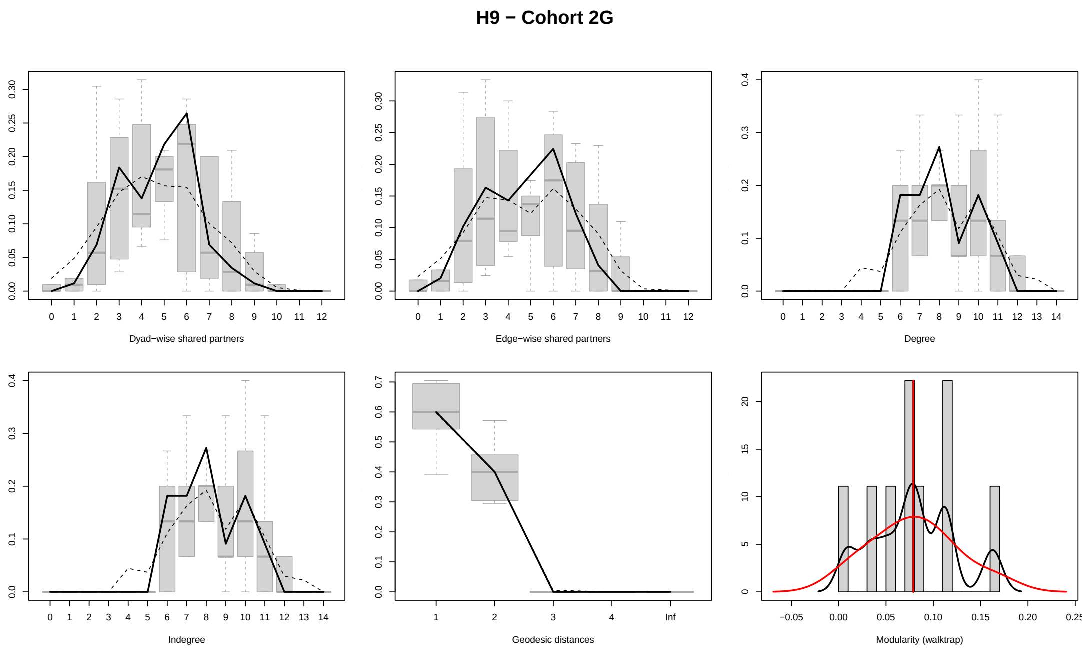

Figure 53. BTERGM model fit statistics of the test of H9 using cohort 2G.

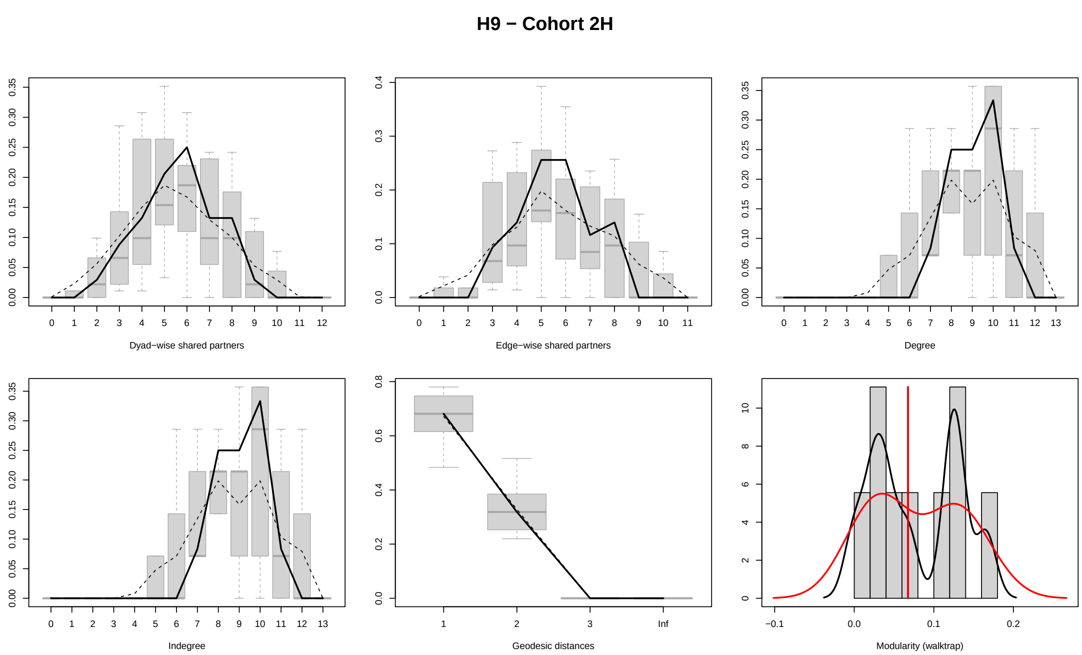

Figure 54. BTERGM model fit statistics of the test of H9 using cohort 2H.

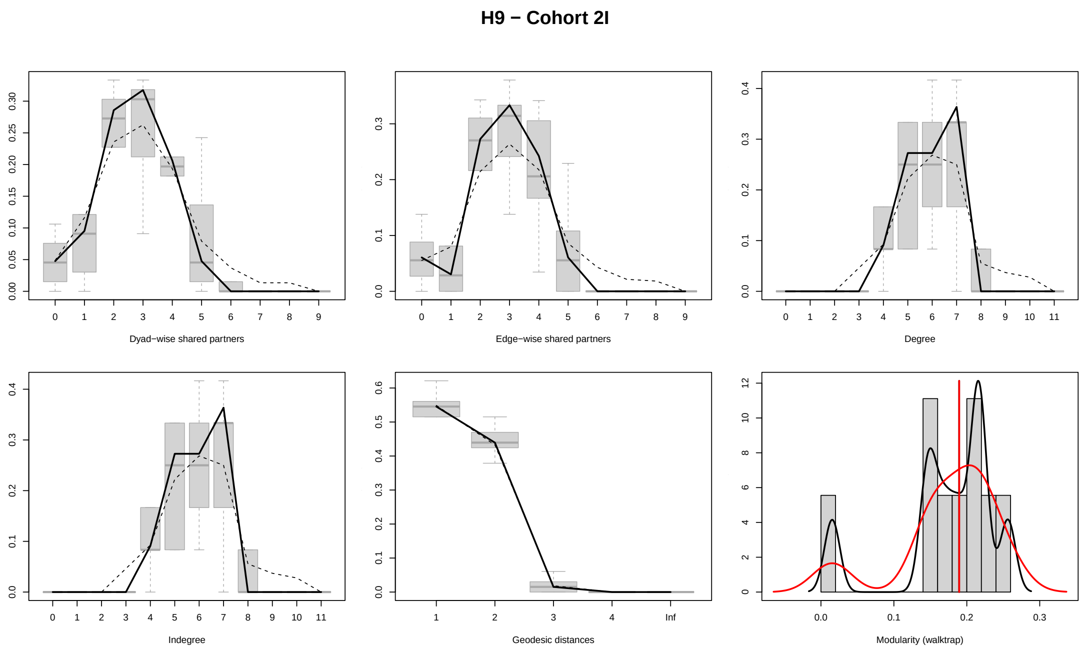

Figure 55. BTERGM model fit statistics of the test of H9 using cohort 2I.

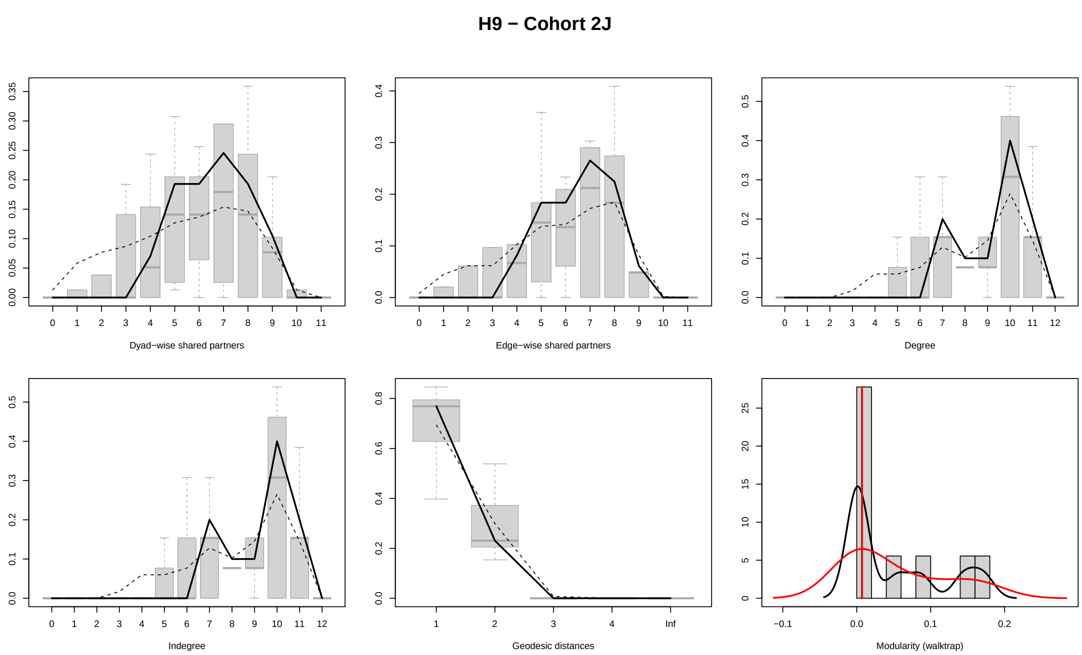

Figure 56. BTERGM model fit statistics of the test of H9 using cohort 2J.

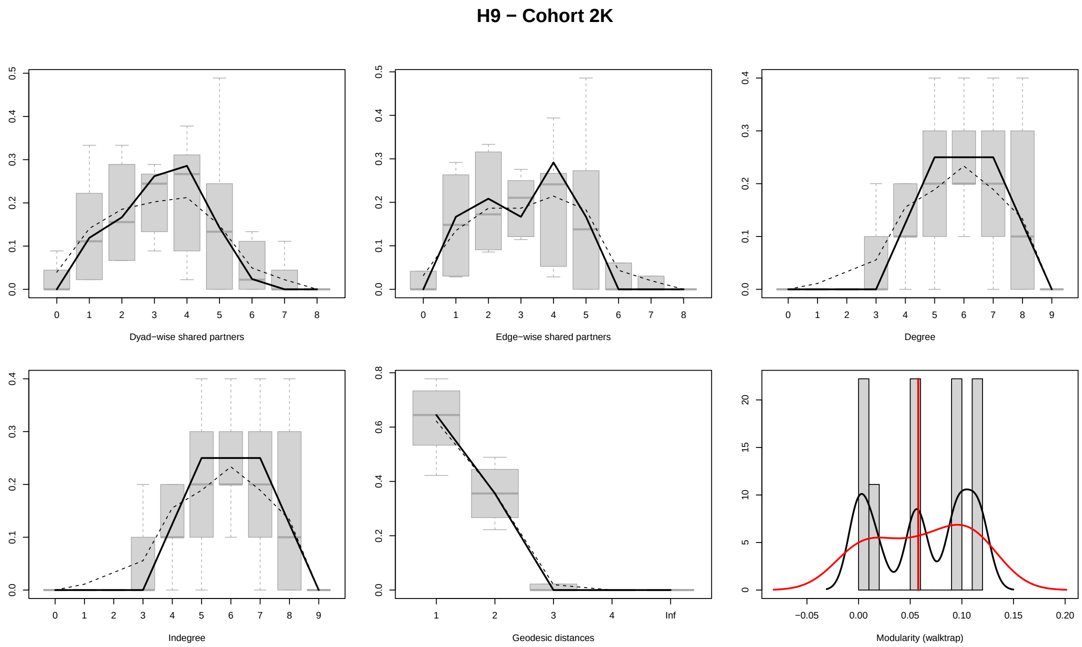

Figure 57. BTERGM model fit statistics of the test of H9 using cohort 2K.

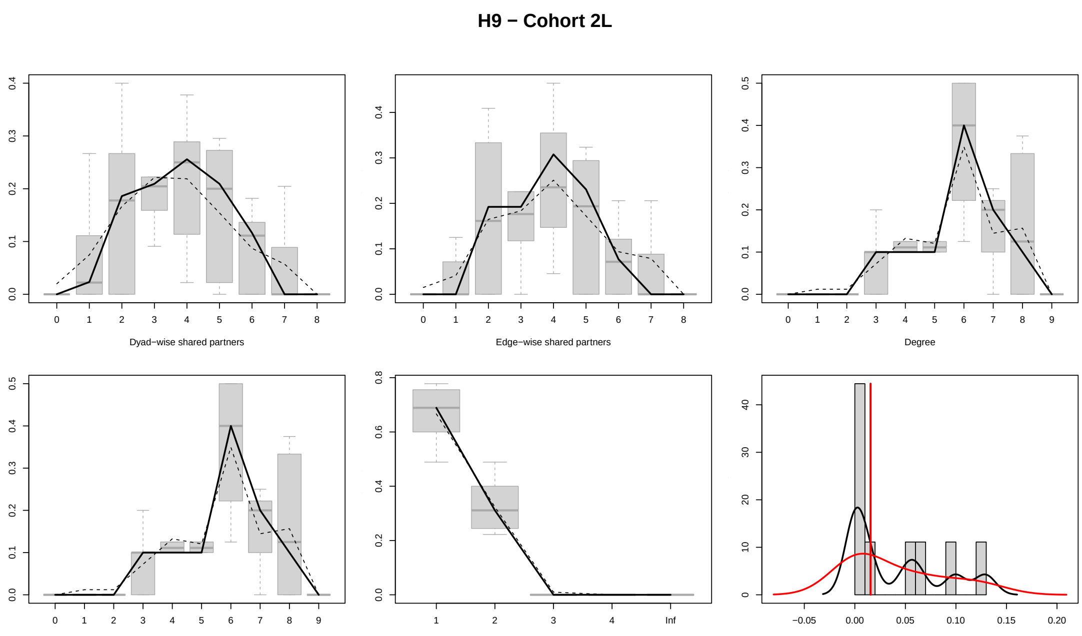

Figure 58. BTERGM model fit statistics of the test of H9 using cohort 2L.

Appendix E: Software Statement

The two-condition study contained in this dissertation was conducted using version 2.3.1 of the Breadboard software for social network experiments (McKnight & Christakis, 2019). The instance was hosted on an Ohio State University server running Red Hat Enterprise Linux version 7.9.

The code used to conduct the experiment is as much a part of the intellectual contribution of this dissertation as this document. It is available for download at https://github.com/Matt-Sweitzer/Dissertation/tree/main/Breadboard.

Analyses and data cleaning processes were conducted in R version 4.1.0 ("Camp Pontanezen"). As of publication, analysis code and data are not available for distribution. However, if the author decides to add them at a later date, they will be located in the "root" directory of the same GitHub repository linked above.

The following R code was used to conduct the conditional uniform graph tests which utilize assortativity as the comparison metric between observed and randomly-generated networks (H2, RQ2, and RQ3):

```
myAssortFn<-function(net){
  igraph::assortativity(intergraph::asIgraph(net), igraph::V(intergraph::asIgraph(net))$PartyID)
}

myCUGTestFn<-function(net, niter, cohort, rnd){
  partyIDs<-network::get.vertex.attribute(net, attr="PartyID")
  nV<-length(partyIDs)
  nE<-network.edgecount(net)/2
  asserts<-vector()
  for(i in 1:niter){
    randnet<-network::as.network(sna::rgnm(1, nV, nE, mode = "graph", diag = FALSE, return.as.edgelist = FALSE))
    network::set.vertex.attribute(x=randnet, "PartyID", partyIDs)
    assorts<-c(assorts, myAssortFn(randnet))
  }
  return(list(myAssortFn(net), sum(assorts > myAssortFn(net))/niter, sum(assorts < myAssortFn(net))/niter))
}
```