A Dynamic Longitudinal Examination of Social Networks and Political Behavior:
The Moderating Effect of Local Network Properties and Its Implication for Social Influence Processes

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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2015

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Abstract

One of the fundamental regularities of human behavior is the interdependency of attributes, attitudes, and actions. Focusing on informal political discussion networks and their roles in shaping one’s political preferences, the purpose of this dissertation is to uncover complex mutual interdependencies and the dynamic processes of which individuals’ political attributes and political discussion networks simultaneously evolve over time. Motivated by a number of recent advancements in studies of dynamic co-evolution of one’s attributes and social networks, the current study proposes and tests comprehensive theoretical accounts of social selection and social influence processes. First, longitudinal dynamics of social selections are examined in terms of demographic and political homophily, political interest and knowledge, availability and intimacy of dyadic relationships, and higher-order network endogenous effects. Second, possible mechanisms of normative and informational social influence and their relationships with dyadic differences of political interest and knowledge, with some graph-theoretical properties of political discussion networks, were examined. Using the Temporal Exponential Random Graph Models and the Generalized Estimating Equations, a series of whole network panel data from a number of large U.S Midwestern universities were used to test the proposed hypotheses. Findings suggest that political preference homophily is not likely to drive the structuring individuals’ political discussion, but
rather political discussion networks were largely driven by one’s exogenous social relationships and network-endogenous processes. The impact of political preference homophily was generally limited, but individuals are more likely to form political discussion ties with those who are more interested in politics. Concerning the possible mechanisms of social network influence, none of the expected interaction effects were found although significant unconditional effects of an alter’s political preferences on an ego’s were observed. A series of supplementary analyses suggested that the other types of social ties – close friends and time-spent together networks – were indeed capable of inducing similarities in political preferences between an ego and alters without explicit political interactions. Moreover, the results suggested that, coupled with more “visible” attributes (smoking and happiness), an ego’s highly interconnected, closure-like local network were more likely to amplify alters’ influence on the ego, therefore suggesting that normative influence is likely within the social influence processes. Implications for the coevolution of social networks and one’s attributes, and suggestions for future research are discussed.
Acknowledgments

First of all, my sincerest gratitude and thanks to my advisor, Dr. Chip Eveland, for all of his unwavering personal and professional support, guidance, and mentorship throughout my four years at Ohio State. He has been a truly inspirational mentor, and without his counsel, this dissertation and my growth as a scholar would not have been possible. Thank you for everything – I am truly a lucky person to have you as my advisor, and I am leaving Ohio State a better scholar and a better person because of you.

I also want to thank my committee members Dr. Michael Neblo, Dr. Neha Gondal, and Dr. Robert Bond for their constructive criticism, professional support and feedback on this project along the way. Without their helps and feedbacks, this dissertation would have not been possible. Special thanks to Dr. David Lazer and Dr. Katherine Ognyanova at Northeastern who have generously agreed to share their wonderful resources and various helps in navigating the data. I also owe a great deal of thanks to Dr. Andrew Hayes, Dr. David Ewoldsen, Dr. Lance Holbert, Dr. Erik Nisbet, Dr. Kelly Garrett, Dr. Paul Beck, Dr. Zheng Joyce Wang, Dr. Roselyn Lee-Won, Dr. Chul-joo “CJ” Lee, and all other mentors at Ohio State who have pushed me to grow as a scholar.

To all my friends, especially to the School of Communication Cohort from 2011 to 2015, thank you for your help, support, encouragements along the way, and just thank
you for being there. You have proven how important and even grateful to have such wonderful social networks around.

I would also like to thank my loving family for being my biggest source of support – both emotionally and financially -- throughout graduate school. Their steadfast love and encouragement has enabled me to achieve my dream.

Finally and most importantly to my wife Jeehye lidia Keum for being my greatest guiding lights and love. Thank you for inspiring me the true meaning of life, thank you for making me smile, thank you for making me laugh, thank you for pushing me but not letting me fall. And after all, thank you for being you.
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Chapter 1: Introduction

“Where Opinion is mobile, bustling, where it goes from one extreme to the other, conversations are frequent, daring, emancipated. Where Opinion is weak, there is no lively talk; where it is strong, there are robust discussions”

– Gabriel Tarde (1898/2014)

One of the fundamental regularities of human behavior is the interdependency of attributes, attitudes, and actions. Over the decades since the Columbia School scholars’ seminal studies of voting behavior (Berelson, Lazarsfeld, & McPhee, 1954; Lazarsfeld, Berelson, & Gaudet, 1944), scholars have repeatedly discovered that individuals’ electoral behaviors are fundamentally conditioned upon the partisan alignments of one’s family, friends, and coworkers (Huckfeldt & Sprague, 1995; Leighley, 1990; Pattie & Johnston, 2000; Sinclair, 2012; Zuckerman, 2005). Basic to this approach is the understanding that social actors are embedded within a social network, where a social network is defined as a set of actors and ties among them representing some substantive relationship (or a lack of such relationship). Actors are surrounded by their personal network, and within the constraints and possibilities afforded by their network, they respond to one another’s opinions, attitudes, or behaviors (Leenders, 2002). Although the notion that human behaviors can be characterized as being mutually interdependent is not
new (Cartwright & Harary, 1956; Festinger, 1950; 1954; Heider, 1946; Newcomb, 1943; 1953), its implication has not been sufficiently understood until recently. Recent theoretical and empirical progress has begun to shed new light on how such regularities are properly explicated. This dissertation contributes to the ongoing scientific inquiries of mutual interdependencies in human political behaviors.

Focusing on the role of informal political discussion networks in shaping political attitudes, this study is motivated by a number of theoretical and practical issues commonly addressed in the influence of social networks on political behaviors.

Much of the prior work regarding the impact of political discussion on political behavior has relied upon egocentric network data derived from sample surveys that aim to capture immediate social environments of discrete individuals (e.g., Mutz, 2002; Zuckerman, 2005; also, see Eveland, Hutchens, & Morey, 2012, and Song & Eveland 2015 for a brief review regarding the critiques of such works). In recent years, scholarly interest in whole social network data in political communication literature has been greatly expanded in order to overcome the limitations of egocentric network data, yet there remain some concerns over the nature of causal inferences using purely observational, cross-sectional network data (see Fowler et al., 2011; Klofstad, 2010; Lazer et al., 2010).

First, to adequately address the problem of causal inferences using network data (Fowler et al., 2011; de Klepper et al., 2010; Lazer, 2001; Lazer et al., 2010; Snijders, Steglich, & Schweinberger, 2007; Steglich, Snijders, & Pearson, 2010), this dissertation builds on past empirical work by examining comprehensive theoretical accounts of social
selection and social influence processes within the context of network-attitude
coevolution. Since social selection and social influence offer identical predictions
regarding the possible outcomes regarding the relationship between social networks and
one’s attitudes or behavior, disentangling the competing impact of selection and influence
is crucial in establishing causal inferences. In response, this study examines dynamic,
joint evolution of political discussion networks and political attitudes using a series of
longitudinal whole-network surveys following the pioneering work of Snijders (2001),
Lazer (2001), Snijders et al. (2007), Lazer et al. (2010), and many others. Longitudinal
whole-network survey data are particularly suitable to uncover such joint dynamics in
mutual interdependencies of individuals’ attributes and network structural changes. This
dissertation situates various psychological, sociological, and interpersonal antecedents of
political discussion (i.e., social selection) (Berelson et al., 1954; Lazarsfeld et al., 1944;
Verba & Nie, 1972; Verba, Schlozman, & Brady, 1995) along with normative and
informational social influence mechanisms (Borgatti & Everett, 1992; Burt, 1987;
Deutsch & Gerard, 1955; Kaplan & Miller, 1987; Price, Nir, & Cappella, 2006) within
the framework of network-attitude coevolutionary dynamics to develop a coherent
theoretical understanding regarding such dynamic processes.

Second, the present study further disentangles empirical mechanisms of
informational and normative influence in social influence processes. Although such
distinctions are often assumed theoretically and analytically by scholars (e.g., Deutsch &
Gerard, 1955; Price et al., 2006), the issue of successfully dissecting informational and
normative influence, particularly within the context of social network influence, has
received a little attention until recently (Sinclair, 2012). This study answers this question using the longstanding theoretical perspective of social capital and its relationship with local network structures (Burt, 1992; 2000; Coleman, 1988; 1990), as well as social cohesion in extant literature (Burt, 1978; 1987; Friedkin, 1984; 1998). By linking theoretical mechanisms of informational and normative influence with local network structures implied in the social cohesion perspective, the present study explores the possibility of offering a critical test of the two mechanisms. By addressing the above issues, this dissertation makes a number of contributions to the existing literature, both theoretically and methodologically.

In what follows, Chapter Two reviews the significance and relevant theoretical traditions concerning political discussion, followed by a brief summary of the current state of the research regarding political discussion. Chapter Three highlights theoretical and methodological needs for a study of network-attitude coevolutionary dynamics using longitudinal whole-network data. Chapter Four and Chapter Five will be devoted to a comprehensive review of various mechanisms of social selection (Chapter Four) and social influence (Chapter Five) that have been accounted for in the extant literature, developing specific hypotheses for the current dissertation. Chapter Six presents methods, measurement, and analytical strategies to test the proposed hypotheses and research questions. Chapter Seven presents the results of the study, and Chapter Eight addresses the conclusions and implications from the study, while also addressing limitations and directions for the future research.
Chapter 2: The Significance of Political Discussion in Modern Deliberative Democracy

Through participation in free, voluntarily associations, citizens of a democracy create legitimate political power that is independent of the state (de Tocqueville, 1835/1945). At its core, interpersonal discussions of politics have long been regarded as fundamental underpinnings of such free, voluntarily associations in modern deliberative democracy and representative government (de Tocqueville, 1835/1945; Habermas, 1989; also see Delli Carpini, Cook, & Jacobs, 2004; Fishkin, 1992; Kim & Kim, 2008). Normative theories of deliberative democracy suggest that any meaningful and legitimate political decisions could be reached by, and only by, the public deliberation of its members (Bohman, 1997). Democracy becomes “democratic” to the extent that citizens can justify their demands for collective action, giving reasons to competing conceptions of common goods to the society, and discuss competing proposals to achieve such common goods (Cohen, 1997; Elster, 1998; Gutmann & Thompson, 1998). As succinctly summarized by Cohen (1997, p. 72), the notion of deliberative democracy hinges on the idea that “the justification of the terms and conditions of [democratic] association proceeds through public argument and reasoning among equal citizens.” Therefore, the concept of deliberative democracy permits us to think of the democratic decision making processes as “procedural” and provisional in nature. The legitimacy of political decisions
could be established if, and only if, such decisions could be subject to free and reasoned discussion among rational and informed citizens (Benhabib, 1996; Cohen, 1997; Elster, 1998). Therefore, political discussion enjoys central attention by scholars as the crucial instrument by which such processes are carried out. Jürgen Habermas (1964/1974, p. 49) therefore claims, “A portion of the public sphere comes into being in every conversation in which private individuals assemble to form a public body.”

Yet the importance of political discussion is not limited to its conceptual relevance to mere procedural and instrumental conceptions of a democracy. As argued by early American sociologists such as Buber (1965), Mead (1934), and Cooley (1922), there is a longstanding theoretical tradition that an individual becomes a “self” out of social interactions and communicative actions with others:

*It is notable that the national self, indeed any group self, can be felt only in relation to a larger society, just as the individual self is felt only in relation to other individuals.* (Cooley, 1922, p. 210).

*The self, as that which can be an object to itself, is essentially a social structure, and it arises in social experience...it is impossible to conceive of a self arising outside of social experience* (Mead, 1934, p. 140).

As rightfully argued by Kim and Kim (2008), only through conversation can citizens produce mutual understanding of their goals, preferences, and the concept of self (as well as the relationship with others) – which are precisely the preconditions of the instrumental view of deliberative democracy. Defined as “non-purposive, informal, casual, and spontaneous political conversation voluntarily carried out by free citizens”
(Kim & Kim, 2008, p. 53), everyday informal political conversation “bridges” the private worlds of individuals to the broader meanings of political spheres. Through informal political conversation citizens come to understand the preferences and perspectives of others as well as their own (Delli Carpini et al., 2004; Walsh, 2004). Moreover, individuals hold multiple and often potentially conflicting considerations toward an issue in question (Alvarez & Brehm, 1995; Feldman & Zaller, 1992; Lavine, 2001; Kim, Wyatt, & Katz, 1999). Until they have a chance to engage in political talk and reflect on their opinion towards an issue, individuals do not usually comprehend that they have conflicting opinion elements. As a result, individuals organize and express their opinions coherently “only when [they] have had an opportunity to express their opinions” by informal conversations regarding political issues (Kim et al., 1999, p. 366).

In a similar manner, yet emphasizing the link between collective and individual aspects of opinion formation, Price (1992) argued that the public, as a developing social entity, forms itself over time through spontaneous arguments, discussion, and collective opposition over an issue. Pan and Kosicki (2001), Gamson (1992), Gamson and Modigliani (1989), and Gitlin (1978) also agree that by informal, spontaneous political conversation citizens can make sense of political meanings, relate their existing knowledge and experience to broader political issues, and develop their own interpretations of symbolic messages surrounding political spheres. Therefore by this process they take part in developing coherent, organized ideas and conceptions of political realities. Indeed, early theorists such as Garbriel Tarde (1899/1989), James Bryce (1888/1973), and John Dewey (1927) anticipated the central role of informal
political conversation in shaping opinion and “producing” democratic societies.

Therefore, as argued by Tarde (1898/1969, p. 300), “the transformation of an individual opinion into a social opinion, into Opinion, is due …at all times, most particularly, to those private conversations.”

The Current State of Informal Political Discussion Research

Following the critical insights of Garbriel Tarde, the Columbia School scholars first revealed the importance of the partisan alignments of one’s friends, coworkers, and families. In their theorizing, social influence processes on voters’ electoral decision-making come into play through informal political discussions and social interactions among voters (Berelson et al., 1954; Lazarsfeld et al., 1944). Also, at least one line of empirical studies of deliberative democratic theory has been the extent of “deliberativeness” in everyday informal political discussions (e.g., Conover, Searing, & Crewe, 2002; Conover & Searing, 2005; Delli Carpini et al., 2004; Karpowitz & Mendelberg, 2011; Mansbridge, 1999; Thompson, 2008). These studies do not necessarily equate informal political discussion with formal, rule-bounded “deliberation” (Conover et al., 2002; Eveland, Morey, & Hutchens, 2011; Rojas et al., 2005; Schudson, 1997; Scheufele, 2000; Wyatt, Katz, & Kim, 2000). Yet, there remains at least an implicit assumption that informal political discussion is a real-world, observable, empirical counterpart to the normative ideals of “deliberation” (e.g., Conover et al., 2002; Moy & Gastil, 2006). Motivated by such imperatives, communication scholarship has repeatedly established a strong theoretical and empirical relationship between political discussion
and a range of “democratic” outcomes (for a broad review, see Schmitt-Beck & Lup, 2013). Informal political discussion is now believed to have a positive and robust causal effect on political knowledge (Eveland & Hively, 2009; Holbert, Benoit, Hansen, & Wen, 2002; Kim et al., 1999; Scheufele, 2000; 2002), political engagement and participation (Leighley, 1990; McClurg, 2003; Scheufele, 2000; Pattie & Johnston, 2009; Valenzuela, Kim, & Zúñiga, 2012), considered opinions (Cappella, Price, & Nir, 2002: Price, Cappella, & Nir, 2002; Mutz, 2006), tolerance (Ikeda, & Richey, 2009), and social integration (Rojas, Shah, & Friedland, 2011). Empirical findings suggest the following causal chain: (a) informal political discussion is likely to increase one’s attention and cognitive elaboration (e.g., Eveland, 2001; 2004; Eveland & Thomson, 2006; Shah, Cho, Eveland, & Kwak, 2005); (b) such attention and cognitive elaboration are likely to increase information mobilization and, as a result, increase political knowledge and political participation (indirectly via knowledge) (e.g., Cho, 2008; Cho et al., 2009; Eveland & Hively, 2009; Feldman & Price, 2007; Hardy & Scheufele, 2009; Holbert et al., 2010; Lemert, 1981; Sheufele, 2002); (c) political discussion also likely to increase participation in various civic and political activities via mobilization and recruitment (e.g., Leighley, 1990; McClurg, 2003; Scheufele, 2000; Valenzuela et al., 2012); this in turn is likely to be positively associated with one’s social integration and social connectedness (e.g., La Due Lake & Huckfeldt, 1998; McClurg, 2003; Settle, Bond, & Levitt, 2011); and (e) further produces lasting effects via civic and political socialization processes (e.g., Hively & Eveland, 2009; McDevitt & Chaffee, 2000; Rahn, Brehm, & Carlson, 1999; Valentino & Sears, 1998; Verba & Nie, 1972; Verba et al., 1995).
One of the most important theoretical and empirical issues in studies of informal political discussion is the extent to which individuals are exposed to a diverse range of political viewpoints, or exposed to agreement and disagreement during political discussion. The persistence of political agreement and disagreement in political discussion has attracted a significant body of scholarship regarding the underlying factors that shape such patterns of exposure (e.g., Bello, 2012; Eveland et al., 2011; Eveland & Hively, 2009; Feldman & Price, 2007; Huckfeldt & Mendez, 2008; Huckfeldt, Mendez, & Osborn, 2004; Klofstad, Sokhey, & McClurg, 2013; McClurg, 2003; 2006; Mutz, 2002; Nir, 2011; Scheufele et al., 2004; Scheufele et al., 2006; Stromer-Galley, 2003; Stromer-Galley & Muhlberger, 2009; Wojcieszak & Mutz, 2009). Exposure to agreement and disagreement is inherently tied not only to the question of ‘deliberativeness’ of informal political discussion, but also to political conversation effects (e.g., Eveland & Hively, 2009; Eveland et al., 2011; Scheufele et al., 2006; Mutz, 2002; Nir, 2011). Although it is not uncommon to find strong homophily based on partisan or ideological similarities (e.g., Bello & Rolfe, 2014; Huckfeldt et al., 2004), scholars also now generally agree that there exists a considerable degree of exposure to disagreement in citizen’s everyday political interactions (Huckfeldt & Sprague, 1995; Mutz & Mondak, 2006; Scheufele et al., 2006).

Another important issue in the extant literature concerns the causal influence direction between social networks and individuals’ attributes (being broadly defined as from attitudes to behaviors). For instance, one of the consistent findings from the literature is that individuals who closely interact tend to be more homogeneous with
respect to their attitudes and behaviors (e.g., Lazarsfeld et al., 1968; Huckfeldt & Sprague, 1991; 1995; Pattie & Johnston, 2000), such that “friends tend to be much more similar than chance alone would predict” (Lewis, Gonzalez, & Kaufman, 2012, p. 68). Some scholars explain such phenomena as instantiations of social selection processes (e.g., Lazarsfeld & Merton, 1954; McPherson, Smith-Lovin, & Cook, 2001). A social selection model would explain such phenomena based on the basic human tendency that similarity increases interpersonal attractions (Festinger, 1957; 1964; Huston & Levinger, 1978; Mutz & Martin, 2001) and the principle of partner choice based on homophily (McPherson et al., 2001). Therefore, such similarity could be directly attributable to one’s active selection of his or her alters based on attributes such as political attitudes or partisan orientation. In contrast, others explain such phenomena as instantiations of social influence processes (Friedkin, 1982; 1998), social contagion (e.g., Bond et al., 2012; Christakis & Fowler, 2007; Nickerson, 2008), or interpersonal social influence (Lazer et al., 2010; Mutz, 2002), such that individuals assimilate their attitudes or behaviors that are deemed as appropriate and rewarding. As a consequence, the central question in this area increasingly focuses on theoretical and empirical distinctions between social influence and social selection. Formulated more generally, since two competing explanations offer identical predictions regarding the possible outcomes, causal inferences regarding the influence of network structure on individuals’ attributes cannot be firmly established without making implicit assumptions or empirical validations of possible confounding effects including selection (Fowler et al., 2011; Lazer, 2001; Lazer et al., 2010; de Klepper et al., 2010; Snijders et al., 2007; Steglich et al., 2010).
Chapter 3: Analytical Challenges in Studying the Impact of Social Network

Most of the prior work on informal political discussion, particularly within political communication scholarship, has relied on cross-sectional, sample surveys available in ANES or GSS that are based on name-generator and name-interpreter techniques (see Eveland et al., 2012; Klofstad, McClurg, & Rolfe, 2009 for a brief review). There is much to value in the current literature, especially the use of probabilistic samples and therefore the generalizability of findings from such studies (e.g., Bello & Rolfe, 2014; Huckfeldt & Sprague, 1995; Sinclair, 2012). However, compared to the whole-network data, the ability to draw causal inferences regarding social network influence using sample survey data is significantly hampered by its limited ability to address alternative explanations that might produce same observable patterns in outcomes – namely: (a) random clustering (e.g., baseline probability), (b) selection effects (e.g., homophily), and (c) contextual effects (Fowler et al., 2011).

First, within the context of addressing the impact of political discussion networks on individuals’ attributes, random clustering denotes the chance (or baseline) probability of observing the degree of similarity between an ego’s (a focal respondent) attitudes or behavior and that of her alters (discussants). Existing studies of egocentric social network data heavily rely on analysis using ego-alter dyads as the unit of analysis while treating
each of dyad as an independent observation (i.e., dyadic independence). Alternatively and more frequently, studies often rely on an aggregation of all possible ego-alter pairs to create an ego’s average scores (and treat them as the properties of an ego) and then such average scores are subjected to conventional statistical analysis. Not only do such practices do not fully account for all possible aspects of a broad network structure outside of an ego’s direct social contacts, but they also fail to address unobserved feedback, including any higher-order endogenous mechanisms between network structure and behaviors (Burk, Steglich, & Snijders, 2007; Steglich et al., 2010). Also, traditional statistical techniques cannot be directly applied to evaluate baseline probability because it violates the fundamental assumption of statistical independence when network data are concerned (Burk et al., 2007; Fowler et al., 2011).

Second, as Steglich et al. (2010) acknowledge, the proper identification of social selection effects requires not only information between connected dyads, but also critically hinges on information between unconnected dyads. Since typical egocentric network data cannot provide such information regarding potential relational ties that were not selected, it “precludes a meaningful assessment of selection processes” (Steglich et al, 2010, p. 339). Also, most of the egocentric network data limits the number of potential alters named by a focal respondent up to 3 to 5 individuals (fixed choice design: Marsden, 1987; 1990; 2005). It is now well understood that such name generator techniques with fixed number of alters are more likely elicit “strong tie” networks, therefore likely to capture a biased, small subset of alters (Marin, 2004; Marsden, 2005). This could have significant implications on the robustness of the statistical analysis using name-generator
data especially for social selection effects, due to possible upward biases in selection effect estimates (Veenstra & Steglich, 2012; Veenstra et al., 2013). Also, it cannot effectively address other plausible alternative explanations based on more complex mutual interdependencies inherent in network data (such as transitivity or preferential attachment).

Finally, it has been suggested that a common, contextual factor could simultaneously influence a focal respondent and her discussants, causing their outcome variables to be similar over time (see Cohen-Cole & Fletcher, 2008, for such critics; also see Fowler & Christakis, 2008a). This is sometimes referred to as “unobserved heterogeneity,” “omitted variable bias,” or “contextual confounds” (Fowler et al., 2011; Klofstad, 2009; Manski, 1993; Shalizi & Thomas, 2011; Wooldridge, 2010), which is well known in econometric literature. This is indeed inherent in many of the existing methods of statistical analyses, therefore not limited to sample survey network data alone.

A commonly recommended solution to this problem is to use a fixed effect model with longitudinal observations (Hausman, 1978; Wooldridge, 2010), or to employ a random effect model (multilevel linear model: Bryk & Raudenbush, 1992; Green, 2008; Snijders & Bosker, 1999).¹ Indeed, multilevel analysis of egocentric data is now widely available after the pioneering work of Snijers, Spreen, and Zwaagstra (1995) and several others (Snijders & Kenny, 2005; van Duijn, van Busschbach, & Snijders 1999). Yet as stated above, typical cross-sectional, egocentric network data cannot effectively rule out

¹ However, adding fixed effects term with few repeated observation can result severe downward bias in estimates (Fowler et al., 2011; Nickell, 1981)
alternative explanations. Therefore, longitudinal observations of whole-network data are preferable over egocentric network data, although it is sometimes not straightforward to employ a multilevel framework due to a more complex interdependency structure and difficulties of observing multiple whole networks over time (Wang, Robins, Pattison, & Lazega, 2013). However, a multilevel modeling of whole-network data could be accommodated using a standard meta-analytic procedure when several networks are available (e.g., Goodreau, Kitts, & Morris, 2009; Lubbers & Snijders, 2007; Snijders & Baerveldt, 2003) although studies rarely deal with multiple whole-networks.

The notion of social selection evokes the view that a network structure is the possible outcome of social interactions between an ego and his or her alters based on certain characteristics. Within this framework, one’s “characteristics” are often treated as static or highly stable over time (such as gender, ethnicity, or religious identification) whereas formations and dissolutions of ties within social networks are implicitly assumed to be dynamic. In contrast, the notion of social influence assumes social networks to be the structural constraints over individuals, therefore network structures are assumed to be time-invariant while “attributes” (e.g., attitudes, knowledge, or behaviors) are treated as something unstable and highly changeable over time (Leenders, 1997). Admittedly, these two competing perspectives are based on fundamentally different sets of assumptions and theoretical considerations. Yet in reality, it is likely that social influence and selection are simultaneously related with each other—known as the reflection problem (Manski, 1993) or autoregressive influence in social networks (Steglich et al., 2010). It is surprisingly difficult, therefore, to distinguish the causal relationship between individual attributes and
social network ties by using purely cross-sectional observations from traditional sample survey data (e.g., Shalizi & Thomas, 2011; Steglich et al., 2010). This analytical challenge has led to the view that it is necessary to study the coevolution of one’s attributes and social networks using two or more waves of whole-network panel data, as presented in Figure 1 (Lazer, 2001; Lazer et al., 2010; de Klepper et al., 2010; Snijders et al., 2007; Steglich et al., 2010; Valente, 2003).

![Diagram](image1)

Figure 1. Conceptual representation of the relationship among network coevolution, social selection, and informational/normative social influence.

Yet the necessity of studying coevolution between networks and attributes is not limited to its methodological or analytical reasons. A longstanding intellectual inquiry in the social sciences has repeatedly attempted to reconcile the bifurcated view of social
structure and agency in human actions (e.g., Alexander, Giesen, Munch & Smelser, 1987; Coleman, 1986; Giddens, 1976). Indeed, as Lazer and colleagues (2010, p. 248) put it, “how people simultaneously construct and are molded by their social milieu is one of the foundational questions of social science.” In other words, a social structure simultaneously offers constraints and opportunities regarding individuals’ attributes (e.g., Beck et al., 2002; Huckfeldt & Sprague, 1987; 1995; Leighley, 1990; Scheufele et al., 2006; Song & Eveland, 2015), but also being reproduced as a attitudinal and behavioral consequence thereof (Leender, 1997). Therefore, individuals’ attributes (and its attitudinal and behavioral consequences) in a given network are, at least partly, a function of the network structure in which such actors are embedded, constituting the complex layer of a mutual interdependency of attributes and network structure that co-evolves over time. As Giddens (1976, p. 121) insists, “Social structures are both constituted by human agency, and yet at the same time are the very medium of this constitution.” This critical insight regarding social structures and human actions has been a recurring theme in many of the theories of social network influence (Burk et al., 2007; Burt, 1992; Davis, 1970; Fowler, 2005; Lazer, 2001; Lazer et al., 2010; Marsden & Friedkin, 1993; Moody & White, 2003; Steglich et al., 2010). The study of coevolution between social networks and individual attributes not only faithfully represents such theoretical imperatives (Coleman, 1986; Eulau, 1986), but also enables us to address the detailed picture of “how” such joint dynamics between social structures and human behaviors unfold over time.
Dissecting Social Selection and Social Influence

The “social selection” in social networks could be understood as the extent to which an individual is likely to change their network ties with others on the basis of certain characteristics or a similarity of such characteristics (Robins, Elliott, & Pattison, 2001). In other words, an ego may prefer to associate (or disassociate) with his or her alters based on a certain range of criteria such as age, gender, or race (McPherson et al., 2001). Therefore, the concept of “social selection” denotes a causal impact from individual-level characteristics to a network structure. In contrast, “social influence” is defined as the change of attributes (attitudes or behaviors) on the basis of the attributes of others. In other words, social influence is “a special instance of causality, namely, the modification of one person’s responses by the action of another” (Cartwright, 1965, p.3). Therefore, contrary to the notion of social selection effects, the concept of a network-based “social influence” denotes the opposite direction of causality—from a network structure to individual behaviors.

Although much research has addressed the theoretical and empirical importance of the distinction between “selection” and “influence,” there still remains some inconsistency, particularly, in the use of the term “selection” and its possible scope within the literature. The most broad and general approach is treating the selection as a tie-generating mechanism based on “any” individual-level features – including time-varying, (potentially) network-endogenous attributes (such as attitudes and behaviors), as well as time-invariant, network-exogenous traits (such as gender or race: Lazer et al., 2010; Kossinets & Watts, 2009; Wimmer & Lewis, 2010). The other approach, based on a more
restrictive usage of the term “selection,” only focuses on time-varying, network-endogenous attributes. Those attributes include political and social attitudes (Bello & Rolfe, 2014; Lazer, 2001; Lazer et al., 2010; de Klepper et al., 2010), cultural taste (Lewis et al., 2012), or drinking behaviors (Knecht et al., 2010; Mercken et al., 2010; Steglich et al., 2010; Wang, Hacken, & Lizardo, 2013). Although the latter approach generally accounts for alternative mechanisms of tie-formation based on time-invariant characteristics in their model estimation (e.g., Lazer et al., 2010; Lewis et al., 2012), the major focus of the analytic approach is, however, appear to be slightly different from the former approach. While the more inclusive use of the term social selection (the former approach) generally aims to comprehensively understand the underlying processes of tie-formation in a given network, the latter, more restrictive approach is more geared towards proper identification and statistically controlling competing explanations in causal inference regarding “change” in individuals’ network-endogenous attributes and the network structure in which they are embedded. Therefore, the theoretical focus of a potential selection effect is generally confined to time-varying, network-endogenous attributes (e.g., political attitudes) that are in direct relation with networks in question (e.g., political discussion networks), since, by its own definition, time-invariant covariates cannot be subjected to “influence” when influence is defined as a change of individual attributes following network exposure.

In this dissertation, I will follow the former approach by assuming “social selection” as a process of constructing network ties based on any individual-level “characteristics,” including both time-varying, network-endogenous attributes as well as
time-invariant, network-exogenous traits (such as gender or race). Despite the similar theoretical consideration with more restrictive approach, this study purposefully adopts more inclusive use of the term social selection. It is now an established practice to use of actor characteristics, regardless of their variability over time, in modeling network dynamics over time (Lusher, Koskinen, & Robins, 2013; Robins, Pattison, Kalish, & Lusher, 2006) in order to comprehensively account for various alternative explanations regarding tie-formation dynamics.

From what will follow and throughout the dissertation, I will use the term “traits” when referring network-exogenous, time-invariant features such as standard demographic measures that has been related to social selection processes (e.g., race or gender). In contrast, we reserve the term “attributes” to exclusively refer a time-varying, network endogenous features such as attitudes or behaviors. Regardless of how prior research have conceptualized and used the various terms, I purposefully make a clear distinction between the term “traits” and “attributes” to avoid any conceptual confusions. In addition, when referring individuals’ given properties as a genetic covariate, including both “traits” and “attributes,” I will use the term “characteristics” as an all-inclusive term.

According to Borgatti and Foster (2003), “a fundamental dimension distinguishing among network studies is whether the studies are about the causes of network structures or the consequences” (p. 1000). Within the context of political discussion networks, in the next chapter I attempt to review several existing theories and empirical evidence regarding social selection (i.e., causes of network structures) and social influence (i.e., the consequences of network structures).
Chapter 4: Network Selection Effects – Social Structures Based on Individual Characteristics

Within the context of informal political discussions, the notion of social selection raises important questions of means, motives, and opportunities associated with the political discussions. The question of who talks, and why they talk about politics (e.g., Cook, Delli Carpini, & Jacobs, 2007; Eveland et al., 2011; Hibbing & Theiss-Morse, 2002; Neblo et al., 2010; Walsh, 2004) and various psychological, as well as sociopolitical correlates of political discussion (Delli Carpini et al., 2004; Lazer et al., 2010; Mondak & Halperin, 2008) appear to be particularly relevant, including the most well-known and parsimonious theoretical accounts of homophily (e.g., Lazarsfeld & Merton, 1954; Coleman, 1958; McPherson et al., 2001).

In what follows, I will start with (a) a general discussion of dyadic-level homophily as the most dominant paradigm addressing the underlying mechanisms of tie-formations (“social selection”) in political discussion networks. Next, (a) other relevant dyadic level covariates, focusing on political interest, knowledge, and exogenous relationships for a given dyad, will be discussed. Lastly, higher-order endogenous effects, such as transitivity and preferential attachments, will be introduced in order to advance more comprehensive theoretical accounts of dynamic social selection processes.
Homophily

According to Rogers and Bhowmik (1970), homophily refers to the tendency of a given dyad, an individual and his or her potential interaction partner, to associate with each other based on certain attributes or traits. To date, the literature on social homophily has distinguished between two related yet confounding notions within the term “homophily” (McPherson et al., 2001; Wimmer & Lewis, 2010). The distinction is largely between inbreeding homophily as a tie-generating mechanism, and baseline homophily as the effect of the availability in potential interaction partners, which is a structural feature of a given network (McPherson & Smith-Lovin, 1987; McPherson et al., 2001). Another related conceptual clarification is the differentiation between status-based homophily (i.e., homophily based on major socio-demographic factors such as race or gender) and value-based homophily (i.e., homophily based on attitudes or beliefs) (Lazarsfeld & Merton, 1954; Marsden, 1987; McPherson et al., 2001; Rogers & Bhowmik, 1970). Here, we reserve the term “homophily” to refer to a tie-generating mechanism, regardless of whether it is status or value-based, such that individuals prefer associating themselves with similar others above and beyond baseline availability effects of a given setting. In contrast, baseline availability effects should be understood as the effect of opportunity structures or the diversity of a network, which captures the distribution of certain characteristics (traits and attributes) of individuals across social settings (for a detailed discussion of the concept, see Eveland & Hively, 2009).
Status-based Homophily in Demographic Factors

One of the most robust findings from the literature is that social relations are more likely among people who are similar along a number of demographic, attitudinal, and behavioral dimensions (McPherson et al., 2001). In addition, certain organizational foci (such as school, work, or voluntary organizations) are known to create highly segregated social contexts following several demographic dimensions (e.g., gender, race, age, or religion), and such foci provide conducive environments for homophilous tie formation (Feld, 1981; McPherson et al., 2001; but see Mutz, 2006). Therefore it is often expected that, all other things being equal, there exists a strong tendency in which an ego would interact with alters similar to him/herself based on a number of factors, including race, ethnicity, gender (Ibarra, 1992; Marsden, 1987; McPherson et al., 2001; Wimmer & Lewis, 2010), and religion (Lazer et al., 2010; Louch, 2000). Research shows that individuals actively self-select their discussion partners based on demographic traits such as race or gender (e.g., Huckfeldt & Sprague, 1995; Marsden, 1987). Therefore, the following hypotheses are offered:

H1: Race homophily will significantly predict the presence of political discussion ties, such that political discussion ties are more likely between individuals of the same race.

H2: Gender homophily will significantly predict the presence of political discussion ties, such that political discussion ties are more likely between individuals of the same gender.
Value-based Homophily in Political Preference

Similar to demographic-based homophily, attitude- or value-based homophily may be a significant factor shaping patterns of tie-formation in social networks (McPherson et al., 2001; Monge & Contractor, 2003). Based on a need for cognitive consistency and balance framework (Festinger, 1957), value homophily has long been understood as a result of the basic human tendency to seek politically similar others while avoiding dissimilar ones (Mutz, 2006). Communication becomes more effective when a transfer of knowledge and attitudes is based on similar meanings and beliefs (Rogers & Bhowmik, 1970). Extant research in social psychology and communication science suggests a message with greater dissimilarity from one’s prior attitudes may motivate biased processing of the message (Chen & Chaiken, 1999; Petty & Cacioppo, 1986). This in turn is likely to produce diminished returns (Feldman & Price, 2007) and result in greater resistance (Festinger, 1957; Zaller, 1992). Although it does not necessarily imply that the preference for attitude consistency could be equated with the avoidance of counter-attitudinal information (e.g., Garrett, Carnahan, & Lynch, 2013), it is well documented that individuals prefer attitudinally congruent information over attitudinally dissimilar information (e.g., Klapper, 1960; Knobloch-Westerwick & Meng, 2009; Stroud, 2010; for opposing views, see Sears & Freedman, 1967; Garrett et al., 2013). Supporting this theoretical perspective, researchers have found substantial matching patterns based on partisan or ideological similarities in political discussion, and it suggests the possibility that people may actively self-select their political discussion.
partners based on their political attitudes (e.g., Bello & Rolfe, 2014; Huckfeldt & Sprague, 1995).

However, surprisingly little empirical evidence suggests that political homophily is the dominant driving factor that shapes patterns of social interaction among ordinary citizens (e.g., Eveland & Kleinman, 2013; Lazer et al., 2010). There are a number of possible reasons why value homophily, or political attitude-based homophily in particular, exerts much weaker effects than often assumed. First, unlike status-based homophily, political attitudes are rarely (and explicitly) considered to be a central subject matter in most organizational settings (such as school, work, or voluntary organizations). Often, certain demographic dimensions such as gender or race are believed to be reasonably correlated with political preferences (Knoke, 1990; McPherson et al., 2001). Therefore, what appears to be value homophily is often driven by baseline availability effects of such demographic dimensions or selection on those characteristics (McPherson et al., 2001). Moreover, a good deal of existing whole network studies are based on formal or informal organizations due to network boundary specification issues (Laumann, Marsden, & Prensky, 1983), wherein a network is treated as a social entity comprised of a fixed list of group members. Such organizational contexts may impose strong constraints on individuals independent of their political attitudes (Lazer, 2001; de Klepper et al., 2010) such that individuals are expected to work together or interact with each other regardless of their similarity (or dissimilarity) in political attitudes (e.g., Lazer, 2001). Also, it is suggested that the misperception of others’ beliefs and political attitudes play a role (Goel, Mason, & Watts, 2010; McPherson et al., 2001; Robbins & Krueger, 2005).
People often misperceive their discussants’ political orientations to be more similar with their own political orientation than they actually are (Goel et al., 2010), yet some have suggested that such patterns are somewhat contingent on the actual frequency of communication (e.g., Eveland & Hutchens, 2013).

Despite some mixed evidence, the above discussion and prior empirical evidence lead us to expect that homophily based on political preferences would be one of the significant predictors of social selection process:

**H3**: Political attitudes homophily will significantly predict the presence of political discussion ties, such that political discussion ties are more likely between individuals of similar political attitudes.

**Sociopolitical Correlates of Political Discussion**

While the intuitive notion of homophily in demographic factors and political attitudes is regarded as a one of the strongest *dyadic-level* predictors of tie-formation, a significant amount of attention also has been devoted to certain sociopolitical correlates. Among them, recent literature on political discussion has emphasized the role of (a) political interest and expertise effects in networks (e.g., Huckfeldt, 2001; Huckfeldt, Ikeda, & Pappi, 2005; Huckfeldt, Pietryka, & Reilly, 2014), and (b) an ego’s exogenous social relationships other than political discussions (e.g., frequency of interaction or multiplexity of relationships) with actual or potential discussion partners (Huckfeldt & Sprague, 1995; Marsden, 1987; Mutz, 2006; Small, 2013).
Political Interest and Knowledge of an Alter

One of the robust and strongest findings from previous studies is that individuals turn to those who they perceive to be an “expert” about politics to reduce information costs (e.g., Downs, 1957; La Due Lake & Huckfeldt, 1998; Huckfeldt, 2001; McClurg, 2006). Those individuals are generally believed to have accurate political knowledge, actively seek relevant information (from mass media or interpersonal sources), and are psychologically involved in politics – therefore, highly interested in politics (e.g., Fiske, Kinder, & Larter, 1983; Fiske, Lau, & Smith, 1990; Zaller, 1990). Available evidence in nationally representative surveys (Huckfeldt, 2001; Huckfeldt et al., 2005) as well as in controlled experiments (Huckfeldt et al., 2014) support this perspective, such that perceived expertise of alters exerts greater influence than dissimilarity of political preferences when an ego received relevant political information from his or her alters (but for an opposing evidence, see Ahn & Ryan, 2014). “Perceived expertise” is often highly correlated with objectively defined characteristics such as one’s political interest, political knowledge, education level, or strength of partisanship (Bartels, 1996; Delli Carpini & Keeter, 1996), and politically knowledgeable informants are believed to provide higher quality information to their discussants (McClurg, 2006). Therefore, individuals are expected to turn to those who are perceived to be more knowledgeable and interested in politics, although others have found that people often mistakenly perceive their discussants to be much more knowledgeable then they actually are (e.g., Ryan, 2011a). Therefore, the following hypothesis is raised:
H4: Political interest and knowledge of one’s alter will significantly predict the presence of political discussion ties, such that political discussion ties are more likely with alters who have higher political interest and political knowledge than an ego.

Dyadic Relationship Between an Ego and Discussants

The findings from egocentric network measurement studies suggest that the nature of the ego-alter relationship also plays an important role in predicting political discussions within such dyads (Klofstad et al., 2009; Marsden, 1987; 2005; Mutz, 2006; Mutz & Mondak, 2006). For instance, evidence suggests that political discussion, because of its potentially contentious and “dangerous” nature, is often avoided in public settings more than in private settings (Elisaph, 1996; 1998; Gamson, 1992; Hibbing & Theiss-Morse, 2002; Mutz, 2002; Schudson, 1997). These studies also suggest that informal political discussion is more likely to take place among socially intimate ties than socially distant ties for a number of reasons.²

Such strong and intimate ties are often the ones an ego is frequently and routinely interacting with in their daily social lives (Marsden, 1987; Pescosolido, 1992; Small, 2013). Therefore, these ties are more likely to provide the opportunities for political interactions as a byproduct of such routine interactions (Klofstad et al., 2009;

² Sometimes research interchangeably uses the public vs. private distinction for intimate (strong) vs. distant (weak) ties. However, at least conceptually, the former refers to the social settings, while the latter refers to the nature of social relationships with discussants (although those two should be reasonably correlated with each other).
Pescosolido, 1992; Small, 2013). In other words, this social “supply” side perspective argues that individuals are likely to discuss “important matters” or political topics with those who are easily available to them because of their routine activities, not by their emotional closeness,\(^3\) such that the sheer availability of such potential alters may trigger a sharing of deeper personal topics (Duneier, 1992; Small, 2009). This “opportunity and availability” for a social interaction is also likely to be related to political interactions as well, as suggested by a number of recent research in political conversation literature (e.g., Eveland et al., 2011; Klofstad et al., 2009). This is also consistent with the logic of the contextual effects literature demonstrating that opportunity structures of potential political interaction partners may significantly condition individuals’ political preferences (Huckfeldt & Sprague, 1987; Straits, 1991).

In addition to such availabilities and opportunities for political interactions, such strong and intimate ties (a) tend to be more homophilous in various socio-demographic dimensions, which are often reasonably well correlated with similarity in political preferences (Knoke, 1990; McPherson et al., 2001). Moreover, (b) social penetration theory (Altman & Taylor, 1973) suggests that such close and intimate ties are more likely to share private facts, common beliefs, values, or opinions towards personally intimate topics (such as religion, health, or politics: Berger & Calabrese, 1970; Morey, Eveland, &

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\(^3\) Conceptually and empirically, the emotional closeness and the availability of socially close interaction partners are likely to be highly correlated. Yet at least conceptually those two concepts are distinguishable from each other, and some research suggests that the level of self-disclosure and subsequent perception of “closeness” (emotional proximity) could be altered as physical proximity (availability) decreases (e.g., Johnson et al., 2009).
Hutchens, 2012). Therefore, a potential disagreement is less likely with such strong ties than weak or socially distant ties (Huckfeldt & Sprague, 1987; Straits, 1991), or at least disagreement, if it occurs, could be tolerated because of their preexisting strong relationships (Morey et al., 2012). Therefore, the frequency of political discussion is generally believed to be higher among more intimate, “core” discussion partners than distant alters such as coworkers or acquaintances (Huckfeldt et al., 1995; Klofstad et al., 2009; Morey et al., 2012).

The notion that intimacy of ties is related to political discussion could also be found in interpersonal communication theories. According to Berger and Calabrese (1975, p. 100), one of the fundamental principles that drives human communication behaviors is uncertainty reduction — “increasing predictability about the behavior of both themselves and others in the interaction.” Uncertainty reduction theory proposes that higher uncertainty about one’s partner or relationship could compel individuals to prefer the exchange of “safer” information (e.g., demographic or less intimate characteristics) while refraining to talk about less visible (and presumably more “intimate”) attributes such as political preferences or religion (Berger & Calabrese, 1975). It further postulates that continued communication interaction reduces the uncertainty involved in such interactions and is positively related to the intimacy level of communication content for a given dyad. In other words, any given dyad is more likely to engage in political discussions if each of the individuals in the dyad have already developed a fair sense of

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4 Yet some research suggests that exposure to disagreement is indeed more likely among weak-tie discussants (e.g., Mutz & Mondak, 2006) when such baseline frequency is controlled for.
how the alter thinks or behaves toward a discussion topic—presumably by frequent discussion of general topics other than politics. Such general interaction may create a sense of shared, common ground that bonds two individuals together and provides “safer” ground in discussing more intimate, sensitive topics such as politics. Recent research generally supports this perspective, such that topic avoidance (purposeful avoidance of a certain topic, including politics: Morey et al., 2012) or conflict avoidance is more likely for socially distant discussants than closer, intimate discussants (Dailey & Palomares, 2004; Knobloch & Carpenter-Theune, 2004).

This leads us to expect a positive relationship between the selection of political discussion partners and (a) the potential availabilities (or opportunities) for interaction, as well as with (b) the intimacy level between a given dyad. Specifically:

**H5a:** The opportunities for interaction between a given dyad will significantly predict the presence of political discussion ties, such that political discussion ties are more likely between a given dyad that routinely interacts with each other.

**H5b:** The intimacy level between a given dyad will significantly predict the presence of political discussion ties, such that political discussion ties are more likely between a given dyad that has strong emotional and social attachment with each other.
Higher-order Selection Models

According to Robins, Elliott, and Pattison (2001), many of the existing approaches in modeling social selection effects implicitly or explicitly assume that social selection processes operate within the *individual* or *dyadic* level, although such an assumption is often unwarranted. Network structure emerges from complex local interactions that produce more complex and higher-order dependences. Modeling such a higher-order selection process requires moving beyond simple dyadic-level analysis, as the current development of statistical modeling of network dynamics suggests (Holland & Leinhardt, 1981; Lusher et al., 2013; Robins et al., 2006; Wasserman & Faust, 1994).

*Triadic Closure*

One well-known social selection process that operates above the dyadic level is the concept of triadic closure. Based on Heider’s (1946) famous notion of cognitive balance, and later Newcomb’s (1953) generalization of cognitive balance to interpersonal relationships, the notion of triadic closure suggests that a person’s (*A*) relationship with other person (*B*), and the other’s (*B*) relationship with a 3rd object (*X*) is interdependent on one another. It is suggested that structurally imbalanced relations (e.g., *A* likes *B*, *B* likes *X*, but *A* dislikes *X*) propel individuals to change their relations towards more balanced states, where balanced states predicts “interpersonal attraction, tendencies to communicate, [and] pressures to uniformity” (Cartwright & Harary, 1956, p. 280). Within the framework of triadic closure, the social selection process could be framed as creating (or dropping) a tie between individuals who both share a third actor.
instance, if \( A \) is a friend with \( B \) and \( B \) is a friend of \( C \), than \( A \) and \( C \) are also likely to become friends with each other (e.g., Davis, 1970; Granovetter, 1973; Newcomb, 1961). In addition, to the extent that the number of commonly connected actors increases (e.g., \( A \) and \( C \) have multiple friends in common), there is a greater chance of attribute similarity between the unconnected actors, which further predicts a higher chance of future tie formation (Robins, Pattison, & Wang, 2009). This transitivity mechanism has indeed been found to be one of the strongest predictors of tie-formation in various contexts (e.g., Box-Steffensmeier & Christenson, 2014; Louch, 2000), as well as the factor directly responsible for the creation of densely interconnected, cohesive subgroups within a network (e.g., Gondal & McLean, 2013). Therefore, the following hypothesis is posited:

\[ \textbf{H6: Transitivity will significantly predict the presence of political discussion ties, such that political discussion ties are more likely between individuals who share one or more common political discussion partners.} \]

\textit{Preferential Attachment}

Another commonly addressed higher-order selection effect is the notion of preferential attachment – “nodes link with higher probability to those nodes that already have a larger number of links” (Barabási & Albert, 1999; Barabási et al., 2002). Implicitly or explicitly, preferential attachment aims to explain the “emergence” of the heterogeneous network structure over time such as the skewed distribution of degrees (i.e., power-law distribution) within a given network as a function of autoregressive
influence of network structures. According to Barabási and Albert (1999; see also Lewis et al., 2012; Newman, 2001), preferential attachment could be explained by the conditional dependency in the social selection process conditional on the degree distribution. Since already well-connected actors could afford a better chance of potential access to resources (such as new information) than actors that have fewer connections, individuals generally prefer making social ties with those who already have a higher number of ties than themselves because of the added value from such ties. This further implies an actor’s initial number of ties has reinforcing effects over time, recruiting additional ties by virtue of already having a larger number of connections in the network. Eveland, Hutchens, and Morey (2013) further suggest that, by virtue of having a large degree distribution, those network hubs are more likely to maintain a diverse set of contacts, and are more easily exposed to political discussion. Based on this logic, the following hypothesis is raised:

**H7:** Degree distributions will significantly predict the presence of political discussion ties, such that political discussion ties are more likely with alters who already have a large number of discussants in the political discussion network.

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5 In a more substantive term, the probability of addition of an edge to a node with \( k \) neighbors is proportional to \( k \) itself.
Chapter 5: Network Social Influence – Attributes Based on Social Structure

There have been two general theoretical frameworks proposed in explaining how individuals might change their attributes as a function of social network influence—one is normative social influence, and the other is informational social influence (Deutsch & Gerard, 1955; Kaplan & Miller, 1987; Marsden & Friedkin, 1993; Price et al., 2006; Sokhey & McClurg, 2012). According to Deutsch and Gerard (1955, p. 629), normative social influence could be defined as “an influence to conform to the positive expectations of others.” Traditionally, normative social influence has been conceptualized in terms of conformity or compliance based on basic motivational needs of social belonging (e.g., fear of isolation) (Deutsch & Gerard, 1955; Noelle-Neumann, 1984; Price et al., 2006). Informational social influence, in contrast, is defined as an influence when individuals “accept the words, opinions, [and] deed of others as valid evidence about reality” (Price et al., 2006, p.49) such that they shift their opinions following relevant arguments and factual information regarding a given issue. Informational social influence, therefore, has been largely understood as a consequence of adopting a viewpoint, information, or opinions of others (Price et al., 2006) as a valid and faithful representation of social reality (Festinger, 1950; Ryan, 2011a). It is especially likely when such viewpoints or opinions emanate from those who are perceived as more politically knowledgeable and (Huckfeldt, 2001) therefore are perceived to be trustworthy (Berelson et al., 1954;
Lazarsfeld et al., 1948). Within the network-oriented research tradition, the notion of normative and informational influence is also identified by other similar names and conceptualizations (e.g., Bello & Rolfe, 2014; Friedkin, 2004; Huckfeldt, 2001; Huckfeldt et al., 2014; Mutz, 2002; Rolfe, 2012; Sinclair, 2012). In what follows, I will briefly review each theoretical perspective and the available empirical evidence.

Normative Influence

Traditionally, normative influence was believed to be a powerful determinant of attitudes and behaviors (e.g., Asch, 1956; Milgram, 1974; Newcomb, 1943; Sherif, 1937). Norm-based explanations of social influence are based on the following premises: (a) people are motivated to respond in a socially appropriate way towards a given situation (Cialdini & Goldstein, 2004); and (b) human behavior is, at least in part, driven by a desire to seek potential social rewards (for compliance) or to avoid social sanctions (for noncompliance) associated with the socially prescribed mode of behavior in a given social settings (Friedkin, 2004; Lapinski & Rimal, 2005).

To the extent that human behavior is motivated by such desires (i.e., seek social rewards or avoid social sanctions), we could further specify conditions in which such normative influence would be more pronounced. First, one needs to be aware of the appropriate behavior in a given situation—what the literature has conceptualized as descriptive or informational norms. Descriptive norms provide “information about what is done” (Lapinski & Rimal, 2005, p.130) regarding the action of others, conveying what is appropriate or acceptable in a given situation. In addition to such information, one
should be aware of the possible consequences or social sanctions imposed when individuals do not conform to such expectations—an “injunctive” norm (Kallgren, Reno, & Cialdini, 2000). That is, if the violation of social norms results in social costs or a disruption of relationships (and therefore serves as a punitive function), then such a norm is classified as injunctive.\(^6\)

One of the important implications from previous research is that norm-based influences do not operate in isolation of social context (Friedkin, 2004), but rather require relevant social reference groups (Glynn, 1997). That is, in order for injunctive normative influence to be successful, one should consider the relevant social reference group regarding one’s attitudes and actions. A clear boundary of a relevant social group is a precondition of one’s subjective perception regarding the possible punitive consequences when one’s actions deviate from the norm of such group (e.g., Shulman & Levine, 2012). Therefore, it is crucial to identify the boundary of the reference group upon which perceptions and behaviors are influenced, although there exist many possible groups against which behaviors may be compared (Marsden & Friedkin, 1993; Schmitt, 1972). At the same time, as Glynn (1997) has suggested, research regarding social norms generally finds that a perceived norm by individuals, once relevant reference groups are determined, play a crucial role in regulating one’s attitudes and behaviors.\(^7\)

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\(^6\) It is quite often the case that descriptive norms and injunctive norms operate simultaneously and therefore are difficult to distinguish empirically.

\(^7\) By definition, a perceived norm may not necessarily be accurate since norms are seldom formally prescribed or explicitly stated (Lapinski & Rimal, 2005).
According to Marsden and Friedkin (1993), the most basic and loosely defined requirement to specify the relevant reference group is the “perception” of relevant others’ attributes. This further implies that the reference group processes are likely to operate from the point of perceivers (Merton, 1968; Merton & Kitt, 1950), depending on how large or small a boundary of relevant social groupings (in relation to the attributes in question) is being considered by perceivers.\(^8\)

As suggested by Simmel (1950), interpersonal observability is then likely to be the key determinant of one’s reference groups (also see Friedkin, 1983; Merton, 1968): “If it is to be effective as a whole, the aristocratic group must be ‘surveyable’ by every single member of it. Each element must be personally acquainted with every other” (Simmel, 1950, p. 90). Since the perception of norms generally emanates from observing others’ relevant attributes, the horizon within which such observations are possible (“horizon of observability,” Friedkin, 1983) would likely determine the nature of descriptive norms. Indeed, Merton (1968, p. 373) further suggested that interpersonal observability (based on an elaboration of Simmel’s notion of “surveyable”) is the extent to which “the role-performances within the group are readily open to observation by others,” as a key condition of informal social control. His notion of observability can be seen as the combination of (a) the availability of a reference group to each individual, and as a flipside of the same coin, (b) the ability of group, as a whole, to observe an

\(^8\) On a related point, there is now a considerable amount of evidence that people make different social categorizations depending on the salience of different traits or attributes (e.g., Lea, Spears, & Watt, 2007; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987).
individual’s attributes (such as attitudes or behavior). Therefore the notion of observability suggests that, by providing appropriate feedback afforded by such visibility, the reference group provides the opportunity to learn what is prevalent in a given system (Friedkin, 1983; Merton, 1968). In other words, observability directly provides descriptive information about the attributes in question (Lapinski & Rimal, 2005). At the same time, by providing possible consequences of deviant attitudes or action from others’ behavior, the reference group effectively exercises social control on an individual especially when his or her attitudes or behaviors depart from the expected patterns of the group.

Other related theoretical considerations, from the injunctive norm perspective, concern the notion of “publicness” (Hayes, Scheufele, & Huges, 2006; Scheufele & Eveland, 2001) or visibility of one’s attitude or behavior itself (Bagozzie et al., 2000; Cialdini et al., 1990). Research suggests that the “publicness” of one’s attributes (visible vs. non-visible attributes: Hayes et al., 2006; Scheufele & Eveland, 2001) may influence whether injunctive norms are more or less effective in regulating one’s attitudes or behaviors (Lapinski & Rimal, 2005). That is, if individuals’ relevant attributes are more easily and directly observable by others than other attributes (e.g., publicly stated racial attitudes vs. implicit racial attitudes), then such traits are more likely to be venerable to public scrutiny and (potential) negative sanctions by others. Therefore, the mere awareness of the possibility of public observation may create the effective preconditions

9 Therefore, the notion of observability has dual meanings: structural properties of social systems (such as a network of given members), and the perceptions of individuals (Merton, 1968).
of normative influence (Friedkin, 1983; 2004). In contrast, research suggests that if attitudes and behaviors are kept private (rather than “publicly” visible), then the expectation of possible social sanctions is generally diffused (Lapinski & Rimal, 2005; Shulman & Levine, 2012), and therefore it is difficult to expect injunctive norms to be effective in regulating one’s attitudes or behaviors.\footnote{This “publicness” or “visibility” of an attribute itself will be more discussed later in the selection titled “The Joint Dynamics of Selection and Influence.”} For instance, research in social psychology suggests that one’s implicit attitudes (obtained via unobtrusive measures such as the Personal Implicit Association Test, or PIAT) and explicit attitudes (obtained via verbal responses) are at best weakly correlated (see Fazio & Olsen, 2003, for a brief review). This is partly because if one’s attitudes or behaviors are able to be observed by others, individuals tend to hide or adjust their responses due to social desirability concerns in explicit measures (Song & Ewoldsen, 2015), especially for domains that have potential aversive consequences if negative attitudes (such as racial attitudes towards Blacks) are publicly expressed (e.g., Fazio & Olsen, 2003; Nosek, 2007).

The above discussions suggest some interesting possibilities regarding the notion of normative social influence. That is, one could expect a greater degree of social influence to the extent that an ego is better able to observe his or her reference group’s relevant attributes (i.e., attitudes and behaviors). Such patterns, if found, would be attributable to the notion of normative social influence, where such “influence” can be defined as the similarity of one’s attributes with that of his or her alters in the reference group. Specifically:

\begin{enumerate}
\item...
\end{enumerate}
H8a: An alter’s political preference will significantly predict the ego’s political preference, with such influence being greater for an ego who is better able to observe the reference group’s political preference.

Regarding the notion of “visibility,” a similar theoretical prediction could be found in Coleman’s (1988; 1990) discussion of a social norm and its relationship to densely interconnected ego-networks. It is suggested that such densely connected ego-networks and “redundant” ties among one’s alters enable individuals to coordinate behaviors with others and, therefore, reinforce social norms (Moran, 2005; Gargiulo & Benassi, 2000; Gulati & Gargiulo, 1999). According to Coleman (1988, p. S107; also see Coleman, 1990), a closure in one’s network that is characterized by densely interconnected, redundant connections that enable embedded actors to “monitor and guide behavior,” and therefore “allows the proliferation of obligations and expectations.” In such closed, highly interconnected networks, actors are more easily able to monitor one another’s attributes (Friedkin, 1983) and collectively coordinate their actions to impose social sanctions than in open or disconnected networks (Burt, 2000; Coleman, 1988; 1990; Granovetter, 1985; Moran, 2005). Therefore, actors embedded in cohesive, tight-knit social relations are more likely to conform to the norms or expectations of others and refrain from behaving opportunistically (Burt & Knez, 1995; Gargiulo & Benassi, 2000). “[N]etworks in which everyone is connected such that no one can escape the notice of others” (Burt, 2000, p. 351) therefore create effective conditions for imposing injunctive norms for embedded actors. Research has shown, for instance, that
social closure and the structural embeddedness of an actor positively predicts economic exchanges of geographically dispersed traders (Colman, 1990), prevention of child delinquency (Parcel & Menaghan, 1993), and successful schooling and education (Coleman, 1990) based on social norms that prevail in a given social system.

The above discussion leads us to expect that normative influences in social networks are, at least partly, a function of social cohesion and tight-knit social relations in which an actor is embedded. Within the context of predicting political preference, alters’ normative social influence on an ego’s political attitudes should increase to the extent an ego is embedded in a network structure that is characterized as more redundant, highly interconnected, closure-like settings. Therefore, the following hypothesis is posited:

**H8b:** The influence of an alter’s political preference on an ego’s political preference will be greater when the ego is more (rather than less) embedded in cohesive, tight-knit networks.

**Informational Influence**

As Kinder (1998) notes, one of the prerequisites of meaningful engagement in public life is the *quantity* and *quality* of information that citizens’ judgments and opinions are based upon. However, citizens do not possess all of the relevant political information nor are they motivated to gather complete information (Downs, 1957; Verba et al., 1995) since acquisition of such information requires certain resources (Brady, Verba, & Schlozman, 1995; Delli Carpini & Keeter, 1996). Therefore, as discussed in the previous chapter, cost-conscious individuals are likely to supplement their lack of information or
relevant knowledge by relying on “shortcuts,” or a local political expert, who provides relevant political information to guide one’s decision (Downs, 1957; La Due Lake & Huckfeldt, 1998; Huckfeldt, 2001; McClurg, 2006; Sokhey & McClurg, 2012). In line with this reasoning, the literature has suggested that social networks increase political knowledge and contribute to voters’ political decision making (Beck et al., 2002; Eveland & Hively, 2009; Richey, 2008; Sokhey & McClurg, 2012).

It is suggested that when individuals form an attitude, they actively incorporate multiple yet competing evaluative judgments into a single summary judgment (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975; Roskos-Ewoldsen & Fazio, 1997; van der Pligt et al., 2000). Zaller’s (1992) accessibility account, although based on a considerably different perspective, also argues that individuals formulate their attitudes based on a range of considerations or information that happens to be salient at the moment of response (also see Zaller & Feldman, 1992, for a similar argument). A large volume of research suggests individuals acquire such political information and factual political knowledge largely from surrounding social networks (e.g., Huckfeldt et al., 2004; Katz & Lazarsfeld, 1955; Ryan, 2011a; Sinclair, 2012), in conjunction with mass media (e.g., Barabas & Jerit, 2009), actively taking cues from various sources to garner information relevant to their judgment (Conover & Feldman, 1989; Kinder, 1998). When individuals gather and aggregate politically relevant information from social networks, the end result of such information aggregation is likely to be conditional upon the initial distributions of information available within the network (e.g., Friedkin & Johnsen, 1999). Moreover, regardless of an ego’s political preference, the number of partisan informants in one’s
social networks positively predicts the number of reasons both for and against a given issue or a candidate that are accessible at the time of judgment (Huckfeldt et al., 2004). Therefore, the social network bears important implications within the context of predicting an ego’s political attitudes from the distribution of his or her alters’ political preferences. Social networks, therefore, exert informational influence by “[transmitting] information to another that changes the latter’s actions from what would have occurred in the absence of that information” (Knoke, 1990, p. 1042).

Research often points to the fact that political preferences and, more importantly, politically relevant information or knowledge, are not evenly distributed among citizens (Downs, 1957; Huckfeldt & Sprague, 1995). First, literature suggests that the cost of information acquisition varies across individuals (Fiorina, 1990; Wolfinger & Rosenstone, 1980). At one extreme, politically motivated individuals – those who are politically interested and already knowledgeable about politics (Delli Carpini & Keeter, 1996; Galston, 2001; Luskin, 1990) – are able to seek out such information at little or no cost than others (Cho et al., 2009; Lau & Redlawsk, 2001; Luskin, 1990; Katz & Lazarsfeld, 1955). In contrast, those who are uninterested or inattentive to politics (e.g., prefer entertainment over political information: Prior, 2005) are found to be less active in seeking out political information from mass media (and presumably less knowledgeable about politics). Therefore, individual differences in political interest and knowledge are expected to create an unequal distribution of politically relevant information among citizens (Mutz & Mondak, 2006).
Those uninterested and less knowledgeable individuals are, ironically however, no less likely to accidentally encounter sources of political information from their surroundings (Downs, 1957) – especially from their social networks (Lazarsfeld et al., 1948; Berelson et al., 1954; McClurg, 2003; Ryan, 2010; Sokhey & McClurg, 2012). One of the most common effects observed from the literature is that people learn from their informants in their surrounding networks (e.g., Beck et al., 2002; Huckfeldt, 2001; Richey, 2008). Since the interpersonal exchange of such political information is not a costly exercise in general (Downs, 1957; also see Lenart, 1994; Kim et al., 1999), citizens are more likely to talk with those whom they perceive to be more knowledgeable and interested in politics when the opportunity arises (e.g., within election settings or with some unexpected political events). Politically motivated and knowledgeable informants in one’s social network are generally expected to provide more contextualized and clear signals regarding how to vote or how to make sense of politics (McClurg, 2003; 2006), therefore enabling less motivated and uninformed citizens to act as if they were informed (Downs, 1957). Also, citizens appear to be reasonably accurate in identifying political expertise among their discussants when they discuss politics even with the presence of political disagreement (e.g., Huckfeldt, 2001). A large volume of literature on the two-

\[ \text{11} \] However, it does not necessarily mean that the accuracy of “perceived expertise” is not at all biased relative to the objectively defined level of political expertise. Some scholars have found that people often mistakenly perceive their discussants to be much more knowledgeable than they actually are (e.g., Ahn & Ryan, 2014; Ryan, 2011a).

\[ \text{12} \] Generally, individuals’ information-acquisition within their social networks is a function of (a) knowing what others know; (b) valuing what that person knows; (c) being able to get access to that information; and (d) perceiving that seeking that information is not too costly (Borgatti & Cross, 2003).
step flow hypothesis, opinion leadership, and diffusion of innovation (Burt, 1999; Coleman, Katz, & Menzel, 1957; Roch, 2005; Weimann, 1983, 1991; Valente & Fosados, 2006) also supports this perspective, in that individuals often rely on others in obtaining relevant information and recommendations for their actions.

The above discussions lead us to expect some directional social influence based on dyadic differences in interest and knowledge. Specifically, one would expect that the political preference of those who are less interested and knowledgeable about politics is systematically affected by more interested and knowledgeable actors (but not vice versa). Indeed, a considerable body of scholarship based on egocentric network research makes such predictions (e.g., Huckfeldt, 2001; McClurg, 2006; Ryan, 2010; 2011), along with a bulk of survey research suggesting that political discussions indeed increase one’s political knowledge (for a brief review, see Schmitt-Beck & Lup, 2013).

Despite relatively consistent theoretical expectations among scholars, however, at least some degree of caution is warranted in the context of “political” influence. Theoretically, the informational mechanism of social influence implicitly or explicitly assumes (a) heterogeneous distribution and non-redundancy of information that individuals possess (Burt, 1992; 2000; Reagan & Zuckerman, 2008), and (b) that interpersonal exchange of information in a social network is the only process by which information that individuals did not know before can be obtained (Ahn, Huckfeldt, & Ryan, 2010; Hinsz, Tindale, & Vollrath, 1997; similar to the notion of a “hidden profile”)

Prior evidence suggests that interpersonal exchange of political information is not costly to do so, therefore social networks are generally conducive to accidental exposure of political information.
in group decision making; see Schulz-Hardt et al., 2006). Within the context of predicting changes in attributes as a function of informational influence, it further implies that the content of political knowledge or information that is being exchanged (or a measure thereof) should closely correspond to the topic or domain of informational social influence being examined (e.g., Katz & Lazarsfeld, 1954; also see Huckfeldt et al., 2014, for a small-group experimental settings that established such correspondence using noble experimental procedures). Katz and Lazarsfeld’s (1954) seminal study on social influence warns of the “polymorphous” nature of social influence; that is, individuals are not simultaneously opinion leaders across several areas but rather “topic-specific” opinion leaders (Goldsmith & De Witt, 2003; Marshall & Gitosudarmo, 1995). Similarly, in the political learning and knowledge literature, scholars generally agree that even political knowledge itself is not likely to be unidimensional in nature (e.g., Iyengar, 1986; Krosnick, 1990). It has been repeatedly demonstrated by a number of empirical studies that domain-specific knowledge can be distinguished from general political knowledge (e.g., Iyengar, 1986; McGraw & Pinney, 1990; Price & Zaller, 1993). Some research further suggests that learning of factual knowledge regarding different domains or different topics could be best predicted by selective exposure to information about those respective issues (Eveland & Schmitt, 2014; Iyengar, 1990; McLeod & McDonald, 1985; Price, 1999), further bolstering the notion that the content of political information that is

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13 In Huckfeldt et al.’s (2014) experiment, participants were allowed to freely solicit bits of information on fictitious candidates’ true (yet unknown) policy positions from other participants, which later researchers estimated the relative contribution of such socially obtained messages on the accuracy of participants’ judgment regarding the candidate’s true policy positions.
being exchanged should be closely aligned with the *topic or domain* of informational social influence being examined.

Unfortunately, however, most of the current research in political learning and expertise effects in observational social network studies generally relies on (a) perceptual measures tapping the overall level of political expertise of alters (e.g., Huckfeldt, 2001; McClurg, 2006; Richey, 2008), or at best (b) a summary measure of general political knowledge (e.g., Huckfeldt & Sprague, 1995; Ryan, 2011a; but see Ryan, 2011b, or Huckefldt et al., 2014 for alternative approaches using experiment treatments using candidate specific knowledge or information rather than general knowledge). Often, a measure of such general political knowledge captures variations in domain-specific political knowledge reasonably well (Delli Carpini & Keeter, 1996). This is because the acquisition and understanding of such issue- or domain-specific knowledge are dependent on information processing efficiency and accuracy, of which are also greatly influenced by general political knowledge levels (Fiske et al., 1990). However, the above discussion leads us to expect that, unless the measurement of political knowledge is constructed in a way that well reflects (a) a heterogeneous distribution and non-redundancy of information in a given social network at a time of measurement, and (b) its *topic or domain* relevance to political judgments in which informational social influences are examined, then the theoretical expectations that underlie the Downsian argument of social learning and informational effects from one’s alters is not likely to be well captured.
Some alternative measurement strategies in news exposure and political learning literature suggests the use of “media attention” (e.g., Brains & Watternberg, 1996; Chaffee & Schleuder, 1986) or its motivational precursor (“political interest”: Chaiken, 1980; Luskin, 1990; Krosnick & Brannon, 1993) may be used as a broad proxy measure of – if not a direct cause of – political learning (for a brief review of media attention measures and its relation with political knowledge, see Eveland, Hutchens, & Shen, 2009). Not only are political interest and media attention positively correlated with each other (Luskin, 1990; Krosnick & Brannon, 1993), they generally positively predict a host of active information seeking behaviors (e.g., Straits, 1991; Strömbäck & Shehata, 2010; Valentino, Hutchings, & Williams, 2004) and political knowledge (Eveland et al., 2009). Therefore, it could be inferred that variation in political interest would be positively (yet modestly) correlated with any domain-specific or issue-specific current political knowledge.

Considering this possibility, one may expect that those who have low motivation to acquire relevant political information (i.e., low political interest) should rely on those who have higher levels of motivation to do so (i.e., high political interest), and as a result, the political preferences of those with low political interest should be systematically affected by the political preferences of those with high political interest. Yet such alternative strategies are not without limitations. Most obviously, political interest is, at best, also a crude proxy measure (compared to the general knowledge measure) that does not directly tap the construct of interest in this context (i.e., a heterogeneous distribution of topic-relevant information that has close correspondence with the political judgment).
Second, the major concern of such an alternative approach is the overreporting bias that undermines the validity of such measures (Althaus & Tewksbury, 2007; Eveland et al., 2009; Prior, 2009). Unlike the measure of general or domain specific political knowledge that has objective evaluative criteria (i.e., “right” vs. “wrong” answer), self-reports of political interest or media attention could be severely affected by social desirability bias or participants’ limited ability to reliably report their true level of interest or attention. Since political interest or attention to media itself is often regarded as an individual difference that stems from socialization (Prior, 2010) and personality characteristics (Mondak, 2010), it is likely that any individual differences on social desirability bias would also be correlated with interest or attention measures as well (Althaus & Tewksbury, 2007). Thus, the potential non-random source of bias can affect estimates of the true impact of social influence based on informational influence mechanisms.

The above discussion suggests that it is not surprising to expect the null effects of dyadic differences in political knowledge or interest between an ego and her alters. Nonetheless, based on prior research on political expertise effect in social networks, the following hypothesis has been raised:

**H9a:** The influence of an alter’s political preference on an ego’s political preference will be greater when the ego has lower (rather than higher) interest and knowledge compared to the alter.

Similar to the discussion of the cohesive network structure and its relationship with normative social influence, it is suggested that certain network structures would
have particular relevance to informational benefits (Borgatti & Foster, 2003; Burt, 2000; Freeman, 1979). This argument has been advanced primarily by Burt (1992; 2000) in his discussion of structural holes as alternative types of social capital. Contrary to Coleman’s (1988; 1990) view of social capital as overlapping ties among one’s alters, Burt equates the lack of such ties – what he has named as “structural holes” (Burt, 1992) – as the condition of social capital. He asserts that such lack of redundancy provides opportunities to acquire new and novel ideas otherwise unavailable in the network (Burt, 2004), to broker and control the flow of information (Burt, 2000), and therefore, “separate[s] nonredundant sources of information, sources that are more additive than overlapping” (Burt, 2000, p. 353). According to Granovetter’s (1973) argument, alters who are strongly interconnected with others (such as “close-knit” networks within a cohesive subgroup) are more likely to provide redundant information to an ego by virtue of their pattern of connections. In contrast, one’s alters who are not directly tied to one another (“loose-knit” network) “are the channels through which ideas, influences, or information socially distant from [an] ego may reach” (Granovetter, 1973, p. 1370). Similarly, the concept of betweenness centrality (Freeman, 1979) – essentially a measure of an extent to which an ego could control the flow of information in the network vis-à-vis other actors (Borgatti, 2005) – suggests that an ego who bridges otherwise unconnected alters has particular advantages in detecting resources, creating opportunities, and acquiring or monitoring relevant information (Burt, 2000; 2004; Krackhardt, 1990). Therefore, it has been hypothesized as an important predictor of informational benefits of networks (Burt, 1997; Sheingold, 1973). Song and Eveland (2015) have found that an ego’s betweenness
positively correlated with the level of political knowledge, especially within politically attentive social groups.

This suggests that informational social influence would be positively associated with the extent to which an ego has a loose-knit local network, which is characterized as a high number of non-redundant contacts (therefore a high number of structural holes) in one’s ego-network. Within the context of political discussion, informational influence would mean that individuals with more non-redundant contacts and structural holes are more likely to obtain relevant political information from their alters (especially alters who are more knowledgeable and attentive about politics), therefore modifying their political attitudes or behavior following alters’ political attitudes or behavior.

However, it is worth noting that Burt’s (2000) discussion of structural holes and information benefits of the local network structure also relies on a very specific assumption that is not always likely to be satisfied within the context of predicting “political” attitudes. The structural holes argument relies on the notion of heterogeneity and non-redundancy of information that individuals possess (Burt, 1992; 2000; 2004; Reagan & Zuckerman, 2008). For instance, in Burt’s (2004) discussion of the concept of structural hole, he posits, “People whose networks span structural holes have early access to diverse, often contradictory, information and interpretations, which gives them a competitive advantage in seeing good ideas” (p. 356). This assertion implicitly assumes that the information and knowledge of which different clusters of networks possess are at least modestly different from each other, that generally are not shared otherwise by brokers, therefore creates added values when integrated with noble perspectives (such as
ones in inter- or cross-disciplinary knowledge production: Jansen, von Görtz, & Heidler, 2010; Reagans & McEvily, 2003). As Rodan (2010, p. 170) acknowledges, “Information brokering therefore depends on the heterogeneity of information or knowledge across contacts and the holes themselves that enable this heterogeneity to be exploited to the broker’s advantage.”

At the very minimum, the assumption that individuals between discrete clusters of a network possess heterogeneous and non-redundant information requires such a network have a clear divide in potential sources of information—either from one’s social network itself or from alternative sources of information such as via the media. The information brokerage role between discrete clusters of a network, therefore, is not likely to create additive values if actors across the discrete clusters have already relatively non-contradictory, homogeneous information about a given subject in the first place. Unlike a managerial “good idea” in organizations (Burt, 2004) or job opportunities in labor markets (Granovetter, 1973; Rees, 1966) that are not likely to be widely shared within a network, typical information or knowledge being exchanged during “political” conversation is highly likely to have originally come from widely accessible news media sources (e.g., Barabas & Jerit, 2009; Mondak, 1995). Therefore, it is hard to conceive that political information prevalent in each of two discrete clusters of a network would be fundamentally unique and heterogeneous from each other. At best, within the context of “political” information exchange, any discernable effect of such “heterogeneous” informational benefits is likely to be observed between politically disagreeable contacts (e.g., between conservatives and liberals), especially within highly polarized and divided
networks, where they also selectively turn to different mediated information sources (e.g., effects of partisan selective exposure on politically contested belief gaps: Hindman, 2009; Veenstra, Hossain, & Lyons, 2014). Yet it is still not clear whether such effects are directly attributable to the informational influence explanation when topological properties of a given network (such as simple centrality measures) are used as a proxy measure of “heterogeneous distribution of relevant topic specific information or beliefs,” absent of direct measure of such relevant topic-specific information or beliefs measures.

Notwithstanding such theoretical and methodological considerations that lead us to expect some null effect, available evidence and theoretical accounts concerning a local network structure of individuals might predict that informational influence, if found, would be more pronounced for those who are embedded in a loose-knit structure that is particularly conducive to acquire more novel and non-redundant information.

Specifically:

**H9b:** The influence of an alter’s political preference on an ego’s political preference will be greater when an ego is more (rather than less) embedded in non-redundant, loose-knit networks

The Joint Dynamics of Selection and Influence

So far we have considered various selection and influence mechanisms separately. Yet as suggested in Chapter Three, it is likely that social influence and selection simultaneously occur within a given network (Manski, 1993; Steglich et al., 2010). Therefore, it is necessary to consider the evolution of attributes and social
networks *at the same time* in order to properly tease out direction of causalities and its implications.

A few studies have utilized whole network panel data, and findings regarding its causalities, not surprisingly, appear to be mixed.\(^{14}\) Yet they generally acknowledge the dynamic, interdependent nature of social selection and social influence. Mercken et al.’s (2010) analysis of coevolution of friendship networks and smoking behavior in Finland found that social selection and influence both played a significant role in coevolving dynamics of smoking behavior and friendship networks. They observed that adolescents adjusted their rate of smoking as a function of their friends’ smoking behavior. At the same time, they found that non-smokers prefer associating with infrequent smokers, whereas heavy smokers prefer making friends with the highest frequency of smoking, when all other effects in the models are controlled. Knecht et al.’s (2010) analysis of Dutch youth classroom networks and alcohol use found stronger social selection effects (i.e., choosing friends based on similarity of alcohol use) than peer influence. In contrast, Steglich et al.’s (2010) investigation of friendship networks and substance use (alcohol and tobacco) in a secondary school in Glasgow, Scotland, found strong peer influence (e.g., respondents’ substance use is assimilated to friends’ use). They also report that social selection effects based on a similarity of substance use (e.g., homophily based on substance use) were substantial, yet lesser than peer influence. In a similar study, Wang,

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\(^{14}\) Empirical studies reviewed here, except Lazer’s (2001) and Lazer et al.’s (2010), all employ SAOM (Stochastic Actor Oriented Model: Snijders et al., 2010) using *RSIENA*, which incorporates the functionality of simultaneously modeling network structure and behavior at time \(t\) (actor attributes) respectively conditional on actor behavior and network structure at time \(t-1\).
Hachen, and Lizardo (2013) observed stronger social selection effects based on drinking similarity than social influence based on students’ communication networks. In contrast, Lazer et al.’s (2010) analysis of an academic cohort of a public policy program found strong conformity tendencies in political attitudes in response to social ties. That is, political attitudes of individuals became more similar over time as a function of social influence from informal interaction ties, whereas political homophily was not a significant and meaningful predictor of the network structural change.

These divergent findings suggest some possible moderating variables in the network-attribute coevolution processes, as indicated in several previous studies: (a) network elasticity and (b) visibility and plasticity of attributes. Here, network elasticity denotes the extent to which network selections are amenable to free choice of individuals, therefore offering a variable range of choices in making ties to potential interaction partners (Lazer, 2001). In contrast, visibility of attributes concerns how noticeable (or “observable”) an attribute is to other actors in a network (e.g., de Klepper et al., 2010). Similarly, plasticity of attributes (Lazer, 2001) indicates the degree to which attributes are changeable as a function of one’s social contacts in their networks.15

Available evidence suggests that formal organizations have relatively low elasticity in their networks compared to informal ties such as friendship ties (de Klepper et al., 2010; Lazer, 2001; Shrader, Lincoln, & Hoffman, 1989; van de Bunt, van Duijn, & Snijders, 1999). That is, the highly task-interdependent and hierarchical nature of social relationships

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15 Visibility and plasticity of attributes are, at least conceptually, distinct constructs. Yet it is likely that visibility and plasticity are highly (although not perfectly) correlated with each other.
contact in formal organizations (e.g., Lazer, 2001; Shrader et al., 1989) makes it difficult to expect high choice in whom an actor interacts with based on their attributes. In such situations, institutionally determined network connectivity patterns naturally force individuals to interact with certain social contacts, which could result in more social influence than social selection (Lazer, 2001; de Klepper et al., 2010). For instance, de Klepper et al. (2010) found that student officers at the Netherlands Naval College tend to adjust their own military discipline as a function of their social network influence rather than change their social network according to their military discipline.

In contrast, informal organizational settings or peer interactions within a school context (e.g., mobile communication networks among friends) offer considerable free choices (therefore greater variability) in making, maintaining, or terminating social ties based on attitudinal and behavioral attributes (Knecht et al., 2010; Steglich et al., 2010; Wang et al., 2013). For instance, in Knecht et al.’s (2010, p. 478) study, they asked 10 to 15 year-old students to nominate up to 12 “best friends in class” to map longitudinal changes in students’ close friendship networks, of which a modest degree of changes in network ties were observed. Similarly, Wang et al.’s (2013) network data came from first-year undergraduate students’ mobile communication networks from one university, of which a changing pattern and considerable turnover rate has been reported. Friendship networks such as those examined above could be characterized as somewhat “malleable” such that network structures have no bearings on institutionalized interaction rules or resource dependencies. Therefore, within such an “elastic” network, one could expect to find more social selection tendencies than social influence, or at least be equally as likely.
to observe both tendencies, than less elastic and deterministic networks such as formal organizational hierarchies (e.g., Lazer, 2001).

In addition to the elasticity of the network, differences in the kind or nature of individual attributes that are being examined (e.g., substance use behavior vs. political attitudes) appear to contribute to such divergent findings. As briefly mentioned in the previous section, some individual attributes are low in their plasticity, in addition to their high visibility (e.g., such as smoking or drinking), whereas others are relatively amenable and susceptible to changes while generally non-visible to others (e.g., political attitudes or opinions that are not expressed publicly). For instance, many studies point to the fact that political attitudes are somewhat malleable and less crystallized in the mass public (Campbell et al., 1960; Converse, 1964; Sullivan, Piereson, & Marcus, 1979). Also, certain policy issues require respondents to simultaneously consider a set of conflicting core values that are hard to reconcile (Alvarez & Brehm, 2002; Lavine, 2001; Zaller, 1992). Therefore, it is often expected to observe a reasonable degree of inconsistency and change over time depending which set of values are accessible at the time of judgment (Zaller, 1992). As a result, political attitudes are often regarded as more malleable and easy to be changed (i.e., high in plasticity) over time and context than more habitual behaviors such as smoking or drinking. In contrast, within the domain of health-related risky behavior, previous research suggests that some unhealthy behaviors (such as smoking or substance use) are based on habitual and spontaneous reactions that are difficult to regulate intentionally (Fazio, 1990; Huijding et al., 2005; Rhodes &
Ewoldsen, 2009; Rhodes et al., 2008), and as a consequence, are less likely to be changed substantially over relatively short time spans.

The above discussion therefore further suggests that characteristics of “attribute” itself, in conjunction with the *nature* of network ties, determine whether selection or influence is to be anticipated, as presented in Table 1 below.

<table>
<thead>
<tr>
<th>High network elasticity</th>
<th>Low network elasticity</th>
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<tr>
<td><strong>Selection:</strong></td>
<td><strong>Selection and Influence:</strong></td>
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<tr>
<td><strong>Low attributes visibility</strong></td>
<td><strong>Influence:</strong></td>
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<td>- De Klepper et al. (2010)</td>
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Table 1. Topologies of network-attributes coevolution as a function of network elasticity and visibility of attributes.

De Klepper et al. (2010) discuss the potential impact of “visibility” of individuals’ characteristics in determining whether selection or influence is to be anticipated in the
process of network-behavior coevolution. According to de Klepper et al. (2010), more visible characteristics may lead to selection whereas non-visible characteristics are more likely to be associated with social influence.

In de Klepper et al.’s (2010) study, they compared the possible implications of visibility between network exogenous “traits” (sex and age) and network endogenous “attributes” (military competence and discipline). Extending the same logic to network endogenous “attributes” that have differing degrees of visibility, it could be argued that the more visible one’s attributes are (such as alcohol consumption: Mercken et al., 2010), the more easily one can observe such attributes than non-visible attributes (such as one’s political attitudes: Lazer et al., 2010). Therefore, such visible attributes are more likely to be considered in the stages of initial tie-formation (“mating” process) than non-visible attributes (e.g., Mercken et al., 2010; van Duijn et al., 2003). In contrast, for less visible attributes such as one’s unarticulated political preferences, opinions, or private acts (such as voting at a voting booth), social selection based on “objective reality” cannot be possible (see Eveland & Hutchens, 2013, for a related discussion). Rather, it requires a greater degree of acquaintance between actors to obtain and evaluate similarity based on

---

16 Note that by its definition, exogenous traits cannot be “influenced” by one’s network, therefore only selection effects are possible, whereas for endogenous attributes both social selection and influence can be possible. Therefore traits and attributes differ in their network dependent “plasticity” (Lazer, 2001).
17 Similarly, Lewis (2011) discusses potential implications of Facebook private profiles (high “privacy” setting) on social selection effects in online social networks. Since personal information is essentially blocked “by default” to all non-friends with private profile settings, such users are less likely to receive friend requests (i.e. lesser social selection by others) due to lack of relevant information (less “visibility”) regarding their demographic profiles.
such attributes (de Klepper et al., 2010; van Duijn et al., 2003), which is hard to be achieved without pre-existing network ties (similar to the logic of uncertainty reduction). As a result, social selection based on attributes with lesser visibility is not generally anticipated (similar to the results reported in de Klepper et al., 2010).

It is not entirely clear, though, whether less visible attributes are always subjective to social influence. By virtue of the fact that it is difficult to “observe” such attributes, there is at least some suggestive evidence that more private forms of individual attributes (such as voting or money donations) are less influenced by social interactions and perceived opinion distributions than more publicly observable activities (such as public attendance at meetings or displaying signs: Scheufele & Eveland, 2001). At minimum, the less visible attributes are likely to be associated with less observability by alters, and therefore undermine the preconditions of normative influence. At the same time, such lower observability by alters may make such attributes (or certain related information, depending on types of attributes) less prevalent and non-redundant within the network, therefore increasing the preconditions of informational influence.\(^\text{18}\)

Not only could the visibility of the attributes, but also the network-dependent plasticity of attributes influence whether selection or influence is to be anticipated. For instance, an ego’s race or gender is not amenable to changes as a function of network

\(^{18}\) For instance, the case of politically contested belief gaps (Hindman, 2009; Veenstra et al., 2014) may present such a situation. Private beliefs regarding contestable political issues (e.g., beliefs about vaccination), unless otherwise publicly articulated, are widely shared and observable by alters. Yet by virtue of such low visibility by alters, once communicated, it could influence other’s opinion via sharing of such “unique” information.
exposure, unlike individuals’ policy-specific opinions or political preferences. Coupled with more visibility, such invariant (e.g., gender or race) or highly stable (e.g., party identification) attributes are more likely to drive social selection processes in network tie-formation than be subjected to social influence processes (e.g., Lazer et al., 2010). In contrast, more plastic attributes of an individual are expected to be associated with social influence – either informational or normative influence – rather than social selection processes (de Klepper et al., 2010; van Duijn et al., 2003).

Given this line of reasoning, it is expected that the visibility and plasticity of an actor’s attributes being studied should determine the degree to which such attributes drive social selection or are subject to social influence. However, the specific direction of causality – more social selection, more social influence, or even no relationship – would seem to be an empirical question to explore. To date has there been no systematic examination conducted regarding the visibility and plasticity of an actor’s attributes in the context of political attitudes. Considering the lack of prior evidence, the following research question was proposed:

**RQ:** What is the impact of the visibility and plasticity of attributes in predicting social selection and social influence? Will the impact of social selection and social influence vary by visibility and plasticity of attributes?
Chapter 6: Methods

This dissertation relies on a series of longitudinal whole network data collected as a part of a residential scholarship program (hereafter denoted as “the survey”: for a detailed description of the data, see Ognyanova et al., 2014). The purpose of the survey was to assess the view of college students on various subjects, including health and political attitudes, and gather data that helps the development and improvement of the scholar program. The survey was conducted in 2008, 2010, 2011, 2012, and 2013.

Upon entering the scholar program, all of the participants are required to reside in the “scholarship house” where they live together until graduation. This unique context of the scholar program (and resulting datasets) provides an ideal settings in which to investigate the dynamic evolution of social selection and influence within naturally occurring social networks. For the purpose of the study, participants of the survey (hereafter denoted as “respondents”) were asked to answer general core questionnaires (tapping their attitudes and various political behaviors) each August, and separate sociometric surveys were administered each November. This procedure was repeated over multiple years until participants left the scholar program due to graduation. The notable feature of this survey includes longitudinally observed social networks from each “chapter” (hereafter denoted as “group”) in a number of large U.S. Midwestern
universities ($N=14$) with panel attribute data. Yet due to fiscal and timing constraints, not all relevant questions are asked in each year. The present study uses network data collected from 2010 to 2013, due to the availability of key measures used in the current study. A total of 1,335 unique individuals have participated in the survey during this four-year period, with resulting participation rate as low as 95.9% to 97.9% for a given year.\(^{19}\)

**Construction of Networks**

For political discussion networks, all respondents were provided with a complete roster of their chapter scholar members and asked to report their political discussion ties (1 = “I frequently discuss politics, social issues, or current events with this Scholar,” and 0 = otherwise).

In order to tap (a) the opportunities for potential political interactions and (b) the intimacy level between a given dyad, two separate network measures of *time spent together* (“I spend a lot of time around this Scholar”) and *close friendship* (“this Scholar is a close friend”) and were utilized. Loosely following the definition provided by Granovetter (1973), scholars have generally treated emotional intensity as whether each ego and alter name each other as “very close friends” (Friedkin, 1990; Haythornthwaite, \(^{19}\) Percent of the unit non-respondents (who did not participated survey yet included as a network partner by others’ nominations) across years were: $N=17$ (2.1%) for 2010, $N=21$ (2.9%) for 2011, $N=16$ (2.08%) for 2012, and $N=32$ (4.1%) for 2013. The total $N$ reported in Table 2 and Table 4 does not include such non-respondents but only presents complete cases who fully participated in the sociometric survey for a given year.

---

\(^{19}\) Percent of the unit non-respondents (who did not participated survey yet included as a network partner by others’ nominations) across years were: $N=17$ (2.1%) for 2010, $N=21$ (2.9%) for 2011, $N=16$ (2.08%) for 2012, and $N=32$ (4.1%) for 2013. The total $N$ reported in Table 2 and Table 4 does not include such non-respondents but only presents complete cases who fully participated in the sociometric survey for a given year.
It is generally believed that such close friendships have strong emotional and social attachments compared to mere acquaintances or distant friends (Granovetter, 1973; Matthews et al., 1998; Wellman & Worthley, 1990). Therefore, these close friendships are expected to have a high level of self-disclosure, especially in terms of the “depth” of disclosure (i.e., intimacy), which can include discussion of politics (i.e., intimacy level: Altman & Taylor, 1973; Collins & Miller, 1994).

The duration of the association for a given social tie (i.e., amount of time spent together) has been regarded as one of the reliable predictors of multiplex social relationships (Dong, Lepri, & Pentland, 2011; Krackhardt, 1992), while others have emphasized the opportunities and availability of potential social interactions (including politics) that can result from such time spent together between an ego and his or her alters (Klofstad et al., 2009; Small, 2009; 2013). As argued in the previous section, the sheer amount of “time spent together” would positively predict the probability of political interactions independent of the emotional closeness of a given dyad.

All network questionnaires (including political discussion network) were anchored on a dichotomized scale, such that a cell entry of a directed adjacency matrix $W_{ij}$ was defined as 1 if an ego reports a relation with her alter, and 0 for otherwise.\textsuperscript{21}

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\textsuperscript{20} Also see Huszti, Dávid, & Vajda (2013), Marsden & Campbell (1984), and Petróczi, Nepusz, & Bázsó (2007) for empirical validations of the concept and relationships among different indicators of network ties.

\textsuperscript{21} Although conceptually having a discussion of politics is a single, undirected concept of interaction between a given dyad, an alter and the ego may not report exactly the same discussion relations. Therefore, the data in this study are directed (asymmetric) in that the directionally of ties are reserved in the analysis (e.g., $W_{ij} \neq W_{ji}$).
Table 2 below summarizes network-level descriptive statistics for all three types of networks (*political discussion, close friendship, and time spent together* networks) across all 14 groups.
<table>
<thead>
<tr>
<th>Network</th>
<th>(1)</th>
<th>Close friendship</th>
<th>Time spent together</th>
<th>Political discussion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
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</tr>
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<td>Ch5 '13</td>
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<td>21.91</td>
<td>.243</td>
<td>1</td>
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</tbody>
</table>

Note: (1) Number of respondents (scholars) in each Chapter network. (2) Average degree. (3) Graph density. (4) Number of weak components. (5) Average path distance. (6) Number of isolates in the network.
Table 2 continued

| Network | (1) | Close friendship | | Time spent together | | Political discussion |
|---------|-----|------------------|------------------|------------------|------------------|
|         |     | (2)  (3)  (4)  (5)  (6) | (2)  (3)  (4)  (5)  (6) | (2)  (3)  (4)  (5)  (6) |
| Ch6 '10 | 60  | 19.60 .166 1 2.08 0 | 22.20 .188 1 1.95 0 | 8.96 .075 2 2.21 1 |
| Ch6 '11 | 54  | 26.29 .248 1 1.82 0 | 26.44 .249 1 1.86 0 | 10.07 .095 2 2.69 1 |
| Ch6 '12 | 59  | 21.32 .183 1 2.08 0 | 27.72 .239 1 1.83 0 | 13.72 .118 1 2.13 0 |
| Ch6 '13 | 57  | 16.77 .149 1 2.09 0 | 28.98 .258 1 1.79 0 | 11.26 .100 1 2.85 0 |
| Ch7 '10 | 67  | 18.92 .143 2 2.17 1 | 24.17 .183 3 2.10 2 | 5.67 .042 7 3.40 6 |
| Ch7 '11 | 55  | 22.61 .209 1 1.94 0 | 28.29 .261 1 1.86 0 | 6.18 .057 5 2.26 4 |
| Ch7 '12 | 58  | 25.34 .222 1 1.96 0 | 29.31 .257 1 1.88 0 | 11.24 .098 1 2.36 0 |
| Ch7 '13 | 58  | 30.72 .269 1 1.79 0 | 40.17 .352 1 1.65 0 | 16.82 .147 1 2.27 0 |
| Ch8 '10 | 50  | 13.56 .138 1 2.46 0 | 17.44 .177 1 2.11 0 | 5.64 .057 4 2.95 3 |
| Ch8 '11 | 55  | 13.34 .123 1 2.50 0 | 19.12 .177 1 2.12 0 | 4.72 .043 4 1.93 2 |
| Ch8 '12 | 61  | 18.29 .152 1 2.17 0 | 21.08 .175 1 1.99 0 | 12.85 .107 1 2.65 0 |
| Ch8 '13 | 49  | 15.10 .157 1 2.24 0 | 23.95 .249 1 1.83 0 | 12.00 .125 2 2.29 1 |
| Ch9 '10 | 38  | 16.89 .228 1 2.05 0 | 16.00 .216 1 2.16 0 | 4.84 .065 2 2.17 1 |
| Ch9 '11 | 37  | 20.48 .284 1 1.82 0 | 19.56 .272 1 1.88 0 | 4.00 .055 4 1.80 3 |
| Ch9 '12 | 40  | 15.40 .197 1 2.17 0 | 23.95 .307 1 1.78 0 | 6.90 .088 4 2.56 3 |
| Ch9 '13 | 32  | 13.68 .220 1 2.19 0 | 18.75 .302 1 1.80 0 | 5.56 .089 1 3.15 0 |
| Ch10 '10| 44  | 14.90 .173 2 2.12 1 | 16.63 .193 2 2.05 1 | 9.86 .114 1 2.52 0 |
| Ch10 '11| 31  | 16.14 .252 1 1.74 0 | 19.29 .321 1 1.72 0 | 6.06 .101 1 1.93 0 |
| Ch10 '12| 35  | 17.20 .253 1 1.89 0 | 23.25 .342 1 1.80 0 | 10.51 .154 1 2.45 0 |
| Ch10 '13| 34  | 17.35 .262 1 1.89 0 | 27.70 .419 1 1.63 0 | 13.47 .204 1 1.92 0 |

Note: (1) Number of respondents (scholars) in each Chapter network. (2) Average degree. (3) Graph density. (4) Number of weak components. (5) Average path distance. (6) Number of isolates in the network. Continued
Table 2 continued

<table>
<thead>
<tr>
<th>Network</th>
<th>(1)</th>
<th>Close friendship</th>
<th>Time spent together</th>
<th>Political discussion</th>
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<td></td>
<td>(2)   (3) (4) (5) (6)</td>
<td>(2)   (3) (4) (5) (6)</td>
<td>(2)   (3) (4) (5) (6)</td>
</tr>
<tr>
<td>Ch11 '10</td>
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<td>18.32 .254 1 1.84 0 6.00 .083 2 2.95 1</td>
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<td>16.75 .270 1 1.83 0 6.81 .109 2 2.67 1</td>
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<td>3.86 .033 8 3.93 7</td>
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<td>19.42 .262 1 1.77 0</td>
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<td>12.80 .188 1 1.96 0</td>
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<td>6.10 .052 2 3.21 1</td>
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<td>24.39 .203 1 1.90 0</td>
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<td>61</td>
<td>18.55 .154 1 2.19 0</td>
<td>28.29 .235 1 1.88 0</td>
<td>7.37 .061 3 3.34 2</td>
</tr>
</tbody>
</table>

Note: (1) Number of respondents (scholars) in each Chapter network. (2) Average degree. (3) Graph density. (4) Number of weak components. (5) Average path distance. (6) Number of isolates in the network.
Variables and Measurements

Table 3 below presents a summary of key variables and their measurement instruments (including their measurement levels) used in the study. The table also includes additional control variables in the social selection and social influence models.

<table>
<thead>
<tr>
<th>Level</th>
<th>Social Selection Model</th>
<th>Social Influence Model</th>
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</thead>
<tbody>
<tr>
<td>Individual</td>
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<td>• Gender (dummy)</td>
</tr>
<tr>
<td></td>
<td>• Political knowledge</td>
<td>• Race (dummy)</td>
</tr>
<tr>
<td></td>
<td>• Controls</td>
<td>• Political party identification</td>
</tr>
<tr>
<td></td>
<td>o Years in school</td>
<td>• Presidential approval</td>
</tr>
<tr>
<td></td>
<td>o Big-5 personality</td>
<td>• Observability</td>
</tr>
<tr>
<td></td>
<td>o Persistent sender effects</td>
<td>• Close-knit structure</td>
</tr>
<tr>
<td></td>
<td>o Persistent receiver effects</td>
<td>• Loose-knit structure</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Controls</td>
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<tr>
<td></td>
<td></td>
<td>o Religions (dummy)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>o Political ideology</td>
</tr>
<tr>
<td></td>
<td></td>
<td>o Years in school</td>
</tr>
<tr>
<td></td>
<td></td>
<td>o Big-5 personality</td>
</tr>
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<td>Dyadic</td>
<td>• Homophily</td>
<td>• Political interest difference</td>
</tr>
<tr>
<td></td>
<td>o Race</td>
<td>• Political knowledge difference</td>
</tr>
<tr>
<td></td>
<td>o Gender</td>
<td>• Controls</td>
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<tr>
<td></td>
<td>o Presidential approval</td>
<td>o Gender homophily</td>
</tr>
<tr>
<td></td>
<td>o Party identification</td>
<td>o Religious homophily</td>
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<td></td>
<td>• Exogenous network</td>
<td>• Euclidian similarity</td>
</tr>
<tr>
<td></td>
<td>o Availability of dyads</td>
<td>• Reciprocity</td>
</tr>
<tr>
<td></td>
<td>o Intimacy of dyads</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Controls</td>
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</tr>
<tr>
<td></td>
<td>o Euclidian similarity</td>
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<tr>
<td></td>
<td>o Reciprocity</td>
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<td>Triadic or</td>
<td>• Transitivity (GWESP)</td>
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<td>higher</td>
<td>• Preferential attachments (GWD-in)</td>
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</tr>
<tr>
<td></td>
<td>• Controls</td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Intransitivity (GWDSP)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Hierarchy (GWD-out)</td>
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</tbody>
</table>

Table 3. The summary of key variables and their measurement instruments.
In what will follow, I will briefly describe the individual-level measurement instruments from the original survey first, followed by additional measures that have been derived from the original measurements for the social selection and the social influence model. Next, dyadic level measures, which have been constructed from the individual-level measures, will be introduced. Lastly, measures for triadic and higher level effects for the social selection model will be presented.

*Individual-level Attribute Measures*

*Political Preference*

For each individual respondent across all groups (2010 networks: \(N=776\); 2011 networks: \(N=694\); 2012 networks: \(N=753\); 2013 networks: \(N=736\), participants’ political preferences were assessed by asking their (a) political party identification and (b) presidential approval. The political party identification was gauged on a 7-point scale (“In general, do you think of yourself as…”) from “Strong Republican” (=1) to “Strong Democrats” (=7), with “Neither/independent” (=4) being the middle point of the scale.

The presidential approval (“Do you approve or disapprove of the way Barack Obama is handling his job as president?”) was anchored on a 5-point scale from “Strongly disapprove” (=1) to “Strongly approve” (=5). Descriptive statistics across four-year periods are presented in Table 4 in page 75.

*Interest in Politics and Political Knowledge*

General interest in politics (“In general, how interested are you in politics and public affairs?”) was initially measured via a 4-point Likert scale from “Very interested”
(=1) to “Not at all interested” (=4). Since the initial response option was reversely
presented in the survey (e.g., scale value 1 denotes “very interested”), scale values were
later recoded in a way that higher values denote higher interest in politics. Descriptive
statistics across the four-year period are presented in Table 4 in page 75.

Respondents’ level of political knowledge was measured via five questions
(including one open ended question) tapping general knowledge about politics, as
suggested by Delli Carpini and Keeter (1993). Responses were scored 0 for incorrect and
1 for correct, then summed to construct a knowledge measure. An open-ended question,
asking about a job or a political office held by Dick Cheney (since 2010 to 2011) and Joe
Biden (since 2012), was recoded as correct if respondents had answered the question as
“Vice president” or “VP” in their response. Descriptive statistics across the four-year
period are presented in Table 4 in page 75.

Demographics

Respondents’ gender (“What is your gender?”) was coded as 1 for Male, and 2 for
Female. Respondents were asked to choose one option that describes their racial category
(“What racial or ethnic group best describes you?”), which was coded as 1 for White, 2
for Black, 3 for Hispanic, 4 for Asian, and 5 for Other (including Native American,
Middle Eastern, and Mixed).

Religion is one of the meaningful and consistent correlates of political attitudes in
the American public, and long has been regarded as one of the significant factors shaping
homophilous social relations (McPherson et al., 2001). In order to control for such
effects, respondents’ religious affiliation (“What is your religion?”) was recorded as Protestant (=1), Catholic (=2), Other Christians (=3), No affiliation (=4), and Other (=5).

Respondents’ years in college (from 1 = Freshman to 4 = Senior) were also measured from self-report of their school years in college. Years in college should be positively (although not perfectly) correlated with the age of the respondents, while tapping any unmeasured changes in respondents’ shared social foci as they transition to more senior years in school.

*The Big-5 Personality*

Recently, a bourgeoning line of literature has begun to suggest evidence of associations between one’s psychological predispositions and the patterns of social interactions in political discussion (Gerber et al., 2012; Hibbing, Ritchie, & Anderson, 2011; Mondak, 2010; Mondak & Halperin 2008; Shook & Fazio, 2009). Big-5 personality traits were assessed using a 10-item inventory of a Big-5 personality measure (“TIPI”: Gosling, Rentfrow, & Swann, 2003; Rammstedt & John, 2007). In administering TIPI, each of the five traits was measured by two items that were presented with a five-step scale from “Strongly agree” (=1) to “Strongly disagree” (=5). Each item consists of two descriptive adjectives separated by a comma (e.g., “Open to new experience, complex”), therefore yielding four adjectives for each of the traits terms. Subscales were computed by averaging the response across two items (Cronbach’s alpha for each of the subscales are presented in the descriptive below). Since the initial response option was reversely presented (e.g., scale value 1 denotes “strongly agree”), scale values were later
re-reversed in a way that higher values denote higher trait characteristics.\textsuperscript{22} Descriptive statistics for all control variables across the four-year period are presented in Table 4 on page 75.\textsuperscript{23}

\begin{footnotesize}
\footnotesize
\text{\footnotesize\textsuperscript{22} During the entire data-gathering period, the TIPI was administered twice, one in each August (with core questionnaire) and later in each November (with sociometrix questions). The present study used the TIPI scale value at the time of each general core questionnaire measurement, which occurred every August. For those who have missing values in the August TIPI scale, scale values that are measured in November were imputed, when such measures were available, to minimize the item nonresponse.}\n\end{footnotesize}

\begin{footnotesize}
\footnotesize\text{\footnotesize\textsuperscript{23} According to Gosling et al. (2003), the goal of the TIPI measure was to create a very short measure of Big-5 personality traits with maximum content validity. It is worth noting that (a) each of the dimensions in TIPI taps several abstract (yet not necessarily highly correlated) natural personality trait terms, and (b) there are only two subscales available within each of the dimensions in TIPI. Therefore, the standard reliability measure (such as Cronbach’s alpha) for the shortened version of Big-5 personality traits (such as TIPI) tends to be somewhat low relative to the conventional criteria (e.g., .75 or higher). Gosling et al (2003) report that psychometrical properties of TIPI are nevertheless adequate based on convergent and discriminant validity, test-retest reliability, and patterns of external correlates with longer (40 item) versions of the measurement. They recommend the use of TIPI in situations where very short measures are needed and personality \textit{per se} is not the primary topic of interest (such as the present study).}\n\end{footnotesize}
<table>
<thead>
<tr>
<th></th>
<th>'10 network (N=776)</th>
<th>'11 network (N=694)</th>
<th>'12 network (N=753)</th>
<th>'13 network (N=736)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Male</em></td>
<td>544 (66.6%)</td>
<td>493 (60.3%)</td>
<td>590 (72.2%)</td>
<td>559 (68.4%)</td>
</tr>
<tr>
<td><em>Female</em></td>
<td>164 (20.1%)</td>
<td>155 (19.0%)</td>
<td>183 (22.4%)</td>
<td>173 (21.2%)</td>
</tr>
<tr>
<td><strong>Race/ethnicity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>White</em></td>
<td>652 (79.8%)</td>
<td>625 (76.5%)</td>
<td>648 (79.3%)</td>
<td>631 (77.2%)</td>
</tr>
<tr>
<td><em>Black</em></td>
<td>35 (4.3%)</td>
<td>32 (3.9%)</td>
<td>32 (3.9%)</td>
<td>30 (3.7%)</td>
</tr>
<tr>
<td><em>Hispanic</em></td>
<td>48 (5.9%)</td>
<td>45 (5.5%)</td>
<td>57 (7.0%)</td>
<td>57 (7.0%)</td>
</tr>
<tr>
<td><em>Asian</em></td>
<td>12 (1.5%)</td>
<td>14 (1.7%)</td>
<td>19 (2.3%)</td>
<td>9 (1.1%)</td>
</tr>
<tr>
<td><em>Other</em></td>
<td>22 (2.7%)</td>
<td>17 (2.1%)</td>
<td>22 (2.7%)</td>
<td>13 (1.6%)</td>
</tr>
<tr>
<td><strong>Religious affiliation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Protestant</em></td>
<td>99 (12.1%)</td>
<td>83 (10.2%)</td>
<td>103 (12.6%)</td>
<td>102 (12.5%)</td>
</tr>
<tr>
<td><em>Catholic</em></td>
<td>416 (50.9%)</td>
<td>339 (41.5%)</td>
<td>326 (39.9%)</td>
<td>386 (47.2%)</td>
</tr>
<tr>
<td><em>Other Christian</em></td>
<td>81 (9.9%)</td>
<td>76 (9.3%)</td>
<td>66 (8.1%)</td>
<td>71 (8.7%)</td>
</tr>
<tr>
<td><em>No affiliation</em></td>
<td>118 (14.4%)</td>
<td>99 (12.1%)</td>
<td>96 (11.8%)</td>
<td>111 (13.6%)</td>
</tr>
<tr>
<td><em>Other</em></td>
<td>92 (11.3%)</td>
<td>97 (11.9%)</td>
<td>56 (6.9%)</td>
<td>116 (14.2%)</td>
</tr>
<tr>
<td><strong>School years</strong></td>
<td>2.54 (1.10)</td>
<td>2.51 (1.12)</td>
<td>2.44 (1.12)</td>
<td>2.40 (1.12)</td>
</tr>
<tr>
<td><strong>Extraversion</strong></td>
<td>3.50 (.88)</td>
<td>3.47 (.90)</td>
<td>3.46 (.93)</td>
<td>3.45 (.98)</td>
</tr>
<tr>
<td>α = .615</td>
<td>α = .635</td>
<td>α = .609</td>
<td>α = .649</td>
<td></td>
</tr>
<tr>
<td><strong>Agreeableness</strong></td>
<td>3.58 (.74)</td>
<td>3.55 (.76)</td>
<td>3.55 (.84)</td>
<td>3.64 (.79)</td>
</tr>
<tr>
<td>α = .284</td>
<td>α = .314</td>
<td>α = .362</td>
<td>α = .283</td>
<td></td>
</tr>
<tr>
<td><strong>Conscientiousness</strong></td>
<td>4.08 (.76)</td>
<td>4.08 (.72)</td>
<td>4.00 (.81)</td>
<td>4.06 (.79)</td>
</tr>
<tr>
<td>α = .468</td>
<td>α = .415</td>
<td>α = .528</td>
<td>α = .546</td>
<td></td>
</tr>
<tr>
<td><strong>Emotional stability</strong></td>
<td>3.78 (.79)</td>
<td>3.74 (.80)</td>
<td>3.73 (.83)</td>
<td>3.79 (.86)</td>
</tr>
<tr>
<td>α = .553</td>
<td>α = .600</td>
<td>α = .554</td>
<td>α = .574</td>
<td></td>
</tr>
<tr>
<td><strong>Openness</strong></td>
<td>3.84 (.74)</td>
<td>3.81 (.72)</td>
<td>3.85 (.75)</td>
<td>3.83 (.79)</td>
</tr>
<tr>
<td>α = .353</td>
<td>α = .342</td>
<td>α = .394</td>
<td>α = .393</td>
<td></td>
</tr>
<tr>
<td><strong>Party identification</strong></td>
<td>4.03 (2.12)</td>
<td>3.88 (2.09)</td>
<td>3.88 (2.16)</td>
<td>3.78 (2.08)</td>
</tr>
<tr>
<td><strong>President approval</strong></td>
<td>2.89 (1.10)</td>
<td>2.88 (0.99)</td>
<td>2.93 (1.05)</td>
<td>2.68 (0.99)</td>
</tr>
<tr>
<td><strong>Political interest</strong></td>
<td>2.39 (.92)</td>
<td>2.41 (.94)</td>
<td>2.36 (0.98)</td>
<td>2.43 (0.95)</td>
</tr>
<tr>
<td><strong>Political knowledge</strong></td>
<td>2.99 (1.20)</td>
<td>2.46 (1.50)</td>
<td>2.65 (1.37)</td>
<td>2.94 (1.19)</td>
</tr>
</tbody>
</table>

Table 4. Descriptive statistics for individual-level measures across years (SDs in parentheses otherwise noted).
**Additional Individual-level Measures**

**Persistent Sender and Receiver Effects for Social Selection Models**

In order to control the cross-time dependencies stemming from any unmeasured, intrinsic tendencies of individuals to send or receive ties (e.g., those who have a high number of outgoing ties in a previous year continue to make a large number of ties in a given year), the persistent sender effect and persistent receiver effect terms were created. This is done by setting (a) the out-degree centrality (for sender term) and (b) the in-degree centrality (for receiver term) of a given node in a previous year as node-level covariates in a given year. For instance, an individual’s persistent sender term and persistent receiver term were set as “5” and “10” in the 2012 political discussion network, respectively, if he or she had 5 outgoing ties and 10 incoming ties in the 2011 political network.

**Individual-level Measures for Social Influence Models.**

In previous discussion of a social influence process, the present study has established several predictions based on an ego’s local network structure. Specifically, the present study predicted that normative social influence is likely to be increased to the extent (a) an ego is embedded in network structures that are characterized as more redundant, highly interconnected, closure-like settings (“close-knit local structure”), and (b) an ego is better able to observe a reference group’s political preferences (“observability”). Likewise, regarding informational influence, the present study predicted that an informational social influence would be increased as a function of (c) an ego’s lack of redundant, highly interconnected ties (“loose-knit local structure”). These
predictions require constructing several node-level measures (as a form of covariates) based on individuals’ local and global network topologies.

*Close-knit local structure.* Following the prediction that an ego’s more redundant, highly interconnected, closure-like (“close-knit”) network would increase the similarity in ego’s and her alters’ political preference (i.e., normative social influence), the present study operationalized such close-knit networks of an ego as the graph density of one’s ego-network. A density of each ego’s ego-network well captures the constraints and opportunities that an ego is facing as a result of their position and pattern of connections that they maintain in their network (Borgatti, 1997; also see Granovetter, 1973, p. 1370). The density of ego-network has been assessed by calculating the number of actual ties among each ego i’s first-step neighbors divided by the number of maximum possible ties (i.e., graph density) using SNA and Egonet package in R.

*Observability.* Following the prediction that the extent to which an ego is better able to observe a reference group’s political preferences would increase the similarity in the ego’s and her alters’ political preferences (i.e., normative social influence), the present study operationalized such observability of an ego as closeness centrality. Closeness centrality (Freeman, 1979) quantifies the overall distance or time required until the arrival of information to all other actors in the network. Thus, closeness centrality is highly correlated with the lack of structural constraints faced by an ego’s immediate alters (Brass, 1984; Borgatti, 2005; Freeman, 1979; Leavitt, 1951), in that an ego becomes more independent (and therefore less likely to be influenced by his or her immediate network climate or from a particular alter) to the extent that the actor can
reach or be reached by other actors via a minimum number of intermediaries. Most importantly for the purpose of the present study, available empirical evidence suggests that closeness centrality is positively correlated with more accurate perceptions regarding the performances of other actors in the network (Friedkin, 1983) or regarding overall political climate (Eveland & Hutchens, 2013). This further suggests that an ego’s horizon of observability (thus able to develop a more accurate perception of the distribution of attributes) increase as an ego’s closeness centrality increases. Following the standard definition provided by Freeman (1979), closeness centrality is defined as:

\[
\text{Closeness centrality} = \frac{1}{\sum D_{ij}}
\]

where \(D_{ij}\) is the shortest path (i.e., geodesic distance) between any given nodes \(i\) and \(j\).

*Loose-knit local structure.* Following the prediction that the extent to which an ego’s lack of redundant, highly interconnected ties (“loose-knit local structure”) would increase the similarity in an ego’s and her alters’ political preference (i.e., informational social influence), the present study operationalized such loose-knit networks of an ego as the betweenness centrality. Betweenness centrality has been often thought to well represent an actor’s unique positions and brokerage roles within a given network (Borgatti, 2005; Freeman, 1979; Wasserman & Faust, 1994). Specifically, betweenness quantifies the extent to which an ego connects alters that are otherwise unconnected within the network, therefore capturing the structural benefits of an ego in exploiting informational control and in receiving non-redundant and new information that is not readily available within their immediate environment (Borgatti, 2005; Burt, 1999; Granovetter, 1973) – which may have important implications in social influence.
processes based on informational benefits (e.g., Song & Eveland, 2015). Betweenness centrality of an ego has been defined as the following:

\[ \text{Betweenness centrality} = \sum_{i \neq v \neq k} \frac{Z_{ik} (V)}{Z_{ik}} \]

where \( Z_{ik} \) is the total number of shortest paths from node \( i \) to \( k \), and \( Z_{ik} (V) \) is the number of shortest paths that pass through node \( v \).

All of the descriptive statistics for node level network measures across the four-year period are presented in Table 5 below.

---

24 It is suggested that some measure of centrality from ego network (e.g., betweenness) is highly correlated with the respective global centrality measure (Everett & Borgatti, 2005).
<table>
<thead>
<tr>
<th></th>
<th>'10 network (N=776)</th>
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<th>'12 network (N=753)</th>
<th>'13 network (N=736)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Egonetwork density</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Close friends</td>
<td>.4020 (.111)</td>
<td>.4255 (.129)</td>
<td>.4157 (.109)</td>
<td>.4269 (.114)</td>
</tr>
<tr>
<td>Time spent together</td>
<td>.4317 (.101)</td>
<td>.4303 (.109)</td>
<td>.4509 (.108)</td>
<td>.4881 (.112)</td>
</tr>
<tr>
<td>Political discussion</td>
<td>.3650 (.137)</td>
<td>.3877 (.144)</td>
<td>.3904 (.136)</td>
<td>.3853 (.137)</td>
</tr>
<tr>
<td><strong>Betweenness centrality</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Close friends</td>
<td>non-normed: 61.20 (93.62)</td>
<td>non-normed: 49.03 (100.9)</td>
<td>non-normed: 60.66 (100.7)</td>
<td>non-normed: 55.73 (95.19)</td>
</tr>
<tr>
<td></td>
<td>normalized: .0180 (.025)</td>
<td>normalized: 0201 (.033)</td>
<td>normalized: .0185 (.027)</td>
<td>normalized: .0190 (.026)</td>
</tr>
<tr>
<td>Time spent together</td>
<td>non-normed: 51.29 (90.80)</td>
<td>non-normed: 44.59 (86.85)</td>
<td>non-normed: 48.54 (86.96)</td>
<td>non-normed: 44.77 (76.92)</td>
</tr>
<tr>
<td></td>
<td>normalized: .0180 (.025)</td>
<td>normalized: 0201 (.028)</td>
<td>normalized: .0185 (.024)</td>
<td>normalized: .0190 (.025)</td>
</tr>
<tr>
<td>Political discussion</td>
<td>non-normed: 62.08 (192.5)</td>
<td>non-normed: 36.60 (105.1)</td>
<td>non-normed: 54.42 (113.9)</td>
<td>non-normed: 53.46 (119.1)</td>
</tr>
<tr>
<td></td>
<td>normalized: .0180 (.042)</td>
<td>normalized: 0201 (.047)</td>
<td>normalized: .0185 (.036)</td>
<td>normalized: .0190 (.035)</td>
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<tr>
<td><strong>Closeness centrality</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>normalized: .0180 (.011)</td>
<td>normalized: .0201 (.014)</td>
<td>normalized: .0185 (.011)</td>
<td>normalized: .0190 (.011)</td>
</tr>
<tr>
<td>Time spent together</td>
<td>non-normed: .4833 (.236)</td>
<td>non-normed: .4756 (.257)</td>
<td>non-normed: .5225 (.237)</td>
<td>non-normed: .5596 (.239)</td>
</tr>
<tr>
<td></td>
<td>normalized: .0180 (.010)</td>
<td>normalized: .0201 (.013)</td>
<td>normalized: .0185 (.010)</td>
<td>normalized: .0190 (.010)</td>
</tr>
<tr>
<td>Political discussion</td>
<td>non-normed: .1763 (.194)</td>
<td>non-normed: .1559 (.204)</td>
<td>non-normed: .2749 (.263)</td>
<td>non-normed: .2999 (.271)</td>
</tr>
<tr>
<td></td>
<td>normalized: .0180 (.021)</td>
<td>normalized: .0201 (.030)</td>
<td>normalized: .0185 (.019)</td>
<td>normalized: .0190 (.018)</td>
</tr>
</tbody>
</table>

Table 5. Descriptive statistics for node-level network measures for three types of networks (SDs in parentheses). Normalized versions of centrality scores are rescaled from 0 to 1 prior to deriving descriptive statistics.
Additional individual-level control measures for social influence models

For models predicting social influence, respondents’ gender, race, and religion were entered as a series of dummy variables. A dummy variable tapping (a) gender of the respondent (*Female* = 1, and *Other* = 0), and (b) two separate dummy variables tapping “White” (* = 1, and *Other* = 0) and “African-Americans” (* = 1, and *Other* = 0),\(^{25}\) and (c) a dummy variable tapping “Protestant” (* = 1, and *Other* = 0) were created from the original measures and entered into the regression equations.\(^{26}\)

In addition to gender and race, respondents’ political ideology was also controlled for in the social influence models. There is a growing evidence that party identification is somewhat distinctive to political ideologies, at least under certain conditions, in that the party identification taps an amalgam of (a) a “running tally” of party performances, (b) a proximity of individuals’ policy positions and that of parties, and (c) some emotional attachments to the parties, therefore more subjective to a short-term fluctuation than political ideologies (Achen, 1992; Campbell et al. 1960; Clarke & McCutcheon, 2009;

\(^{25}\) Since (a) the majority of the respondents were White (approximately 75 to 80%), and (b) the race of the president at the time of the survey (Barack Obama) could affect the political attitudes at least for presidential approval, only White and African American dummies were included. Preliminary analysis of the social influence model (with GEE analysis: more will be introduced at the later section) using a more detailed racial categorization did not reveal any notable and significant impact of racial categories other than ones included in the final models.

\(^{26}\) Originally all religious categorizations were entered as a series of dummy variables (“no religion” as the reference category) in the social influence equations. However, preliminary analysis did not reveal any notable and significant impact of additional religious categories other than ones included in the final models, therefore they were omitted in the final analysis and presentation reported here.
In contrast, political ideologies are generally considered as more long-term, stable belief systems and worldviews (Converse, 1964; Jost, Nosek, & Gosling, 2008). In addition to such theoretical distinctiveness, from an empirical standpoint, a respondent’s self-placement of ideology tends to be the one of the strongest predictors of party identification and overall political preferences (e.g., Smith, 1999). Therefore, it is crucial to partial out the possible effects of ideologies in establishing the causal effects of alters’ political preferences on that of an ego’s. A respondent’ self-placement of ideology (“In general, do you think of yourself as...”) was gauged from “extremely liberal” (=1) to “extremely conservative” (=7), with “moderate” (=4) being the middle point of a 7-point scale (2010: $M = 3.92, SD = 1.53$; 2011: $M = 3.98, SD = 1.50$; 2012: $M = 4.09, SD = 1.52$; 2013: $M = 4.13, SD = 1.45$).

Available evidence suggests that those who are more politically knowledgeable or more interested in politics are more likely to engage in various political behaviors, including discussion of politics with others (Delli Carpini & Keeter, 1996; Klofstad, 2011; Lau & Redlawsk, 2001; Luskin, 1990). To control for such independent effects of an ego in estimating ego-alter dyadic effects, an ego’s political interest and knowledge (as individual-level predictors) were also included in the models.

---

27 It should be stressed that, when compared to presidential approval, the party identification is more stable than approval, therefore would have more plasticity.  
28 A supplementary analysis without political ideology (otherwise identical model specification) did not alter the pattern and substantial interpretation of the results reported in the results section.
Dyadic-level Measures

Homophily

Within the context of social selection, respondents’ gender and race were used in defining demographic homophily at a dyadic level. From the initial gender categories (i.e., Male and Female), a dyadic measure of gender homophily was derived such that a tie was identified as homophilous in terms of gender if an ego (main respondent) and her alter were the same gender (1 = ego and alter have same gender, and 0 for otherwise). Racial homophily was defined in the same way as gender homophily (e.g., 1 = ego and alter have same race, and 0 for otherwise) from the initial 5 categories (see the above section for the detailed racial categories). Those dyadic demographic homophily variables were also used in the social influence model to partial out potential demographic selection effects in estimating social influence models.

In estimating the social selection model, two separate measures of political preference homophily were defined based on (a) political party identification and (b) approval of president Obama. The measures were created in a way that a tie was regarded to be more homophilous to the extent as an ego (i) and her alter (j) have smaller absolute differences in their party identification or the presidential approval:

\[ \text{Preference homophily} = |\text{Preference}_i - \text{Preference}_j| \]

Dyadic Political Interest and Knowledge Difference.

For models estimating social influence, a set of measures tapping dyadic differences (between an ego and her alter) in political interest and in political knowledge was created. Since such dyadic differences imply directionalities of influence (e.g., alters
who are more interested in politics should exert more influence on an ego’s political preference, but not for vice versa), the dyadic differences in political interest and knowledge measures were constructed in a way that a higher value of the measure represents greater dyadic influence from alters to an ego, such that:

\[
\text{Interest difference}_{ij} = \text{Interest}_{\text{alter } j} - \text{Interest}_{\text{ego } i}
\]

\[
\text{Knowledge difference}_{ij} = \text{Knowledge}_{\text{alter } j} - \text{Knowledge}_{\text{ego } i}
\]

**Availability and Intimacy of Dyads for Concurrent and Lagged Networks**

In order to tap the “availability” and “intimacy” level of a given dyad for political discussions, two separate networks of time-spent together, and close friends were entered as an exogenous edge covariate effect term. Exogenous edge covariate effects on probabilities of political discussion ties are specified as the following:

\[
\text{Exogenous edge covariate (w → x)}_{ij} = \sum_{i,j} W_{ij} X_{ij}
\]

where \( W_{ij} \) is the directed exogenous network ties between a given dyad \((i,j)\), and \( X_{ij} \) is the directed political discussion network ties for the same dyad \((i,j)\). In modeling concurrent exogenous network effects, cell entries of \( W_{ij} \) were constructed from the current years’ time-spent together and close friendship networks, whereas for lagged exogenous network effects, cell entries of \( W_{ij} \) were constructed from the previous years’ time-spent together and close friendship networks.
Additional Dyadic-level Controls for Social Selection Models

Similarity in network positions. Within the context of social selection, one of the alternative sources of the attribute similarity is the similarity in one’s network positions (“structural equivalence” perspective: Burt, 1987; Lorraine & White, 1971). According to this theoretical account, to the extent two individuals have identical or similar patterns of connections to all other actors in a given social networks, they are exposed to a similar set of relationships and undergo similar socialization processes, therefore they are likely to have similar attributes (Burt, 1987; Friedkin, 1984; Lorraine & White, 1971; White, Boorman, & Breiger, 1976). Although the structural equivalence perspective mainly suggests possible alternative mechanisms of social influence (e.g., how individuals are embedded in a social structure affects individuals’ attributes), such an alternative source of similarity in attributes, nevertheless, could in turn affect how individuals choose to associate with others as a results of such similarity. Therefore it could potentially bias the parameter estimates from social selection processes, although specific directions and magnitudes of such potential bias is largely unclear. In order to control for this possibility, individuals’ similarities in network positions also need to be controlled (as a form of dyadic covariates) in the social selection model. Using Leender’s (2002) and Fujimoto and Valente’s (2012) measure of the equivalence proximity, one’s structural similarities in network positions (vis-à-vis other actors) in each group’s network was measured as the following:

\[
EP_{ij} = \frac{\left(\hat{i} - \tilde{j}\right)\left(\hat{i} - \tilde{j}\right)^{1/2}}{\sqrt{2g}} \left(1 - a_{ij}\right)
\]

for \(i, j = 1, \cdots, N\), \(i \neq j\)
where a vector \( \hat{i} \) being the stack of the \( i^{th} \) row and column of adjacency matrix \( \mathbf{X} \) (political discussion network), \( \hat{j} \) is the stack of the \( j^{th} \) row and column of \( \mathbf{X} \), and \( g \) being the number of actors in a given network (Fujimoto & Valente, 2012; Leender, 2002).  

Lagged reciprocity for exogenous and endogenous networks. One of the most basic and powerful principles driving human behavior is the notion of reciprocity. From the network science perspective, reciprocity for a dyad is often thought to be increased with trust, social exchange of resources, or equal legitimacy in a given dyadic relationship (Leifeld & Schneider, 2012; Monge & Contractor, 2003). Reciprocity is also expected to increase the probability of political discussion ties, such that (a) if one person talks about politics to his or her alters, then such alters are more likely to talk back regarding political issues being raised by an ego at later waves, or (b) if one person nominates his or her alter as a close friend or as someone who regularly spent time with, then such alters are more likely to nominate the ego as whom they talk with about politics at later waves. In order to capture such interdependency patterns that span different time points, the lagged reciprocity effects for exogenous and endogenous networks effects were set as the following:

\[
\text{Lagged exogenous reciprocity (} w_{t-1} \rightarrow x_t)_{ij} = \sum_{l,j} W_{(t-1)ji} X_{(t)ij}
\]

\[ \hat{j} = 1 - \hat{j} \]

29 In this formula, \( \hat{j} \) is defined by \( \hat{j} = 1 - \hat{j} \) where 1 is a \((2g \times 1)\) vector of ones (“1”), which converts the Euclidean “distance” into a measure of structural “similarity” rather than distance. For a detailed discussion of the formula, see Fujimoto and Valente (2012).
Lagged endogenous reciprocity \((x_{t-1} \rightarrow x_t)_{ij} = \sum_{i,j} X_{(t-1)ji}X_{(t)ij}\)

where \(W_{(t-1)ji}\) is the directed exogenous network ties between a given dyad \((j,i)\) at time \(t-1\), and \(X_{(t-1)ji}\) is the directed political discussion network ties between the given dyad \((j,i)\), and \(X_{(t)ij}\) is the directed political discussion network ties between the given dyad \((i,j)\).

**Triadic and Higher-order Level Measures**

**Transitivity**

It is now well known in the literature that simple Markov models for ERGMs are easily subjective to degeneracy problems in modeling social selection dynamics (Goodreau, 2007; Schweinberger, 2011). Following the new model specifications proposed by Snijders et al. (2006) and Robins et al. (2006), a transitivity parameter was operationalized using GWESP (geometrically weighted edgewise shared partner), a curved exponential family ERGM term (Goodreau, 2007; Hunter, 2007; Hunter et al., 2008) that expresses the effect of a number of k-triangles over a tie between node \(i\) and \(j\) as a base of a triangle. More specifically, the GEWSP models a linear combination of an entire distribution of triangles \((i,h,j)\) for a given unique dyad \((i,j)\) in the network, \(T_{ij}\), of which effect is *weighted to produce decreasing return* by a decay parameter, \(\Phi\), as following:

\[
GWESP (X, \Phi) = e^{\Phi} \sum_{i=1}^{n-1} \{1 - (1 - e^{-\Phi})^i\} T_{ij}
\]
where $T_{ij}$ is defined as the count of “connected” edges $(i,j)$ in network $X$ that share exactly $h$ neighbors in common (i.e., number of closed triangles connecting $i$ and $j$) as following:

$$T_{ij} = \sum_{h \neq i,j} X_{i/h}X_{j/h}$$

**Preferential attachment**

Similar to the transitivity parameter, the preferential attachment parameter has been operationalized using a GWD-indegree (geometrically weighted in-degree distribution) term as the following:

$$\text{GWD}_{\text{indegree}}(X, \Phi) = e^\Phi \sum_{i=1}^{n-1} \left\{ 1 - (1 - e^{-\Phi})^i \right\} D_i(X)$$

where $D_i(X)$ is the number of nodes in the network $X$ whose in-degree equals $(i)$, and $\Phi$ is the decay parameter that quantifies the *decreasing* return of the degree distribution effects as the number of degree itself increases.

**Additional Controls for Triadic and Higher-order Effects for Social Selection Models.**

*GWDSP.* The current study also controlled for GWDSP (geometrically weighted dyadic shared partner distribution) as an additional control, in order to properly estimate the higher order effect that is nested under a lower-order effect. The GWDSP term is identical to the GWESP term except the fact that it does not require a base of a triangle $(i,j)$ to be connected. Instead, the GWDSP term models the $k$-twopath (i.e., a set of $k$ distinct paths that has lengths of two) that join the same pair of nodes $i$ and $j$ (regardless
of whether or not they are connected), of which effect is also \textit{weighted to produce decreasing return} by a decay parameter, $\Phi$, as the following:

$$GWDSP (X, \Phi) = e^{\Phi} \sum_{i=1}^{n-1} \{1 - (1 - e^{-\Phi})^i\} L_{2ij}$$

where $L_{2ij}$ is defined as the count of $k$-twopaths in the network $X$ that connect a dyad $(i,j)$.\(^{30}\)

\textit{GWD-outdegree.} Similar to GWD-indegree effects, another curved exponential term that represents concurrent endogenous feedback is the GWD-outdegree effect. Contrary to the GWD-indegree term that models preferential attachments (i.e., people prefer to talk about politics with whom a lot of other people regularly turn to), GWD-outdegree represents a slightly different conceptual phenomenon, a global “hierarchy” in political discussion networks due to an unequal degree distribution, despite its similar mathematical definitions (Snijders, 2011). That is, a highly skewed “outdegree” distribution could signify the situation that only a few people initiate political discussions to a lot of alters, producing unequal distribution of outdegrees in a given network. In order to partial out such effects, GWD-outdegree is specified as an identical model parameter to GWD-indegree term except the direction of ties being reversed (using outgoing ties instead of incoming ties) in its calculation of degree distributions.

\(^{30}\) Since it is not required to be “connected,” a pair of nodes $(i,j)$ is considered as a dyad rather than an edge (Geometrically Weighted “Dyadic” Shared Partner). When the GWDSP term is simultaneously included in the ERGM along with the GWESP term, it conceptually represents that the lower order effects are controlled for in estimating the effects of the higher order terms.
Analysis strategy for social selection: TERGM analysis

For modeling dynamics of social selection this study utilizes the Temporal Exponential Random Graph Models (TERGM) technique, a time-series extension of Exponential Random Graph Models that has been proposed by Robins and Pattison (2001) and Desmarais and Cranmer (2012).

An ERGM framework, including temporal ERGM, aims to model a given observed network structure based on underlying (and unknown) stochastic social processes that might give rise to the observed networks (Lusher et al., 2013; Hunter & Handcock, 2006; Robins, Pattison et al., 2006). Within the ERGM framework, any given observed network structure can be understood as a one possible realization of stochastic network-generating processes under a certain probability distribution, conditional on a fixed number of nodes within the network (Lusher et al., 2013; Robins et al., 2006), which is formally expressed as follows:

\[ P(X = x) = \left( \frac{1}{k} \right) \exp \left[ \sum_A \eta_A g_A(x) \right] \]

where \( X \) is the set of every possible network configuration of a network with the same size of nodes, \( P(x) \) denotes the probability of observing a given network from \( X \), \( A \) denotes all possible network local configurations (e.g., reciprocity, transitivity, degree distribution, etc.), \( \eta_A \) is the vector of non-zero parameters corresponding to each of the configurations that are conditional on the rest of a network, \( g_A(x) \) denotes respective network statistics (i.e., count) for corresponding network local configurations, and \( k \) is the normalizing constant of the probability distribution (Robins et al., 2006). Here, each network tie \( X_{ij} \) is regarded as a random variable \( X_{ij}=1 \) if observed or \( X_{ij}=0 \) otherwise.
The probability of a network tie being present in a given network is then explained in terms of a set of local configurations that imply certain dependency structures in the network.

A temporal extension of the ERGM framework starts with a sparse adjacency matrix representing an observed network that can be partitioned into $z$-blocks, each of which represents any possibly conceivable partition of the network (e.g., discrete observation points from time-series network data). Such TERGM specification can be formally expressed as follows:

$$P(X_z | X_{-z} = x_z | x_{-z}) = \left(\frac{1}{k}\right) \exp \left[ \sum_A \eta_A g_A(x_z \cup x_{-z}) \right]$$

where $X$ is the set of every possible network configurations of a network with the same size of nodes, with $z$-subscript $(X_z)$ representing the $z$-th block of the network and $-z$ subscript $(X_{-z})$ representing the rest of the network that is not represented by the $z$-th block, and $(x_z \cup x_{-z})$ denotes the complete network generated by inserting $x_z$ into the $z$-th block of $X$ while holding the rest of the network, $x_{-z}$, being constant. Therefore, $g_A(x_z \cup x_{-z})$ represents a vector of network statistics from such a complete network.

According to Desmarais and Cranmer (2012), because of its actor-driven orientation and capacity to simultaneously model dynamic tie-formation in social networks and evolution of actor behavior, the Stochastic Actor Oriented Model (SAOM) is often viewed as the most appropriate statistical framework of studying “coevolution” of social networks and individual attributes. Often, SAOM is explicitly compared with ERGM/TERGM framework (and implicitly assumed to be opposite), in that ERGM/TERGM is oriented towards more “network-level” interpretation, whereas
SAOM is more oriented towards “actor-based” explanation, in addition to its ability to explicitly model coevolutionary dynamics in a single comprehensive model specification (Desmarais & Cranmer, 2012). Yet, as suggested by a number of scholars (e.g., Desmarais & Cranmer, 2012; Leifeld & Cranmer, 2014), SAOM and ERGM/TERM offer fairly comparable explanations regarding the underlying social processes of tie-formation in an observed network. The critical difference of the two lies on specific assumptions on which those two mathematical models are making, therefore a brief review of the model assumptions is necessary.

1. Does change in networks occur sequentially or simultaneously (not necessarily sequentially)? The SAOM makes a very explicit and detailed assumption about the network change processes compared to ERGM, in that the process of network change only occurs by changing one tie at a time (Desmarais & Cranmer, 2012; Snijders, van de Bunt, & Schweinberger, 2010; Holland & Leinhardt, 1977). This assumption, proposed by Holland and Leinhardt (1977) as the “conditional independence” assumption, allows researchers to “break up” complex network change processes to its smallest and simplest possible mechanisms. Within this framework, any complex higher-order processes could be represented as a “cumulative” result of simpler, basic processes. In contrast, in ERGM/TERM, the underlying processes could be expressed as the joint change processes – what Desmarais and Cranmer (2012) have termed as “component-by-component” change processes – which do not impose such restrictions. For instance, in SAOM, two ties that are not directly connected to each other cannot simultaneously make ties towards each other (therefore form a reciprocal tie at time t+1 conditional on their null tie at time
t) since the change in networks are assumed to be sequential – one actor must create a tie towards another first, and in the next phase of network change, other actors form a reciprocated tie, conditional on previously connected ties. In contrast, in the ERGM/TERM, it is possible to model the probability of network change from non-tie to reciprocated tie, therefore allowing researchers to examine a wide range of possible network tie-formation processes. According to Desmarais and Cranmer (2012), one benefit of assuming such sequential network generation in the SAOM is that the SAOM is more robust against the degeneracy problem. Yet recent developments of ERGM suggest that inclusion of realization dependent terms (i.e., Curved exponential family model; Hunter, 2007) such as GWESP, GWDSP, or GWD parameters (instead of simple Markov dependence terms such as simple triplets) can largely avoid degeneracy problems in ERGM (Hunter & Handcock, 2006; Snijders et al., 2006).

2. Does the conditioning of actor behaviors on past realization of networks depend on actual observed networks (ERGM) or simulated networks (SAOM)? Another nontrivial difference between the ERGM/TERGM and the SAOM is that the SAOM has the built-in capability of modeling actor-behavior change as a function of past-realized network (i.e., “network-behavior coevolution model”). Because the SAOM stochastically “simulates” changes between any two observation points, in the behavior evolution equation the SAOM also generates the prior states of network realization to model actor-behavior at time $t$, just as in the network evolution model the immediately prior state of actor-behavior is simulated for modeling network evolution. Since the SAOM assumes “continuous changes” during any observation moments (Snijders et al., 2010; Steglich et
al., 2010), the actual observed whole network data is only useful for generating a mathematical representation of the network-attribute coevolution model at given observation points. Therefore, the actual observed network at time \( t-1 \) is not the same network (or actor behavior) that is used to model behavior (or network) at time \( t \) – the entire estimation is based on simulated behavior (or network) from such a mathematical model that takes into account “unobserved changes” between observations. This is the direct consequence of adopting the assumption that any network or behavior changes follow stochastic and “sequential” change process (Desmarais & Cranmer, 2012; Steglich et al., 2010). In contrast, when the conventional approach of modeling actor-behavior is used (either based on a logistic regression or a network-based regression model) with the ERGM, the actor-behavior at time \( t \) is conditional on the actual observed network at time \( t-1 \) – since it is impossible to use intermediate change states in estimation as the SAOM does via simulations. Yet as Desmarais and Cranmer (2012) suggest, if the underlying process of network change is theoretically closer to the ERGM than the SAOM, then the ERGM may be preferred in estimating coevolution models.31

In the present study, each of the outlined hypotheses discussed in the above section was examined by analyzing whether individuals are likely to form network ties as a function of similarity in their attributes, including political attitudes (Hypotheses 1 to 6, and Research Question 1). Statistical analyses were conducted with the ERGM package in Statnet suite, R (Handcock et al., 2013; Hunter et al., 2008), specifying a single sparse

31 Yet, it is often not clear a priori whether one of the two alternative approaches provides more appealing and appropriate representation of underlying social change processes.
matrix of longitudinally observed network for each of the groups – therefore conditions the realization of the network in each year on previous realization of the network in estimating each group’s TERGM (Hanneke & Xing, 2007; also see Desmarais & Cranmer, 2012). Specifically, each group’s year-series observations of network data (e.g., Group 1’s network from 2010 to 2013, with a total $k$ number of unique nodes across years) were merged into a single sparse matrix ($3k \times 3k$) with block-diagonal structures, where constraints across waves were imposed such that nodes in different waves were not allowed to create ties during the estimation process. Some of the graph-theoretic properties of the networks (e.g., in- and out-degrees, reciprocity, or exogenous networks) from previous years’ observations were set as node or edge covariates for a given year, such that observations from year 2010 to 2012 were set as node or edge-level covariates for observations from year 2011 to 2013, respectively.

Table 6 below reports hypothesized tie-generating mechanisms tested for social selection dynamics in the present study, corresponding specifications, and their substantial interpretations.
## Table 6. TERGM model specifications, associated hypothesized effects, and their interpretations.

<table>
<thead>
<tr>
<th>Effect / Hypothesis</th>
<th>TERGM Specification</th>
<th>Substantive interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network Evolution: Selection effects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>H1</strong>: Race homophily</td>
<td>(nodematch)</td>
<td>Actors prefer making ties to others with same race</td>
</tr>
<tr>
<td><strong>H2</strong>: Gender homophily</td>
<td>(nodematch)</td>
<td>Actors prefer making ties to others with same gender</td>
</tr>
<tr>
<td>(Control) Religion homophily</td>
<td>(nodematch)</td>
<td>Actors prefer making ties to others with same religion</td>
</tr>
<tr>
<td><strong>H3</strong>: Political attitude similarity</td>
<td>(absdiff)</td>
<td>Actors prefer making ties to others with similar political preference <em>(party identification and approval of Obama)</em></td>
</tr>
<tr>
<td>(Control) Political interest of an ego</td>
<td>(continuous covar)</td>
<td>The tendency that actors with higher values on interest send out more ties</td>
</tr>
<tr>
<td>(Control) Political knowledge of an ego</td>
<td>(continuous covar)</td>
<td>The tendency that actors with higher values on political knowledge send out more ties</td>
</tr>
<tr>
<td><strong>H4</strong>: Political interest of an alter</td>
<td>(continuous covar)</td>
<td>The tendency that actors with higher values on interest receive more ties</td>
</tr>
<tr>
<td><strong>H4</strong>: Political knowledge of an alter</td>
<td>(continuous covar)</td>
<td>The tendency that actors with higher values on political knowledge receive more ties</td>
</tr>
<tr>
<td>(Control) Personality of an ego</td>
<td>(continuous covar)</td>
<td>The tendency that actors with higher values on each dimensions of big-5 personality receive / send out more ties</td>
</tr>
<tr>
<td>(Control) School year of an ego</td>
<td>(binary covar)</td>
<td>The effect of school year on probability of receiving / sending ties</td>
</tr>
</tbody>
</table>

Continued
Table 6 continued.

<table>
<thead>
<tr>
<th>Effect / Hypothesis</th>
<th>TERGM Specification</th>
<th>Substantive interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network Evolution: Structural effects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Control) Edges (intercept)</td>
<td>(density)</td>
<td>Baseline probability of network ties (baseline control)</td>
</tr>
<tr>
<td><strong>H5a/H5b: Concurrent exogenous networks</strong></td>
<td>(Edgewise covar)</td>
<td>Propensity to make ties based on exogenous relationship <em>(friendship network and time-spent together network)</em></td>
</tr>
<tr>
<td>(Control) Lagged reciprocated ties</td>
<td>(binary covar)</td>
<td>The tendency to reciprocate at time <em>t</em> if an ego received ties from alters at previous time point (<em>t-1</em>)</td>
</tr>
<tr>
<td><strong>H5a/H5b: Lagged exogenous network</strong></td>
<td>(Edgewise covar)</td>
<td>Propensity to make ties at time <em>t</em> based on lagged (<em>t-1</em>) exogenous relationship <em>(friendship network and time-spent together network)</em></td>
</tr>
<tr>
<td>(Control) Persistent sender effect</td>
<td>(binary covar)</td>
<td>The effect of out-going ties at previous time point (<em>t-1</em>) on tendency to send out ties at time <em>t</em></td>
</tr>
<tr>
<td>(Control) Persistent receiver effect</td>
<td>(binary covar)</td>
<td>The effect of incoming ties at previous time point (<em>t-1</em>) on tendency to receive ties at time <em>t</em></td>
</tr>
<tr>
<td><strong>H6: Transitivity</strong></td>
<td>(gwesp)</td>
<td>Tendency for actors to form transitive patterns</td>
</tr>
<tr>
<td>(Control) In-transitivity</td>
<td>(gwdsp)</td>
<td>Tendency for actors to form intransitive patterns</td>
</tr>
<tr>
<td><strong>H7: Preferential attachments</strong></td>
<td>(gwidegree)</td>
<td>Tendency for actors to be chosen by multiple alters</td>
</tr>
<tr>
<td>(Control) Out-degree popularity</td>
<td>(gwodegree)</td>
<td>Tendency for actors to make ties towards multiple alters</td>
</tr>
</tbody>
</table>
Analysis strategy for social network influence: GEE procedures

For modeling dynamics of social influence, this study fits a series of linear regression models based on the generalized estimating equations procedure (GEE; Zeger & Liang, 1986). The GEE, which represents an extension of a generalized linear model (GLM) framework, provides a solution for modeling correlated and clustered responses such as ones from longitudinal panel designs or from social network data. Instead of modeling the within-subject covariance structure directly, the GEE estimates the marginal (population average) expectations of an outcome variable as a function of predictors using quasi-likelihood methods without assuming the normal distribution of outcomes nor the independence of observations. Unlike subject-specific models that represent the expected level of change in focal dependent variable as a function of a predictor variable for a “single individual,” the GEE represents an averaged effect of a unit change in a predictor variable for the whole populations (Ghisletta & Spini, 2004; Hu et al., 1998). One of the advantages of the GEE approach over other alternatives in modeling social network influence is that the sandwich estimator, a commonly used estimation methods for the GEE, converges to the true variance-covariance matrix even if the correlation structure is mis-specified. It therefore offers consistent and unbiased estimates of standard errors for the parameter estimates for clustered and correlated responses (Hardin & Hilbe, 2013).

In order to evaluate the normative and informational social network influence as outlined in the previous chapter, a series of GEE regression equations was estimated, modeling an ego’s political preference (party identification and approval of Obama) as a
function of an ego’s political preference at previous time point, and of an alter’s current and previous political preference while controlling for an ego’s demographics, ideology, interest, and knowledge. First, the GEE equations estimating an unconditional effect of an alter’s political preference on that of an ego’s are specified as the following:

\[
\hat{Y}_{ego,t} = a + b_1 Y_{ego,t-1} + b_2 Y_{alter,t} + b_3 Y_{alter,t-1} + \sum b_k X_{ego}
\]

where \(Y\) denotes political preference (party identification and approval of Obama respectively), \(a\) denotes the intercept of the regression equation, and \(X_{ego}\) denotes a series of control variables. The inclusion of lagged political preference of an ego \(Y_{ego,t-1}\) helps to control any intrinsic (and not explicitly controlled) propensity associated with political preferences being modeled, while the inclusion of a lagged political preference of an alter helps control the effect of homophily (therefore it partials out confounding effects of possible social selection effects), which has been proposed and validated by several previous studies examining a social network influence in different contexts (Fowler & Christakis, 2008a; 2008b; Carrington, Scott, & Wasserman, 2005). For the GEE equations estimating party identification as a dependent variable, the analysis controls for an ego’s gender (a dummy variable tapping Female), race (two dummy variables tapping White and African-Americans), dyadic gender homophily and religious homophily (dummy variables coded as “1” if an alter and an ego share same gender and religion, respectively), an ego’s years in school, political ideology, political interest, and political knowledge. For the GEE equations estimating approval of Obama as a dependent variable, an identical set of controls plus Protestant dummy and agreeableness
The key interest in both of the GEE models lies in the direction and magnitude of the regression coefficient $b_1$, which quantifies the contemporaneous effects of alters’ political preference on that of an ego.

Next, a series of conditional effect models as a function of an ego’s political preference at previous time point, and of alters’ concurrent and previous political preference, focal moderators, and their product terms with alters’ concurrent political preference, along with control variables, were specified as the following:

\[
\hat{Y}_{ego,t} = a + b_1Y_{ego,t-1} + b_2Y_{alter,t} + b_3Y_{alter,t-1} + b_4M_{ego} + b_5M_{ego}Y_{alter,t} + \sum b_kX_{ego}
\]

where $M_{ego}$ denotes the mean centered proposed moderators (i.e., dyadic interest and knowledge difference, betweenness centrality, closeness centrality, and ego-network density). Here, the regression coefficient $b_2$ quantifies the conditional effect of alters’ political preference on that of an ego especially when the level of moderator, $M_{ego}$, is set to its sample mean value. The regression coefficient $b_5$ quantifies the extent to which the conditional effect of alters’ political preference, $\theta_{Y_{alter,t}\rightarrow Y_{ego,t}}$, is being moderated by the level of proposed moderator, $M_{ego}$. Therefore, unlike the “unconditional” GEE model, a conditional GEE model allows the effect of alters’ political preference on that of an ego, $\theta_{Y_{alter,t}\rightarrow Y_{ego,t}}$, to depend linearly on level of a moderator variable.

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32 Preliminary analysis using a complete set of religion dummies and Big-5 variables indicated that there exist no discernable and independent effects of additional variables other than the Protestant dummy and agreeableness. To simplify the presentation of the results, only the Protestant dummy and agreeableness were controlled in the final model and reported in results. Inclusion of omitted variables did not alter the substantive conclusion reported in the analysis.
Treatment of Missing Data Using Multiple Imputation

The presence of missing data in social networks poses significant challenges for statistical modeling of the network data and substantive interpretation of results from such models, although such issues are not unique to social network analysis. Research on handling of missing data in social networks generally distinguishes two sources of missing data: (a) unit non-response, and (b) item non-response (e.g., Huisman & Steglich, 2008). Unit non-response denotes missing data due to boundary specification issues or refusal of potential respondents to participate in a survey, whereas item non-response means that only particular information of an alter or an ego – a response to one specific question, for instance – is omitted. Previous studies often point to the fact that the presence of missing data, particularly resulting from unit non-response, can bias the parameter estimates for certain network-level statistics (e.g., Burt, 1987; Costenbader & Valente, 2003; Kossinets, 2006; Wang, Shi, McFarland, & Leskovec, 2012) and for centrality measures (Borgatti, Carley, & Krackhardt, 2006; Kossinets, 2006; Wang et al., 2012).

A more recently proposed method for the handling of missing data (e.g., Robins, Pattison, & Woolcock, 2004; Gile & Handcock, 2006; Handcock & Gile, 2010) is often based on the model comparison approach, in that researchers estimate and compare the results from incomplete (inclusion of partially described ties) and complete data (using only fully described ties) using otherwise identical model specifications. Although such treatment effectively deals with missing information on ties, a more complicated scenarios arises with the presence of missing information on nodal attributes (e.g., item
non-response for certain key covariates). The current software implementation of network analysis, especially for the ERGM framework, does not accept any missing data in modeling of focal covariate effects for social selection. Any missing information on nodal covariates therefore requires researchers to (a) artificially drop such nodes with missing covariates from the network mapping, or (b) omit such variables from the analysis, both of which suggest non-random sources of bias in parameter estimates relative to true estimates that would have been obtained under the presence of full information on focal nodal covariates.

The present study deals with several source of missing data: (a) a unit non-response due to refusal in sociometric questionnaire (i.e., who do not complete the survey but are included in the network as a result of others’ nominations as network partners), (b) and a item non-response due to refusal or omission of answers to certain questions. First, a unit non-respondent from each of cross-sectional networks was effectively excluded from the network mapping, since there were only a few individuals who failed to participate in each of the cross-sectional network survey as indicated in high response rate (also see footnote #19 for a number of non-respondents across years). Second, in order to address the issue of missing data due to item non-response for certain key covariates (and uncertainty of parameter estimates from such imperfect data), the multiple imputation of missing covariates using expectation-maximization with bootstrapping algorithm (using Amelia II: see Honaker, King, & Blackwell, 2011) was
employeda. This approach has been used in several previous studies (e.g., Bearman & Moody, 2004; Fowler & Christakis, 2008b).

For the TERGM analysis, any missing responses in key nodal covariates are multiply imputed ($N=10$), including key independent variables (e.g., party identification and approval of Obama). Next, identical model specifications for TERGMs were repeatedly estimated for a number of post-imputation datasets ($N=5$) across all 14 groups’ networks, which resulted in 70 different model estimates.34 Next, once results from post-imputation datasets were obtained, the parameter estimates across all the TERGM results were summarized by the meta-analytic procedure described in Lubbers and Snijders (2007). Employing Hierarchical Linear Modeling with known level-1 variance (“$V$-known model”), the parameter estimates from TERGM ($\hat{\theta}_g$) can be split into an true parameter estimates (the average effect size: $\mu_\theta$), deviations associated with each group and imputation datasets ($U_g$), and the error variance of estimates ($e_g$), shown as the following:

$$\hat{\theta}_g = \mu_\theta + U_g + e_g$$

In estimating the meta-level regression above, the error variance ($e_g$) is assumed to be known and constrained to be equal to the squared standard error of each level-1 estimate. The population parameter estimates, or the average effect size, $\mu_\theta$, quantifies the extent to

---

33 Respondents’ gender, race, and religious affiliations are assumed to be exogenous to the network influence, therefore any missing data (if exists) were imputed using Last Value Carrying Forward (LVCF) methods instead of multiple imputation.

34 Originally, 10 post-imputed datasets were created by multiple imputation procedures. Due to a time constraint in fitting a TERGM model to the data, only 5 imputations were used in the final TERGM analysis.
which the effect of a variable occurs across chapter networks while accounting for any missing information on key nodal covariates. Its significance level has been assessed by deriving a $t$ ratio of the estimated average effect size relative to its standard error (Lubbers & Snijders, 2007) using HLM software.

For the GEE analysis, complete post-imputed datasets ($N=10$) were used. Also, after multiple imputation of the missing data, post-imputed party identification and approval of Obama values were replaced with the original missing values from the initial data. This procedure therefore let the cases with originally missing DVs to be deleted during the analysis (multiple imputation then deletion, or simply known as MID technique: von Hippel, 2007). While some researchers suggest the discrepancy of results between MID and inclusion of imputed DVs may be minor (e.g., Johnson & Young, 2011), using post-imputation values for DVs in analyses is generally a discouraged practice. Also, since the current specification of GEE modeling social network influence includes concurrent and lagged values of DVs for an ego and alter at the same time, using imputed Y values in GEE may add unnecessary noise to the estimates. Upon fitting the identical GEE model to 10 imputed datasets with the MID technique, the results across the multiple imputed datasets were averaged into a single parameter estimate following Rubin’s (1987) rule for combining the point and variance estimates. Next, a pooled estimate and its significance were evaluated by deriving a $Z$-value under the null hypothesis that a pooled estimate is equal to zero.
Preliminary Results from Network Random Permutation Test

Before addressing the results of the TERGM and the GEE analyses, I will first address the evidence of non-random clustering of individuals within the political discussion networks according to their political preferences (i.e., *party identification* and *approval of Obama*), which is presented in Table 7 and Figure 2 below. As discussed in Chapter 3: Analytical Challenges in Studying the Impact of Social Network (on p. 12), one of the plausible alternatives explaining the distribution of political preferences within political discussion networks is chance (or baseline) probabilities. Specifically, it is plausible to conceive that observed patterns of which an ego and his or her alters are similar to each other with respect to their political preferences (i.e., the “clustering” of political preferences) is not by any systematic processes but merely due to a chance (baseline) probability. In order to rule out such an alternative explanation, the random matrix permutation test has been performed.

The logic of the random matrix permutation test used here is as follows: if the observed clustering of political preferences in the networks is indeed based on pure chance probabilities, then the clustering of political preferences assessed from the randomly generated networks are expected to be similar to that of the observed network.

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However, if observed clustering is significantly different from the randomly generated networks, we could reasonably conclude that such clustering is indeed based on some systematic processes within the networks.

In order to assess the baseline probability, the observed network has been compared to 1,000 randomly generated networks in which the “values” of political preferences for each node have been randomly reshuffled with one another, yet the network topologies (i.e., observed network structures) and overall distribution of political preferences have been reserved to be the same as the observed network (Cacioppo, Fowler, & Christakis, 2009; Christakis & Fowler, 2013). For the purpose of this test, “clustering” is defined as an observed correlation between an ego’s political preference and that of connected alters, and the observed correlation coefficient has been compared with the distribution of correlations from the 1,000 randomly generated networks with random permutations.

Figure 2. The density plot comparing the observed correlation and the distribution of correlations from matrix random permutation (N=1,000), 2013 political discussion network.
Figure 2 above presents the results of the random permutation test (using approval of Obama) for the 2013 political discussion network. The observed correlation between an ego’s approval and that of connected alters (red solid line: \( r = .0985 \)) resides outside of the confidence intervals from randomly permuted networks (\( M = -.0011, SD = .0171, Min = -.0456, Max = .0645 \)). This overall pattern was largely consistent across years with different “political preferences” as a criterion variable. The observed correlation coefficients across years with different criterion variables significantly differ from the distribution of the correlations from 1,000 replications with random matrix permutation, as presented in Table 7 below. In essence, the random matrix permutation test suggests that a tendency towards clustering based on political preferences in the political discussion networks is significantly more likely than expected solely by chance (therefore significantly more likely than baseline probabilities).

<table>
<thead>
<tr>
<th>Year 10</th>
<th>Year 11</th>
<th>Year 12</th>
<th>Year 13</th>
</tr>
</thead>
<tbody>
<tr>
<td>Party ID</td>
<td>Obs – Perm (M)</td>
<td>Obs – Perm (M)</td>
<td>Obs – Perm (M)</td>
</tr>
<tr>
<td></td>
<td>.0905</td>
<td>.1276</td>
<td>.1721</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Approval</th>
<th>Obs – Perm (M)</th>
<th>Obs – Perm (M)</th>
<th>Obs – Perm (M)</th>
<th>Obs – Perm (M)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>.0391</td>
<td>.0751</td>
<td>.0899</td>
<td>.1012</td>
</tr>
<tr>
<td></td>
<td>[-.003, .080]</td>
<td>[.027, .121]</td>
<td>[.054, .122]</td>
<td>[.065, .133]</td>
</tr>
</tbody>
</table>

Table 7. Observed clustering (correlation b/w ego and alter’s party identification and approval of Obama) across years.

Note: Cell entries are the mean values of the difference score between observed correlation coefficients (“Obs”) and the correlation coefficients from 1,000 randomly permuted networks (“Perm”), with 2.5th and 97.5th value representing 95% confidence intervals presented in the brackets.
The results of the network random permutation test presented above, however, do not reveal the nature of the associations that drive such observed relationships. Below the results of TERGM analyses attempt to provide the evidence of possible social selection dynamics. That is, is observed clustering of individuals within political discussion networks indeed attributable to social selection processes?

Hypothesis Testing Results for TERGM analyses

Table 8 below presents the meta-analytic summary of the TERGM analyses with 5 multiply imputed datasets per 14 group networks. The cell entries of Table 8 contain unstandardized coefficients for population estimates with their robust standard errors in parentheses, along with their variance components that quantify the group-level variations of parameter estimates (with Chi-square statistics in parentheses). One could interpret a summary coefficient in Table 8 as the “average effect size” following the standard interpretation of the meta-analysis technique. Or, alternatively, it could be regarded as a population-average estimate in terms of log-odds of ties conditional on all other effects presented in the model, while taking the uncertainty of such estimates (based on any group level variations or missing nodal covariates) into account.
<table>
<thead>
<tr>
<th>Homophily effects</th>
<th>Mean estimates (SEs)</th>
<th>Group Variance (Chi-square)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (nodematch)</td>
<td>.290 (.074)**</td>
<td>.071 (223.679)***</td>
</tr>
<tr>
<td>Race (nodematch)</td>
<td>.100 (.088)</td>
<td>.104 (231.401)***</td>
</tr>
<tr>
<td>Religion (nodematch)</td>
<td>.082 (.044) #</td>
<td>.023 (117.400)***</td>
</tr>
<tr>
<td>Obama approval (absdiff)</td>
<td>-.005 (.028)</td>
<td>.010 (106.247)***</td>
</tr>
<tr>
<td>Party identification (absdiff)</td>
<td>-.024 (.012) #</td>
<td>.002 (81.549)***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Nodal covariates / controls</th>
<th>Mean estimates (SEs)</th>
<th>Group Variance (Chi-square)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extraversion, in- ties</td>
<td>.040 (.028)</td>
<td>.010 (130.005)***</td>
</tr>
<tr>
<td>Extraversion, out- ties</td>
<td>-.093 (.023)**</td>
<td>.007 (128.334)***</td>
</tr>
<tr>
<td>Openness, in- ties</td>
<td>.002 (.028)</td>
<td>.010 (86.074)***</td>
</tr>
<tr>
<td>Openness, out- ties</td>
<td>.035 (.032)</td>
<td>.014 (147.587)***</td>
</tr>
<tr>
<td>Agreeableness, in- ties</td>
<td>-.016 (.022)</td>
<td>.005 (69.320)***</td>
</tr>
<tr>
<td>Agreeableness, out- ties</td>
<td>.008 (.032)</td>
<td>.014 (201.988)***</td>
</tr>
<tr>
<td>Consciousness, in- ties</td>
<td>.013 (.027)</td>
<td>.009 (85.366)***</td>
</tr>
<tr>
<td>Consciousness, out- ties</td>
<td>.010 (.043)</td>
<td>.026 (242.845)***</td>
</tr>
<tr>
<td>Emotional stability, in- ties</td>
<td>-.004 (.037)</td>
<td>.018 (105.618)***</td>
</tr>
<tr>
<td>Emotional stability, out- ties</td>
<td>-.038 (.034)</td>
<td>.016 (180.090)***</td>
</tr>
<tr>
<td>1st year, in- ties</td>
<td>-.179 (.068) *</td>
<td>.056 (92.050)***</td>
</tr>
<tr>
<td>1st year, out- ties</td>
<td>-.271 (.075)**</td>
<td>.074 (300.596)***</td>
</tr>
<tr>
<td>2nd year, in- ties</td>
<td>-.136 (.055) *</td>
<td>.036 (82.343)***</td>
</tr>
<tr>
<td>2nd year, out- ties</td>
<td>-.005 (.049)</td>
<td>.028 (96.225)***</td>
</tr>
<tr>
<td>3rd year, in- ties</td>
<td>-.126 (.053) *</td>
<td>.036 (73.504)***</td>
</tr>
<tr>
<td>3rd year, out- ties</td>
<td>-.084 (.098)</td>
<td>.127 (267.734)***</td>
</tr>
<tr>
<td>Political interest, in- ties</td>
<td>.127 (.023) ***</td>
<td>.007 (107.173)***</td>
</tr>
<tr>
<td>Political interest, out- ties</td>
<td>.084 (.025) ***</td>
<td>.009 (170.722)***</td>
</tr>
<tr>
<td>Pol knowledge, in- ties</td>
<td>.023 (.018)</td>
<td>.004 (86.347)***</td>
</tr>
<tr>
<td>Pol knowledge, out- ties</td>
<td>.024 (.018)</td>
<td>.004 (119.105)***</td>
</tr>
</tbody>
</table>

Table 8. Meta-analysis results of the TERGM estimates predicting tie-formation in political discussion networks (N=70)
Table 8 continued.

<table>
<thead>
<tr>
<th></th>
<th>Mean estimates (SEs)</th>
<th>Group Variance (Chi-square)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Lagged (t-1) structural effects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pol disc, t-1 ties</td>
<td>.902 (.103) ***</td>
<td>.134 (122.858) ***</td>
</tr>
<tr>
<td>reciprocated pol disc, t-1 ties</td>
<td>.101 (.068)</td>
<td>.051 (60.896) ***</td>
</tr>
<tr>
<td>friendship ties, t-1</td>
<td>.385 (.092) **</td>
<td>.104 (.122.606) ***</td>
</tr>
<tr>
<td>reciprocated friendship, t-1 ties</td>
<td>.175 (.081) #</td>
<td>.080 (96.123) ***</td>
</tr>
<tr>
<td>time spent together, t-1 ties</td>
<td>.246 (.094) *</td>
<td>.109 (190.151) ***</td>
</tr>
<tr>
<td>reciprocated time spent, t-1 ties</td>
<td>-.042 (.074)</td>
<td>.066 (93.942) ***</td>
</tr>
<tr>
<td>Persistent Sender, pol disc</td>
<td>.011 (.009)</td>
<td>.001 (339.623) ***</td>
</tr>
<tr>
<td>Persistent Receiver, pol disc</td>
<td>.053 (.028) #</td>
<td>.011 (293.841) ***</td>
</tr>
<tr>
<td>Persistent Sender, friendship</td>
<td>-.028 (.006) **</td>
<td>.0004 (187.010) ***</td>
</tr>
<tr>
<td>Persistent Receiver, friendship</td>
<td>-.022 (.014)</td>
<td>.002 (128.628) ***</td>
</tr>
<tr>
<td>Persistent Sender, time spent</td>
<td>-.026 (.007) **</td>
<td>.001 (375.779) ***</td>
</tr>
<tr>
<td>Persistent Receiver, time spent</td>
<td>-.019 (.015)</td>
<td>.003 (158.17) ***</td>
</tr>
<tr>
<td><strong>Concurrent (t) structural effects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Edges (intercept)</td>
<td>20.069 (2.155) ***</td>
<td>64.213 (703.57) ***</td>
</tr>
<tr>
<td>Friendship network</td>
<td>1.625 (.049) ***</td>
<td>.030 (111.988) ***</td>
</tr>
<tr>
<td>Time spent together network</td>
<td>1.759 (.090) ***</td>
<td>.108 (317.579) ***</td>
</tr>
<tr>
<td>Euclidian similarity, pol disc</td>
<td>-26.173 (2.308) ***</td>
<td>79.479 (810.668) ***</td>
</tr>
<tr>
<td>Preferential attachment, GWD-in</td>
<td>1.568 (.360) **</td>
<td>1.754 (309.76) ***</td>
</tr>
<tr>
<td>(Decay parameter $\Phi_{in}$)</td>
<td>1.816 (.190) ***</td>
<td>.522 (544202.44) ***</td>
</tr>
<tr>
<td>Activity effects (GWD-out)</td>
<td>-.409 (.384)</td>
<td>2.036 (1031.105) ***</td>
</tr>
<tr>
<td>(Decay parameter $\Phi_{out}$)</td>
<td>1.192 (.242) ***</td>
<td>.837 (418016.15) ***</td>
</tr>
<tr>
<td>Transitivity (GWESP)</td>
<td>.529 (.028) ***</td>
<td>.009 (88.183) ***</td>
</tr>
<tr>
<td>(Decay parameter $\Phi_{T}$)</td>
<td>1.288 (.103) ***</td>
<td>.157 (130028.22) ***</td>
</tr>
<tr>
<td>Anti-transitivity (GWDSP)</td>
<td>-.166 (.013) ***</td>
<td>.001 (434.135) ***</td>
</tr>
<tr>
<td>(Decay parameter $\Phi_{D}$)</td>
<td>2.151 (.117) ***</td>
<td>.207 (357009.17) ***</td>
</tr>
</tbody>
</table>

While revealing some marginal influences of nodal covariates and homophily-based predictors, the meta-analysis summary of TERGMs uncovered substantial effects of concurrent and lagged cross-network effects (from close friendship and from time spent together networks to political discussion networks). First, a political discussion tie
between any given dyad that shares the same gender (Hypothesis 1) is estimated to be 33% more likely ($\mu_\theta = .290, SE = .074, p < .01$) than a dyad that consists of different gender. This can be contrasted with the result of race homophily, which did not reach the conventional level of significance (Hypothesis 2: $\mu_\theta = .100, SE = .088, p = \text{n.s.}$). For value-based homophily, the average estimate for approval of Obama was also found to be nonsignificant (Hypothesis 3: $\mu_\theta = -.005, SE = .028$). In contrast, homophily based on party identification was only marginally significant (Hypothesis 3: $\mu_\theta = -.024, SE = .012, p < .10$).\(^\text{35}\)

Regarding Research Question 1, it is worth noting that an individual’s presidential approval is likely to be more malleable and easily changeable (therefore having more \textit{plasticity} than one’s party identification) depending on the accessibility of relevant considerations at the moment of judgment (Edwards, Mitchell, & Welch, 1995; Zaller, 1992). On a related note, by virtue of relative stability in one’s party identification over time (Goren, 2005; Green & Palmquist, 1990; Schickler & Green, 1997), one would reasonably ascertain his or her alter’s party identification, even if such judgment is based on certain heuristic cues (Olivola & Todorov, 2010; Rule & Ambady, 2010). Therefore, an ego’s or his or her alters’ party identification would likely have more \textit{visibility} than

\[^{35}\] The political preference based homophily effects have been tested using \textit{absdiff} term in the TERGM specification, which adds one network statistic equal to the sum of $\text{abs}(-)$ for all edges $(i,j)$ in the network, where \textit{preference} is defined as a continuous variable. Therefore, the negative and significant coefficient (such as one for \textit{PID} reported in the result) indicates that a tie between a given dyad is more likely to the extent that the \textit{absolute difference} in their political preferences becomes smaller (i.e., \textit{similar} political preferences).
approval of Obama. Such visibility (relative to presidential approval) may better enable individuals to self-select with whom they choose to associate based on party identification rather than based on approvals, although the magnitude of such an effect appears to be much more nuanced. Therefore, the differential empirical patterns between the two political preference homophily variables could be an indication that attributes that have differing degrees of plasticity and visibility have different implications for social selection dynamics, as implied in the discussion of Research Question 1. Nevertheless, compared to gender homophily ($\mu_\theta = .29, SE = .07, p < .01, \text{Odds ratio} = 1.336$) or other exogenous structural effect estimates (e.g., *concurrent friendship network*: $\mu_\theta = 1.625, SE = .049, p < .001, \text{Odds ratio} = 5.078$), the magnitude of the party identification homophily effect was minuscule and limited, consistent with the results reported in Lazer et al (2010).\footnote{Using the maximum possible value for party identification homophily (=5), a tie between a strong democrat and a strong republican is estimated to be approximately 12\% less likely compared to a dyad with exactly the same political preference (Odds ratio = $\exp[-.024 \times 5]$, conditional on all other effects presented in the model).}

Second, the meta-analysis revealed some significant node-covariate effects in social selection dynamics. Although included as a control, an ego’s political interest ($\mu_\theta = .084, SE = .025, p < .001$) was found to be a significant predictor of one’s out-going ties. That is, an ego who is more interested in politics is more likely to form a tie with his or her potential alters, irrespective of alters’ political interests. Yet the same model specification did not reveal any comparable effect for general political knowledge ($\mu_\theta = .024, SE = .018, p = \text{n.s.}$). The political interest of an alter (Hypothesis 4) also had
significant and positive effects on predicting political discussion ties ($\mu_\theta = .127, SE = .023, p < .001$), suggesting that individuals (a) prefer making political discussion ties towards those who are more interested in politics, similar to the results observed by Huckfeldt (2001). Or, alternatively, (b) those who are interested in politics are more likely to be targeted from alters who are also interested in political interests (considering the significant effect of an ego’s interest). Yet similar to the result observed for out-going ties, general political knowledge of an alter ($\mu_\theta = .023, SE = .018, p = n.s$) was found to be nonsignificant in predicting outgoing ties in political discussion networks.

Although the present study did not offer specific predictions, there were a few significant and discernable nodal covariate effects that deserve to be mentioned. School “seniority” appears to be positively related to the probability of political discussion ties, which is evident in negative and significant coefficients for a series of dummy variables tapping freshmen (for incoming ties, $\mu_\theta = -.179, SE = .068$; for out-going ties, $\mu_\theta = -.271, SE = .075$), sophomore (for incoming ties, $\mu_\theta = -.136, SE = .05$), and junior year (for incoming ties, $\mu_\theta = -.126, SE = .053$, all $p < .05$, all relative to senior year in college being the reference category). It is also notable to find that none of the variables tapping the influence of Big-5 personality traits were significant in models for social selection dynamics, except for extraversion on out-going ties ($\mu_\theta = -.093, SE = .023, p < .01$).\footnote{The direction of the effect for extraversion was, however, in opposite direction from what would have been expected based on the conceptual definition of “extraversion.”}

It is possible that such limited effects for Big-5 traits are due to the highly correlated (and analytically overlapping) control variables in the model. For instance, the
persistent sender and persistent receiver effect term\textsuperscript{38} can be seen as somewhat conceptually overlapping with Big-5 traits, in that such terms both aim to capture any stable (and not explicitly modeled) tendencies of actors making or receiving ties. For close friendship networks, the out-degree of a node $i$ at a previous year had small yet negative effects in predicting political discussion ties for a given year (approximately 3\% less likely to have a political discussion tie: $\mu_\theta = -.028, SE = .006, p < .01$), similar to the effects observed from time-spent together network ties (approximately 3\% less likely to have a political discussion tie, as one’s out-degree from a previous year increases: $\mu_\theta = -.026, SE = .007, p < .01$). For political discussion networks, along with null effects of the persistent receiver term, the persistent sender effect term also generally had limited effect.

Third, the meta-analysis found substantial and discernable effects of lagged and concurrent cross-network effects on the political discussion network (Hypothesis 5a and 5b). The odds of any two individuals having frequent political discussions in a given year were about 46.96\% more likely ($\mu_\theta = .385, SE = .092, p < .01$) if they had close friendship ties \textit{in a previous year}, or about 27.89\% more likely ($\mu_\theta = .246, SE = .094, p < .05$) if they had time-spent together ties \textit{in a previous year}. These effects remained significant with the presence of lagged effects of political discussion itself (i.e., effect of the political discussion tie for a given dyad at a previous year), which increased the odds

\textsuperscript{38} This is done by using \texttt{nodeicov()} and \texttt{nodeocov()} term in \texttt{ergm}, which add single network statistics to the model equaling the total value of indegree($j$) or outdegree($i$) for all edges ($i,j$) in the directed networks.
of a political discussion tie for a given year about 126.45% more likely (or 2.46 times more likely: \( \mu_\theta = .902, SE = 103, p < .001 \)) when the dyad had political discussion ties previously.

For concurrent cross-networks, the effects of both exogenous networks (close friendship and time spent together networks) were also significant and substantial. The odds of a dyad having frequent political discussion ties increased about 5.07 times (or 407.84% more likely: \( \mu_\theta = 1.625, SE = .049, p < .001 \)) based on the concurrent close friendship network ties, and about 5.80 times (\( \mu_\theta = 1.759, SE = .090, p < .001 \)) based on the concurrent time-spent together network ties. Therefore, results supported the notion that the availability (H5a) and intimacy (H5b) for a given dyad significantly predicts the presence of political discussion ties, irrespective of whether such availability and intimacy effects are modeled as lagged or concurrent influences.

Lastly, the meta-analysis found significant concurrent “endogenous” network effects, above and beyond the effects of lagged and concurrent cross-network structural effects. As shown in Table 8, the transitivity parameter (GWESP) (Hypothesis 6: \( \mu_\theta = .529, SE = .009, p < .001 \)) was found to be a positive predictor of tie-formation in political discussion networks, such that on average the odds of a dyad having political discussion ties increased by .529 (1.69 times more likely in terms of likelihood) with the presence of two-path that close the base of a triangle. However, this additional increase of the odds decreased roughly by a \( k \)-power of .72 (e.g., \( \log \text{odds} = 0.529 \times 0.72^k \)) for each
additional $k$ triangle that already close the triads.\textsuperscript{39} It is also notable to find that the in-transitivity parameter was negatively significant ($GWDSP$, or geometrically weighted dyadwise shared partner distributions: $\mu_\theta = -.166, SE = .013, p < .001$), suggesting that the tie-formation within transitive triads is generally prohibited \textit{unless} they are involved within the process of closing an open triad. Likewise, the meta-analysis also indicated a substantial and positive impact of preferential attachment ($GWD$-indegree, Hypothesis 7: $\mu_\theta = 1.568, SE = .360, p < .001$) on probability of political discussion ties, along with nonsignificant and negative impacts of unequal out-degree distribution ($\mu_\theta = -.409, SE = .384, p = n.s.$), such that the odds of a node recruiting additional political discussion ties increased by 1.568 (approximately 4.79 times more likely in terms of likelihood) as a number of existing indegree of a node increases. Yet again, this additional benefit of drawing more ties by virtue of having a large number of ties followed decreasing return, such that this preferential attachment effect has decreased by a $k$-power of .83 (e.g., log odds $= 1.568 \times .83^k$) for an additional $k$-number of existing ties.

All in all, the TERGM analysis and its meta-analysis summary indicated that (a) homophily based on political preferences was rather limited, and (b) the structures of political discussion networks are better explained by lagged and concurrent cross-network effects, (c) along with some significant structural-endogenous mechanisms within the political discussion network itself, as summarized in the Table 9.

\textsuperscript{39}This is done by plugging in the average estimate of the decay parameter for transitivity term ($\lambda = 1.288$) to the GWESP equation presented on page 110. See Hunter (2007) for detailed information regarding the calculation of this curved exponential family term.
<table>
<thead>
<tr>
<th>Effect / Hypothesis</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network Evolution: Selection effects</strong></td>
<td></td>
</tr>
<tr>
<td><strong>H1</strong>: Race homophily</td>
<td>Not supported</td>
</tr>
<tr>
<td><strong>H2</strong>: Gender homophily</td>
<td>Supported</td>
</tr>
<tr>
<td>Religion homophily (control)</td>
<td></td>
</tr>
<tr>
<td><strong>H3</strong>: Political attitude homophily</td>
<td>Partially supported (for PID only)</td>
</tr>
<tr>
<td>Political interest / knowledge of an ego (control)</td>
<td></td>
</tr>
<tr>
<td><strong>H4</strong>: Political interest of an alter</td>
<td>Supported</td>
</tr>
<tr>
<td><strong>H4</strong>: Political knowledge of an alter</td>
<td>Not supported</td>
</tr>
<tr>
<td>Personality / School year of an ego (control)</td>
<td></td>
</tr>
<tr>
<td><strong>Network Evolution: Structural effects</strong></td>
<td></td>
</tr>
<tr>
<td>Edges (intercept) (control)</td>
<td></td>
</tr>
<tr>
<td><strong>H5a/H5b</strong>: Exogenous networks</td>
<td>Supported</td>
</tr>
<tr>
<td>Lagged reciprocated ties (control)</td>
<td></td>
</tr>
<tr>
<td><strong>H5a/H5b</strong>: Lagged exogenous network</td>
<td>Supported</td>
</tr>
<tr>
<td>Persistent sender / receiver effect (control)</td>
<td></td>
</tr>
<tr>
<td><strong>H6</strong>: Transitivity</td>
<td>Supported</td>
</tr>
<tr>
<td>In-transitivity (control)</td>
<td></td>
</tr>
<tr>
<td><strong>H7</strong>: In-degree distribution (popularity)</td>
<td>Supported</td>
</tr>
<tr>
<td>Out-degree distribution (activity) (control)</td>
<td></td>
</tr>
</tbody>
</table>

Table 9. Summary results of the hypotheses testing for TERGM analysis.
Hypothesis Testing Results for GEE analyses

The result of the random network permutation test suggested that there is a significant tendency towards the clustering of individuals following their similarities in political preferences. Yet the meta-analysis summary of the TERGMs did not support the notion that individuals are significantly likely to change their political discussion ties based on political preferences of their potential alters. At best, respondents’ party identification was marginally significant, and the magnitude of the effect was rather limited compared to other structural factors presented in the model.

Given the significant clustering of individuals documented in the network random permutation test, it is likely that the observed patterns were resulted from social influence processes rather than from social selection. Below the results of the GEE analyses aim to address such an alternative possibility, of which summary results are presented in Table 10. The full results for above GEE regression equations are presented in Table 11 and Table 12. The GEE specification outlined in the previous chapter (Chapter 6) estimates a series of regression equations modeling an ego’s political preference (party identification and approval of Obama) as a function of alters’ concurrent political preference, demographic factors (ego’s race, gender, religion, and a series of dummy variables tapping demographic-based homophily), and political correlates such as interest, knowledge, and ideology. Furthermore, all GEE regressions control for an ego’s and alters’ political preferences at prior waves (Cacioppo et al., 2009; Carrington et al., 2005; Fowler & Christakis, 2008b). In estimating GEE regressions, all observations were collapsed to a single 2-wave panel data set with a lagged dependent variable, in a way
that the observations of ego and alters’ political preferences from 2011 to 2013 were set as primary dependent (ego’s) and independent (alters’ preference) variables, while the observations from 2010 to 2012 were set as lagged observations.\textsuperscript{40} The key interests in these GEE models are, therefore, the direction and the magnitude of coefficients modeling the effects of concurrent alters’ political preferences while controlling for an ego’s prior preferences. Furthermore, by controlling an alter’s prior preference, the estimates for alters’ concurrent political preferences are set to be unconditional with respect to possible social selection effects in the GEE models. In addition, multiple observations for an ego across alters within waves are controlled for, while independent working correlations are assumed in the analyses.\textsuperscript{41}

The cell entries of Table 10 (also for Table 11 and Table 12) contain unstandardized coefficients with their pooled robust standard errors in parentheses (averaged across 10 multiply imputed datasets by Rubin’s rule) along with their p-values, of which were derived from Z-value approximation based on the mean value of the point estimates against pooled robust standard errors.

\textsuperscript{40} The data from the first wave (2010 data) do not have lagged observations (i.e., observations from 2009 data) due to the availability of key measures, therefore “concurrent” observations were set from the data from 2011. In collapsing year-series observations, all egos in each year were treated as distinctive observations.

\textsuperscript{41} Independent working correlations are shown to be unbiased and consistent in estimating parameter estimates in GEE models even if the correlation structure is mis-specified (Christakis & Fowler, 2013; also see Schildcrout & Heagerty, 2005).
Table 10. Summary results for key social influence parameters in GEE models estimating ego’s party identification and approval of Obama as a function of alters’ party identification and approval of Obama (imputed N=10).

The first two hypotheses (for normative social influence) posited that an ego’s political preference is more likely to be similar to alters’ political preferences, with such similarities being moderated by the degree of an ego’s observability (i.e., an ability to accurately perceive the attributes of a reference group: H8a) and by the extent to which an ego is embedded in a dense, close-knit interconnections (H8b). These two predictions were tested by estimating a set of conditional effect GEE models using the closeness
centrality (H8a) and the ego-network density (H8b) as the focal moderators. Likewise, the next two hypotheses (for informational social influence) posited that an ego’s political preference is more likely to be similar to alters’ political preferences, with such similarity being moderated by the dyadic differences in political interests between an ego and his or her alters (H9a), and the extent to which an ego is embedded in a non-redundant, loose-knit network (H9b). The results are reported in the “normative influence” panel in Table 10.

Most notably (and contrary to initial expectations), Hypothesis 8a and Hypothesis 8b were not supported by the data, such that none of the interaction coefficients quantifying normative social influence reached traditional levels of statistical significance. The result for informational social influence was largely consistent with normative influence, such that none of the interaction coefficients have reached the conventional level of statistical significance. Therefore, Hypothesis 8 and Hypothesis 9 were not supported by the data.

There are some additional results that deserved to be mentioned. First, the GEE analyses overall indicated a substantial degree of autoregressive influence (see Table 11 and Table 12 for complete details for such coefficients). In other words, an ego’s political preference at a prior wave positively and strongly predicted the ego’s political preference at the current wave (all $b = .650$ or greater for party identification; all $b = .537$ or greater for approval of Obama, all $p < .05$), showing substantial stability over time in political preferences.
Second, the GEE analyses found that there exists a significant and discernable “unconditional” effect of an alter’s political preference on that of an ego’s, following the autoregressive influence of one’s political preferences itself. As shown in Table 10, the political preference of one’s alters have emerged as one of the most consistent and strongest predictors of political preference of a focal respondent. On average per each alter, there was at least a .035 to .049 scale point increase (based on a 7-point scale, depending on model specifications) in an ego’s party identification with a one unit change in a directly connected alter’s party identification. Similarly, with a one unit change in a single alter’s approval of Obama, an ego’s approval is also expected to increase about .096 to .102 scale point (based on 5-point scale) in the direction of alters’ approval, controlling for ego’s and alters’ lagged approvals. Therefore, an additive effect across all pairs of alters increases an ego’s party identification as little as .33 to as much as .44 units (in the 7-point scale) to the direction of the directly connected alters if an ego is surrounded by alters who share the same political preference (given an average of 3 to 6 directly connected alters, depending on specific years in the data). Yet this also means that an effect of an alter’s political preference would cancel out each other when an ego is surrounded by alters with “diverse” political preferences. Similarly, having such a number of alters with the same level of presidential approval brings an ego’s approval to be increased by a .288 to .612 scale point if surrounded by alters who share the same level of political preferences among them, approximately equivalent to the effect of other correlates, such as ideology (for party identification: all b from -.335 to -.414).
<table>
<thead>
<tr>
<th>Main effect</th>
<th>Interest</th>
<th>Betweenness</th>
<th>Closeness</th>
<th>Egonet density</th>
</tr>
</thead>
<tbody>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(intercepts)</td>
<td>2.843 (.499)**</td>
<td>2.879 (.503)**</td>
<td>2.822 (.500)**</td>
<td>2.882 (.504)**</td>
</tr>
<tr>
<td>White (dummy)</td>
<td>-.517 (.138)**</td>
<td>-.516 (.138)**</td>
<td>-.511 (.134)**</td>
<td>-.409 (.133)**</td>
</tr>
<tr>
<td>Black (dummy)</td>
<td>-.220 (.309)</td>
<td>-.217 (.309)</td>
<td>-.220 (.307)</td>
<td>-.200 (.300)</td>
</tr>
<tr>
<td>Female (dummy)</td>
<td>-.085 (.113)</td>
<td>-.084 (.113)</td>
<td>-.080 (.111)</td>
<td>-.066 (.110)</td>
</tr>
<tr>
<td>Gender homophily</td>
<td>.012 (.051)</td>
<td>.012 (.051)</td>
<td>.005 (.046)</td>
<td>-.013 (.045)</td>
</tr>
<tr>
<td>Religious homophily</td>
<td>-.040 (.045)</td>
<td>-.041 (.044)</td>
<td>-.039 (.044)</td>
<td>-.024 (.041)</td>
</tr>
<tr>
<td>School years (ego)</td>
<td>.051 (.056)</td>
<td>.051 (.055)</td>
<td>.048 (.054)</td>
<td>.036 (.055)</td>
</tr>
<tr>
<td>Ideology (ego)</td>
<td>-.337 (.053)**</td>
<td>-.336 (.053)**</td>
<td>-.335 (.052)**</td>
<td>-.339 (.054)**</td>
</tr>
<tr>
<td>Pol interest (ego)</td>
<td>.052 (.049)</td>
<td>.037 (.051)</td>
<td>.054 (.049)</td>
<td>.052 (.048)</td>
</tr>
<tr>
<td>Pol knowledge (ego)</td>
<td>-.023 (.050)</td>
<td>-.022 (.049)</td>
<td>-.022 (.050)</td>
<td>-.025 (.050)</td>
</tr>
<tr>
<td>Focal predictors</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alters’ PID</td>
<td>.041 (.015)**</td>
<td>.041 (.014)**</td>
<td>.041 (.014)**</td>
<td>.035 (.015)*</td>
</tr>
<tr>
<td>Ego’s lagged PID</td>
<td>.662 (.042)**</td>
<td>.661 (.042)**</td>
<td>.663 (.041)**</td>
<td>.661 (.042)**</td>
</tr>
<tr>
<td>Alters’ lagged PID</td>
<td>-.014 (.014)</td>
<td>-.014 (.013)</td>
<td>-.013 (.013)</td>
<td>-.013 (.013)</td>
</tr>
<tr>
<td>Interest difference</td>
<td>x alters’ PID</td>
<td>-.005 (.028)</td>
<td>-.002 (.005)</td>
<td></td>
</tr>
<tr>
<td>Betweenness</td>
<td></td>
<td></td>
<td></td>
<td>-.118 (.156)</td>
</tr>
<tr>
<td>Closeness</td>
<td>x alters’ PID</td>
<td></td>
<td></td>
<td>-.2.495 (2.858)</td>
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<tr>
<td>Egonetwork density</td>
<td>x alters’ PID</td>
<td></td>
<td></td>
<td>-.601 (.444)</td>
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<tr>
<td>No. of observations</td>
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<td>4,261</td>
<td>4,261</td>
<td>4,261</td>
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<td>Residual Deviance</td>
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<td>3306.19</td>
<td>3305.336</td>
<td>3273.641</td>
</tr>
<tr>
<td>Null Deviance</td>
<td>17939.95</td>
<td>17939.95</td>
<td>17939.95</td>
<td>17939.95</td>
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Table 11. GEE estimating ego’s PID as a function of alter’s PID, political discussion network (imputed N=10).
<table>
<thead>
<tr>
<th></th>
<th>Main effect</th>
<th>Interest</th>
<th>Betweenness</th>
<th>Closeness</th>
<th>Egonet density</th>
</tr>
</thead>
<tbody>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(intercepts)</td>
<td>2.191 (.032)**</td>
<td>2.163 (.320)**</td>
<td>2.216 (.315)**</td>
<td>2.179 (.319)**</td>
<td>2.225 (.310)**</td>
</tr>
<tr>
<td>White (dummy)</td>
<td>-.085 (.091)</td>
<td>-.086 (.091)</td>
<td>-.097 (.089)</td>
<td>-.094 (.091)</td>
<td>-.069 (.094)</td>
</tr>
<tr>
<td>Black (dummy)</td>
<td>.421 (.228)#</td>
<td>.416 (.228)#</td>
<td>.423 (.229)#</td>
<td>.416 (.230)#</td>
<td>.463 (.216)*</td>
</tr>
<tr>
<td>Female (dummy)</td>
<td>-.033 (.090)</td>
<td>-.035 (.090)</td>
<td>-.043 (.090)</td>
<td>-.036 (.091)</td>
<td>-.039 (.088)</td>
</tr>
<tr>
<td>Gender homophily</td>
<td>.009 (.031)</td>
<td>.010 (.031)</td>
<td>.021 (.030)</td>
<td>.015 (.032)</td>
<td>.038 (.028)</td>
</tr>
<tr>
<td>Protestant (dummy)</td>
<td>-.087 (.097)</td>
<td>-.086 (.097)</td>
<td>-.089 (.095)</td>
<td>-.081 (.097)</td>
<td>-.090 (.095)</td>
</tr>
<tr>
<td>Religious homophily</td>
<td>.010 (.033)</td>
<td>.012 (.033)</td>
<td>.011 (.033)</td>
<td>.008 (.032)</td>
<td>.015 (.031)</td>
</tr>
<tr>
<td>School years (ego)</td>
<td>-.039 (.039)</td>
<td>-.040 (.039)</td>
<td>-.034 (.037)</td>
<td>-.033 (.038)</td>
<td>-.037 (.037)</td>
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<tr>
<td>Ideology (ego)</td>
<td>-.195 (.032)**</td>
<td>-.195 (.032)**</td>
<td>-.195 (.031)**</td>
<td>-.194 (.032)**</td>
<td>-.197 (.031)**</td>
</tr>
<tr>
<td>Pol interest (ego)</td>
<td>-.059 (.045)</td>
<td>-.046 (.047)</td>
<td>-.067 (.043)</td>
<td>-.059 (.044)</td>
<td>-.047 (.043)</td>
</tr>
<tr>
<td>Pol knowledge (ego)</td>
<td>-.008 (.037)</td>
<td>-.008 (.037)</td>
<td>-.011 (.037)</td>
<td>-.007 (.037)</td>
<td>-.011 (.037)</td>
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<td>Agreeableness (ego)</td>
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<td>.053 (.057)</td>
<td>.057 (.057)</td>
<td>.055 (.057)</td>
<td>.050 (.055)</td>
</tr>
<tr>
<td>Focal predictors</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alters’ approval</td>
<td>.102 (.020)**</td>
<td>.100 (.020)**</td>
<td>.101 (.020)**</td>
<td>.098 (.020)**</td>
<td>.096 (.020)**</td>
</tr>
<tr>
<td>Ego’s lagged approval</td>
<td>.557 (.041)**</td>
<td>.558 (.041)**</td>
<td>.553 (.040)**</td>
<td>.557 (.040)**</td>
<td>.537 (.041)**</td>
</tr>
<tr>
<td>Alter’s lagged approval</td>
<td>-.076 (.016)**</td>
<td>-.077 (.016)**</td>
<td>-.076 (.016)**</td>
<td>-.075 (.016)**</td>
<td>-.075 (.016)**</td>
</tr>
<tr>
<td>Interest difference</td>
<td>-.024 (.028)</td>
<td>-.014 (.008)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>x alters’ approval</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Betweenness</td>
<td>1.339 (.682) *</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>x alters’ approval</td>
<td>-.150 (.160)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Closeness</td>
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<td></td>
<td></td>
<td></td>
<td>2.984 (.1970)</td>
</tr>
<tr>
<td>x alters’ approval</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.563 (.536)</td>
</tr>
<tr>
<td>Egonetwork density</td>
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<td></td>
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<td>-.290 (.331)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>-.177 (.120)</td>
</tr>
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<td>No. of observations</td>
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<td>4619</td>
<td>4619</td>
<td>4619</td>
<td>4619</td>
</tr>
<tr>
<td>Null Deviance</td>
<td>5083.594</td>
<td>5083.594</td>
<td>5083.594</td>
<td>5083.594</td>
<td>5083.594</td>
</tr>
</tbody>
</table>

Table 12. GEE estimating ego’s approval as a function of alters’ approval, pol discussion networks (imputation N=10).
Supplementary GEE Analyses

Despite the evidence for non-random clustering of individuals’ political preferences in political networks (assessed from the random network permutation test), neither the results of the TERGM nor the GEE analyses clearly supported the idea that the political discussion network is indeed responsible – either by social selection or by informational/normative social influence processes – for creating such similarities of political preferences. Especially for the hypotheses concerning the mechanisms of normative (H8) and informational (H9) social influence, the initial expectations regarding such mechanisms were not supported by the data. Instead, the GEE analysis uncovered a substantial unconditional effect of political preferences of one’s alter on that of an ego’s, suggesting a possibility that the observed similarity is based on a much simpler person-to-person contagion process.

The first alternative explanation that accounts for these unexpected findings concerns the possibility that some third variable would cause both of the political discussion networks and similarities of political preferences, therefore political discussion networks and similarities of political preferences are epiphenomenally related. There exists at least some suggestive evidence that people may reasonably infer political preferences of political candidates via implicit cues such as race and gender (Koch, 2000; Mcdermott, 1998), or even from physical attractiveness (Riggle et al., 1992) such as facial cues (Rule & Ambady, 2010) – presumably without explicit political interactions. These findings may suggest similar inference processes for those with whom one routinely interacts (such as close friends) under certain conditions. Furthermore, by virtue
of their significance as a reference group, those with whom individuals routinely interact may be capable of inducing similarities in their political preferences without “actual” political interactions – although we may expect reasonably high correlations between actual political interactions and such routine activities (e.g., availability effects: H5a). Further, political preferences of individuals, especially within university settings, are sometimes correlated with majority-minority positions within networks (e.g., Lazer et al., 2010; Song & Eveland, 2015). Therefore, what appear to be similarities of political preferences may be confounded with the overall availability and composition of groups, which also predict political discussion ties.

To address such possibilities, additional GEE models, presented in Table 13 and Table 14, were estimated using close friendship and time-spent together network ties (instead of political discussion network ties) using otherwise identical model specifications. First, close friend “only” networks, where dyads with political discussion ties are removed from the original close friend networks (therefore capturing close friend ties that do not discuss politics) were created. Next, two sets of GEE models were estimated using close friends “only” networks and using the “original” close friend networks that include political discussion ties. If those two close friends networks – one with and one without political discussion ties – produce identical patterns, it would suggest that an ego’s close friends are also likely to induce similarities in political preferences without explicit political interactions. Further, if patterns from “close friends only” networks are indeed comparable to the results from political discussion networks, then it would further support the notion that some other types of social relations,
“independent” of political discussion ties, might produce similarity in political preferences presumably without explicit political interactions.

Likewise, results from time spent together “only” network, where political discussion ties are removed (i.e., capturing time spent ties that do not discuss politics), are compared with results from the original time spent together network. Under the same logic that other types of networks could induce political preference similarities without explicit political interactions, the key interest in this supplementary analysis lies in the direction and magnitude of effects from those other types of networks – one with and the other without political discussion ties. That is, are other types of social relations, without explicit political interactions, capable of inducing similarities in political preferences?
<table>
<thead>
<tr>
<th></th>
<th>Pol disc network</th>
<th>Friends “only” network</th>
<th>Friends w/pol discussion</th>
<th>Time spent “only”</th>
<th>Time spent w/pol discussion</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Unconditional main effect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alters’ PID</td>
<td>.041 (.015)**</td>
<td>.041 (.014)**</td>
<td>.042 (.012)**</td>
<td>.022 (.013)#</td>
<td>.029 (.011)**</td>
</tr>
<tr>
<td><strong>Normative influence</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alters’ PID</td>
<td>.035 (.015)*</td>
<td>.037 (.014)**</td>
<td>.038 (.011)**</td>
<td>.015 (.013)</td>
<td>.022 (.011)*</td>
</tr>
<tr>
<td>Closeness</td>
<td>-2.495 (2.858)</td>
<td>-2.803 (6.922)</td>
<td>-4.636 (5.459)</td>
<td>-.207 (6.764)</td>
<td>-.293 (.5.645)</td>
</tr>
<tr>
<td>x alters’ PID</td>
<td>-.515 (.423)</td>
<td>-.571 (.881)</td>
<td>-.519 (.630)</td>
<td><strong>-1.980 (.849)</strong></td>
<td><strong>-1.833 (.716)</strong></td>
</tr>
<tr>
<td>Ego-network density</td>
<td>-.601 (.444)</td>
<td>-.835 (.467)#</td>
<td>-.765 (.419)#</td>
<td>-.544 (.415)</td>
<td>-.691 (.382)#</td>
</tr>
<tr>
<td>x alters’ PID</td>
<td>-.041 (.075)</td>
<td>-.076 (.065)</td>
<td>-.055 (.057)</td>
<td>.032 (.067)</td>
<td>.014 (.062)</td>
</tr>
<tr>
<td><strong>Informational influence</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alters’ PID</td>
<td>.041 (.014)**</td>
<td>.040 (.014)**</td>
<td>.041 (.011)**</td>
<td>.022 (.013)#</td>
<td>.029 (.011)**</td>
</tr>
<tr>
<td>Interest difference</td>
<td>-.005 (.028)</td>
<td>-.039 (.029)</td>
<td>.024 (.021)</td>
<td>-.045 (.025)#</td>
<td>.038 (.018)*</td>
</tr>
<tr>
<td>x alters’ PID</td>
<td>-.002 (.005)</td>
<td>-.004 (.006)</td>
<td>.002 (.004)</td>
<td>.001 (.005)</td>
<td>-.004 (.004)</td>
</tr>
<tr>
<td>Knowledge difference</td>
<td>-.023 (.023)</td>
<td>-.013 (.025)</td>
<td>-.015 (.019)</td>
<td>.025 (.022)</td>
<td>.010 (.017)</td>
</tr>
<tr>
<td>x alters’ PID</td>
<td>.006 (.006)</td>
<td>.004 (.005)</td>
<td>.005 (.004)</td>
<td>-.004 (.005)</td>
<td>-.001 (.003)</td>
</tr>
<tr>
<td>Betweenness</td>
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<td>-1.041 (.864)</td>
<td>-1.593 (1.402)</td>
<td>-.583 (.843)</td>
<td>1.024 (1.540)</td>
</tr>
<tr>
<td>x alters’ PID</td>
<td>-.118 (.156)</td>
<td>-.023 (.227)</td>
<td>.031 (.134)</td>
<td>.085 (.200)</td>
<td>-.209 (.177)</td>
</tr>
</tbody>
</table>

Table 13. Summary results for key social influence parameters in additional GEE models estimating an ego’s party identification as a function of alters’ party identification, using close friendship and time spent together network (imputed $N=10$). Friends only and time spent only networks exclude political discussion ties.
Table 14. Summary results for key social influence parameters in additional GEE models estimating an ego’s approval of Obama as a function of alters’ approval of Obama, using close friendship and time spent together network (imputed N=10). Friends only and time spent only networks exclude political discussion ties.
The second and the third column (labeled as friends “only” and friends with political discussion) of Table 13 report the GEE models estimating an ego’s party identification as a function of alter’s party identification, and the latter two columns report the results estimated from time spent together networks. Table 14 reports the identical model specifications for the presidential (Obama) approval as a dependent variable.

First and foremost, the patterns of the results were largely consistent with the results obtained from the political discussion networks. First, both close friend network ties and time spent together network ties, irrespective of whether they contain political discussion ties or not, had a substantial effect in predicting an ego’s political preferences. This finding further suggests the possibility that the significant unconditional effect of political preferences observed from political discussion ties are somewhat blended, or even driven by, other types of social relations such as close friendship or time spent together networks.

Second, regarding the hypothesized mechanisms of social influence, all of the interaction coefficients for informational influence (with dyadic differences in interest and knowledge, and betweenness centrality) were found to be nonsignificant, which is consistent with the results from political discussion networks. However, for interactions concerning the normative social influence, the effects of one’s alters on the ego’s political party identification (but not for approvals of Obama) was significantly conditioned by an ego’s closeness centrality within the time spent together networks ($b = -1.833$, $SE = .716$, $p < .05$), and this was at odds with the results observed from the political discussion
networks (which was in the same direction yet not significant). To further understand the nature of the moderation by closeness centrality within time spent together networks on the impact of alter’s party identification on that of ego’s, the conditional effects of an alter’s PID ($X$) on that of an ego’s ($Y$) were probed using a pick-a-point approach at the sample mean (being “moderate”) and plus and minus one standard deviation from the mean (being “high” and “low,” respectively), as presented in Figure 3. The pattern suggested that the impact of alters’ party identifications were more pronounced when an ego’s closeness centrality was lower than the mean relative to when an ego’s closeness centrality was higher than the mean. This suggests that ego’s ability to accurately perceive direct (in one’s ego-network) and indirect (a group as a whole) political preferences further limit the impact of a particular alter’s political preference.
Figure 3. Conditional effects of an alter’s party identification (X) on an ego’s party identification (Y) as a function of an ego’s closeness centrality on time spent together network (M) at values of sample -1SD (“low”), sample mean, and sample +1SD (“high”), with all other covariates in their sample mean levels.

Note: The plot is based on the results from the original time spent together network (last column in Table 13) that includes political discussion ties. Results without political discussion ties (“time spent only network”) was largely consistent with the reported result.
The research question raised in Chapter 5 asked the impact of the visibility of attributes in predicting the direction of social selection and social influence. As the summary of the TERGM analyses (reported in Table 8 and Table 9) suggests, it appears that party identification had marginally impacted the social selection processes (therefore partially supported Hypothesis 3) whereas presidential approval did not. This empirical pattern was largely consistent with the logic of attribute visibility effects as implied in the Research Question. However, the results of the GEE analyses (reported in Table 10) did not reveal a differential empirical pattern across different types of political preferences (approval vs. party identification) as implied in the Research Question.

One alternative account that may explain such null differences concerns the nature of visibility and observability of political attitudes as opposed to other types of attributes (e.g., behaviors). From the perspective of normative social influence, political “attitudes” – whether it is party identification or presidential approval – may be considered as essentially “personal” and “private” in nature (Eliasoph, 1996; 1998; Gamson, 1992; Mutz, 2002; Schudson, 1997), and therefore would have less visibility and observability (Hayes et al., 2006). Research suggests that when it comes to college students’ political attitudes, overall perceptual accuracy regarding one’s peers appears to be rather limited (Eveland & Hutchens, 2013). This may further imply that political preferences may have limited visibility – and therefore presumably have less plasticity – due to the difficulty in accurately perceiving others’ political preferences, although individuals are inadvertently influenced by their immediate alters as a result of social
contagion processes (as evidenced in significant unconditional effects of directly connected alters).

In order to explore such alternative possibilities based on visibility and plasticity of attributes, a set of additional GEE models was estimated using two different types of attributes – smoking behaviors (with the close friends network), and happiness (with the time spent together network).\(^{42}\) In addition to the fact that smoking behaviors are highly visible due to its manifest behavioral characteristics, research suggests that the initiation, maintenance, and even cessation of smoking behaviors are somewhat susceptible to peer influence (Christakis & Fowler, 2008; Powell, Tauras, & Ross, 2005; Urberg et al., 1997). Also, despite the fact that a psychological state of happiness itself has less visibility, its behavioral manifestation within interpersonal interaction settings may have visibility to others. Fowler and Christakis (2008b) suggest that happy individuals may behave in a way that is helpful, nice, or generous to others, or alternatively, by merely displaying positive emotions they could signify their internal psychological state of happiness to others. In either case, this suggests a rather high degree of visibility (and observability) of happiness in everyday settings.

In order to test this alternative possibility, an ego’s smoking behavior (“how often do you currently smoke cigarettes?”) was modeled as a function of an alter’s smoking behavior within the close friendship network. Likewise, an ego’s happiness (“how happy or unhappy would you say you are, in general?”) was modeled as a function of alters’

\(^{42}\) Close friends and time spent together networks used in this analysis were based on the original network measurements, which include some overlapping political discussion ties in respective networks.
happiness within the time spent together network. In estimating smoking and happiness, additional controls (ego’s stress at time t, extraversion, and consciousness) and an otherwise identical model specification for normative social influence models were utilized. One additional consideration has guided the decision on which networks were used to estimate the influence of peer smoking and peer happiness. Previous research, including several social network studies (Christakis & Fowler, 2008; Mercken et al., 2010; Steglich et al., 2010), consistently indicates that peer relations (e.g., friendship) is one of the strongest predictors of individuals’ smoking behavior. In predicting individuals’ happiness, however, it appears to be the case that the physical distance and the time segmentation (time spent together) associated with such physical distance is more influential in predicting an ego’s happiness (e.g., Cacioppo et al., 2009; Fowler & Christakis, 2008b). Although all of one’s alters are located in the same geographical locations within the context of the present study, they do vary in terms of the amount of time they share together. Table 15 below reports the results of those additional GEE models.

43 Since there was no equivalent measurement tapping the “informational” influence within the context of smoking and happiness, only normative social influence specifications were tested for this additional analysis. Smoking was measured via a 5-point scale from “Never” (=1) to “Everyday” (=5). Happiness was measured via a 7-point scale from “Completely unhappy” (=1) to “Completely happy” (7). In estimating models, all covariates were multiply imputed with MID methods (N=10), therefore dependent variables with originally missing data were excluded by listwise deletion.

44 In those studies, researchers found that a more physically close social relationship (e.g., immediate neighbors and nearby friends) were better predictors of an ego’s loneliness or happiness than distal neighbors and friends. However, using the same FHS dataset they found no discernable difference of those different types of alters (with differing distances) in predicting an ego’s smoking level.
<table>
<thead>
<tr>
<th></th>
<th>DV: Smoking (close friends network)</th>
<th>DV: happiness (time spent network)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Closeness</td>
<td>Egonet density</td>
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<tr>
<td><strong>Controls</strong></td>
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<td></td>
</tr>
<tr>
<td>(intercepts)</td>
<td>.625 (.258)*</td>
<td>.599 (.259)**</td>
</tr>
<tr>
<td>White (dummy)</td>
<td>-.264 (.108)*</td>
<td>-.242 (.107)**</td>
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<tr>
<td>Black (dummy)</td>
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</tr>
<tr>
<td>Female (dummy)</td>
<td>.239 (.059)**</td>
<td>.239 (.058)**</td>
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<td>Gender homophily</td>
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<td>Protestant (dummy)</td>
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<td>-.057 (.068)</td>
</tr>
<tr>
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<td>-.052 (.025)*</td>
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<td>School years (ego)</td>
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<td>.052 (.034)</td>
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<tr>
<td>Stress (ego)</td>
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<td>-.028 (.047)</td>
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<tr>
<td>Extraversion (ego)</td>
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<td>.053 (.029)*</td>
</tr>
<tr>
<td>Consciousness (ego)</td>
<td>-.141 (.039)**</td>
<td>-.137 (.039)**</td>
</tr>
<tr>
<td><strong>Focal predictors</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alters’ smoke / happiness</td>
<td>.142 (.023)**</td>
<td>.146 (.021)**</td>
</tr>
<tr>
<td>Ego’s lagged smoke / happiness</td>
<td>.173 (.049)**</td>
<td>.171 (.048)**</td>
</tr>
<tr>
<td>Alters’ lagged smoke / happiness</td>
<td>-.167 (.052)**</td>
<td>-.165 (.050)**</td>
</tr>
<tr>
<td>Closeness</td>
<td>3.174 (3.783)</td>
<td>-2.851 (7.01)</td>
</tr>
<tr>
<td>× alters’ smoke / happiness</td>
<td>-2.047 (2.410)</td>
<td></td>
</tr>
<tr>
<td>Egonetwork density</td>
<td>- .496 (.278)**</td>
<td>-1.301 (.458)**</td>
</tr>
<tr>
<td>× alters’ smoke / happiness</td>
<td>.283 (.161)**</td>
<td></td>
</tr>
<tr>
<td><strong>No. of observations</strong></td>
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<td>8,800</td>
</tr>
<tr>
<td>Residual Deviance</td>
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<td>4327.59</td>
</tr>
<tr>
<td>Null Deviance</td>
<td>4994.69</td>
<td>4994.69</td>
</tr>
</tbody>
</table>

Table 15. Summary results for key social influence parameters in additional GEE models estimating an ego’s smoking and happiness, using close friendship and time spent together network (imputed N=10)
The results of the additional GEE analysis suggest that the attributes with better visibility and plasticity compared to political preferences are more likely to play a role in social influence processes. First, within the context of predicting one’s smoking behaviors (1st and 2nd columns in Table 15), a directly connected alter’s smoking behavior had a substantial and significant effect on that of an ego ($b = .142$ to $.146$, all $p < .001$). This effect was qualified by a marginally significant predicted interaction effect with one’s ego-network density ($b = .283$, $SE = .161$, $p < .10$). This suggests that if an ego is surrounded with a more cohesive, close-knit network, then he or she would become more susceptible to alters’ influence, in that as an ego’s ego-network density increases 1SD from the sample mean then the impact of a directly connected alter’s smoking on that of an ego is expected to increase about 23.66%. Likewise, in models predicting an ego’s happiness (3rd and 4th column in Table 15), the conditional effect of alters’ happiness was significantly moderated by an ego’s ego-network density ($b = .148$, $SE = .066$, $p < .05$), further providing evidence that the visibility and plasticity of one’s attributes are likely to produce differential patterns regarding the impact of such variables within the social selection process.

It is also noteworthy that, unlike the results obtained from the previous GEE model predicting an ego’s party identification from time spent together network ties, none of the interaction coefficients capturing the observability of an ego (i.e., closeness centrality) had significant results. It may further suggest the possibility that different attributes (e.g., political attitudes vs. health related attributes) would have different boundaries of relevant references groups, such that one may consider broader political
climates (as suggested by the closeness interaction) compared to smoking or happiness, which appear to be more influenced by one’s immediate social contacts (as suggested by the ego-network density), although this interpretation is somewhat speculative.
Chapter 8: Discussion

Focusing on informal political discussion networks and their roles in shaping one’s political preferences, this dissertation sought to uncover complex mutual interdependencies and their dynamic processes of which individuals’ political attributes and political discussion networks simultaneously evolve over time. Much of the prior work on this topic, especially within political communication literature, has relied upon purely egocentric network data derived from sample surveys (e.g., Bello & Rolfe, 2014; Sinclair, 2012), or at best based on cross-sectional whole network data (e.g., Song, 2015; Song & Eveland, 2015). This study, which is rare in its ability to overcome the limitations of such approaches, offers a number of unique contributions – both theoretically and methodologically – to the existing literature concerning dynamic coevolution of one’s social networks and political attributes. Motivated by a number of recent advancements in studies of dynamic coevolution of one’s attributes and social networks (Lazer, 2001; Lazer et al., 2010; Snijders, 2001; Snijders et al., 2007), the current study has proposed and tested a comprehensive theoretical account of social selection and social influence processes.

First, the present study accounts for comprehensive theoretical explanations of dynamic social selection processes, based on various sociological, political, and interpersonal antecedents of political discussion (Berelson et al., 1954; Berger &
Calabrese, 1970; Lazarsfeld et al., 1944; Verba & Nie, 1972; Verba et al., 1995) across multiple levels of analysis. Second, this study attempted to bridge existing theories of normative and informational influence (Deutsch & Gerard, 1955) with many of the graph-theoretical properties of political discussion networks (egonetwork density, closeness, and betweenness centrality) using the longstanding theoretical perspective of social cohesion and its relationship with local network structures (Burt, 1992; 2000; Coleman, 1988; 1990; Friedkin, 1984; 1998). Therefore the present study attempted to provide more convincing evidence concerning possible mechanisms of social influence by offering a set of empirically testable propositions. Lastly, coupled with multiple imputation techniques, the use of whole network panel data – three different types of social relations with four years of panel observation across 14 different groups – provided unprecedented opportunities to draw reasonably justifiable conclusions concerning the causalities between attributes and social network ties. Drawing upon this unique dataset with the use of a proper set of inferential network analysis techniques, the present study aimed to address common methodological criticisms raised against purely ego-centric based or cross-sectional social network studies while also acknowledging the limitations of such data and analytical approaches.

Summary of Results

First, the preliminary analysis using a random matrix permutation test (presented in Chapter 7) indicated that there is a significant tendency towards clustering based on similarities of political preferences, such that an ego’s and her alters’ political preferences
are similar to each other was greater than what we would have expected if such clustering was purely due to chance alone.

Second, the TERGM analyses found that the effect of race homophily (H1) was rather small and nonsignificant. In contrast, gender homophily (H2) was found to be significant and its magnitude of effect was rather substantial when compared to race homophily. Most importantly, the TERGM analyses found weak and generally limited evidence of political preference homophily (H3). Homophily based on presidential approval was not significant at all, and homophily based on political party identification was only marginally significant. This can be contrasted with the result obtained from the matrix random permutation test, which indicated that the clustering of political preference within political discussion is more likely than chance would dictate. Since the matrix random permutation test does not control for other possible mechanisms (e.g., social selections based on dimensions other than political preferences) but only controls for baseline probabilities that emerge from network topologies, this divergent finding between the permutation test and the TERGM analyses appears to be, at least partly, a function of the controls implemented in the TERGM analyses. Alternatively, one could interpret these empirical patterns as an indication that individuals are more likely to have similar political attitudes not mainly by social selection but mainly by the result of social influence. In addition, this differential result across two political preference homophily suggested that an attribute with less plasticity (political party identification) is more likely to play a role in social selection processes (RQ1).

Third, the TERGM analyses indicated that political interest of an alter (H4), availability of a given dyad (“time-spent together” networks: H5a), and intimacy of a
given dyad (“close friendship” networks: H5b) were among the significant factors shaping political discussion networks. The result for political interest of an alter (H4) showed that a probability of incoming ties are more likely for those who have higher political interest, which suggests that those with high political interest are more likely to have incoming political discussion ties from others. The positive and significant effect of political interest was also replicated for out-going ties (political interest of an ego: included as a control), such that individuals who have high political interest are also more likely to send out political discussion ties. However, this pattern was not replicated by political knowledge (H4), such that neither incoming ties nor out-going ties are particularly affected by one’s general political knowledge levels. In terms of the effects of exogenous social relationships, both time-spent together (H5a) and close friendship networks (H5b) exerted a strong influence on political discussion networks, such that lagged and contemporaneous effects of two exogenous networks significantly predicted the probability of political discussion ties even after controlling for the autoregressive influence of one’s political discussion ties at a previous year with a given dyad.

Fourth, the TERGM analyses found significant and substantial effects of transitive closure (as a form of GWESP: H6) and preferential attachment (as a form of GWD-indegree: H7). Specifically, the transitive closure effect was found to be a highly significant predictor of tie-formation in political discussion networks. Likewise, the preferential attachment term (GWD-indegree) indicated that on average there exists a strong preferential attachment pattern across networks. The robust and significant effects of the transitivity and preferential attachment term were further bolstered by the null effects of activity effects (GWD-out) and significantly negative in-transitivity effects
(GWDSP). These contrasting patterns (between GWD-indegree vs GWD-out, and between GWESP vs. GWDSP) indicated that political discussion ties that are being involved in such higher-order effects are not likely to be created unless they close a triangle (as opposed to open-triads as implied in in-transitivity) or directed towards a certain node that many others also discuss politics with (as implied in in-degree effects).

Fifth, the present study did find a significant and robust “unconditional” effect of alters’ political preferences on that of an ego. However, concerning the mechanisms of normative social influence, the empirical pattern did not support evidence regarding a significant moderating effect of closeness centrality (H8a) nor ego-network density (H8b) on the relationship between political preferences of an ego and her alters. This was also true for informational social influence, such that neither the dyadic differences in information/knowledge (H9a) nor betweenness centrality (H9b) significantly interacted with alters’ political preference in predicting an ego’s preference.

Sixth, a series of supplementary analyses found that the observed patterns from the friends “only” network and the time-spent “only” network (i.e., close friends and time spent together networks excluding dyads that have political discussion ties) were largely consistent with the results obtained from the political discussion networks. This suggests the possibility that the significant unconditional effects observed from political discussion ties are likely to be confounded with the effects of other types of social relations. The results from other types of social relations indicated that the other types of social ties (close friends and time-spent together networks) were indeed capable of inducing similarities in political preferences between an ego and his or her alters without explicit political interactions.
Further, the results of the additional analysis suggested that the attributes with better visibility and plasticity (i.e., smoking and happiness) are more likely to play a role in social influence processes (RQ1) compared to political preferences. Most notably, the results suggested that the conditional effects of an alter’s smoking or happiness on that of an ego are significantly moderated by one’s ego-network density. That is, to the extent an ego was embedded in a highly cohesive, closure-like network (as measured by one’s ego-network density), alters’ smoking and happiness had greater impact on the ego’s smoking and happiness. This empirical pattern therefore further provided evidence for normative influence processes in producing similarities of attributes, such that the social network influence through a cohesive network structure can produce similarities of attributes – especially when coupled with more “visible” attributes (i.e., smoking and happiness).

Limitations

The findings from the present study have numerous important implications for our understanding of the nature of political discussion. Yet it is also important to recognize methodological details and limitations of the present studies in interpreting the findings.

Sampling Considerations

Although the present study considered multiple networks from a number of large U.S. Midwestern universities, its study population concerns relatively young adults within a university setting. Previous studies using whole network data have generally relied on such settings (Eveland & Kleinman, 2013; Lazer et al., 2010; Levitan & Visser, 2009; Klofstad, 2009; Wang et al., 2013; Wimmer & Lewis, 2010) or a similar context within primary and high schools (Goodreau et al., 2009; Merck et al., 2010). Yet it is
not uncommon to find social network studies concerning more heterogeneous social settings such as the military (de Klepper et al., 2010), the Framingham Heart Study participants and their offspring cohorts (Fowler & Christakis, 2008; Christakis & Fowler, 2007), formal organizational settings (such as government agencies: Lazer, 2001), fields of professional occupations (such as lawyers: Lazega, Mounier, Snijders, & Tubaro, 2012), or emerging scientific communities (Barabási et al., 2002; Gondal, 2011). It is now well known that college student samples such as the dataset used in the current study, compared to general populations, exhibit presumably less socio-demographic variation, less established political attitudes, and more unstable peer group relations (for a broad overview, see Sears, 1986; for an opposing view, see Druckman & Kam, 2009). Therefore it is possible that the use of a student population (and the peculiarities associated with this sample in particular) could have affected the results in a systematic way. Also, such different contexts in which one’s social networks reside have important implications for the “elasticity” of network ties, such that certain social ties within formal organizational settings or more general adult populations could have ties that are less elastic due to mutual resource dependencies or externally imposed logics of tie-formation. The current study did not account for this.

On a related point, it is also worth mentioning that the use of “whole” network data requires researchers to clearly define relevant network boundaries (Laumann et al., 1989; Marsden, 2005), wherein a list of group members that maintain certain eligibility criteria (such as memberships or a participation in some activities) is required in order to specify the boundaries of networks. In such a situation, pre-defined network eligibility criteria may imply less socioeconomic variation in a given group. For instance, the
participants of the present study mainly come from large Midwestern universities (mostly Research 1 universities), and receive scholarship support from a private foundation, which requires them to have certain extracurricular experience in their high school years. The scholarship is also targeting a certain demographic background (e.g., demonstrated financial need) as an eligibility criterion for the scholarship support. As a result, the demographic composition of this sample is somewhat different from that of the typical general population and biased towards certain socio-demographic factors (e.g., fewer females, fewer racial minorities, and more Catholics).\textsuperscript{45} This could have further limited our ability to detect any significant social selection effects based on certain demographic dimensions and/or political attitudes while undermining the preconditions of informational social influence processes in particular (which requires a considerable degree of heterogeneity in information distributions within the networks). For instance, the TERGM analyses have found that race homophily was not a significant predictor of tie formation in political discussion networks, which contradicts what Wimmer and Lewis (2010) and Lazer et al (2010) found in their analyses using similar social networks formed in college settings. One possible explanation for this null effect of racial homophily in the current study is the relatively low degree of variation in racial categories (approximately 80% of respondents were white), which may have diminished the impact of the racial selection relative to what would have occurred in a more racially heterogeneous sample (such as Wimmer and Lewis’s [2010] or Lazer et al.’s [2010] data).

\textsuperscript{45} Among 14 different universities in which scholar houses are located, two universities are considered Catholic universities.
One of the strengths of the present study, that it relies on multiple social networks across a number of different U.S. universities rather than a single group (Lazer et al., 2010; Levitan & Visser, 2009) or even multiple groups collected from a single university (Klofstad, 2009; Song & Eveland, 2015); this is clearly, in many ways, an important improvement that could address the limitations of prior research. However, as stated above, different “contexts” of social networks and relevant network boundary specification issues appear to have important implications for the diversity of demographic compositions of a group.

**Missing Data and Non-response**

According to Eveland and Morey (2011), one of the inherent disadvantages of panel data is the issue of panel attrition and missing data. The present study dealt with the missing data problem by utilizing several of the best available methods. First, actors’ stable, non-changing (or hardly changing) characteristics such as gender, race, and religion were assumed to be exogenous to one’s social networks (e.g., cannot be changed as a result of social ties: Wimmer & Lewis, 2010). Therefore gender, race, and religion were imputed using the last value carry forward method (LVCF), in that the value of a particular variable at time t is used in imputing missing values for the same subject at time t+1. Second, all other time-varying actor-attribute variables were imputed using multiple imputation procedures described in the methods section, such that all missing values for item non-response were imputed across each cross-sectional dataset. Therefore, any missing values due to early panel exit and late panel entries (i.e., entering and leaving the scholar program) were effectively excluded from the multiple imputation procedures. Lastly, for missing network ties from network non-respondents (i.e., those
who do not complete network surveys but are included in the network as a result of nomination by others), those individuals were excluded from network mapping since the number of network non-respondents for a given year were generally very small (i.e., less than 5% at most). Researchers generally agree that a very low level of missingness in network data such as the present study are not likely to create severe bias in parameter estimations (Huisman, & Steglich, 2008; also see Borgatti et al., 2006; Wang et al., 2012).

Yet especially for whole network data, the issue of “changing compositions” (Huisman & Snijders, 2003) presents another challenge for the issue of missingness. In empirical research using whole network data, a composition of the groups’ networks may change due to actors that join or leave the network at some point in time. This presents a non-random source of variation that potentially affects the overall parameter estimates of statistical models. For the context of the present study, approximately half of the respondents were either joining (due to entering college and the scholar program) or leaving (due to graduation) the networks at each given wave, which presents a significant amount of non-random missing data on edge and nodal characteristic measures in longitudinal models. Yet until now, there has been no systematic assessment of how such composition changes would affect the overall parameter estimates in terms of the magnitude and significance levels (relative to true estimates) of network inferential statistics – except several studies conducted within SAOM frameworks (Hipp et al., 2015; Huisman & Snijders, 2003). This lack of systematic assessment regarding the impact of network missing data is especially true in regression-based frameworks assessing social network influence (such as the one used in this analysis). Therefore, it
would be fruitful for future research to investigate how such composition changes in
whole network data would affect the overall parameter estimates (relative to true known
estimates, e.g., Hipp et al., 2015), or compare relative performances and trustworthiness
of different estimation techniques based on systematic simulations for social selection
models (e.g., TERGM vs. SAOM network evolution functions) or for social influence
models (e.g., GEE vs. SAOM behavioral evolution functions vs. linear network
autocorrelation models).

**Measurement Considerations**

There are some measurement issues that should be addressed in this study. First,
as with most ERGM/TERGM analyses at this point, the social network ties for the
present study have been defined as a nominal response during the data collection phase,
such that all social relations – including “close friends” and “time-spent together”
networks – are declared as binary relations (e.g., “1” for yes, and “0” for otherwise)
rather than as valued social ties (e.g., Eveland & Kleinman, 2013). There is indeed a
strong tendency in network science that nearly all of the analytical tools are based on
binary ties (Borgatti, Everett, & Johnson, 2013) since most of the statistical analysis of
network data was developed from the graph-theoretic framework. The analysis of valued
network data has a relatively small literature despite recent development of statistical
inferential techniques (e.g., Krivitsky, 2012). Therefore it is not unusual – or, rather, it is
typical – to gather information regarding social ties in this way in whole network studies.
However, constraining the initial responses to binary indicators or dichotomizing
observations of valued data after data collection are discouraged practices in general,
since (a) it could cause loss of information, and (b) it can cause considerable ambiguity in how respondents interpret the measurement instruments.

Literature suggests that when a complete roster is provided to respondents, the network measurement is fairly robust to random measurement errors (Borgatti et al., 2006; Wang et al., 2012). Also, studies generally agree that the network measurement provides fairly accurate and valid information on the most important relationships, such that the measurement of networks tends to elicit long-term, typical patterns of interactions such as close friendships or regular interactions (Hammer, 1984; Kogovsek & Ferligoj, 2005). However, it is somewhat ambiguous whether “discussion of politics” would be classified the same as close friendships or time spent together relationships within respondents’ mental representations – and therefore would have similar validity – when participants recall such interactions.

To further complicate the matter, the political discussion network measurement in this study asked to report ties if a respondent “frequently discusses politics, social issues, or current events” with his or her potential alters, without specifying the exact meaning of the term “frequent” by suggesting some quantifiers (such as “once a week” or “almost every day”) but leaving the judgment of what “frequent” would mean to the respondents’ discretion. This issue has been received little attention among scholars (for related discussion of the meaning and accuracy of typical political discussion measurement, see Fitzgerald, 2013; Morey & Eveland, 2015), and there exists some suggestive evidence that such ambiguities in question wording and a lack of agreed upon definitions among respondents could undermine the quality of the data (e.g., Walsh, 2004). Yet the implications for such ambiguity in network measurement has not been sufficiently
addressed within the extant literature (but for notable exceptions, see Eveland et al., 2010; Fitzgerald, 2013; Morey & Eveland, 2015).

For the present study, it is not entirely clear whether, and how, such ambiguity in question wordings systematically affected the quality of the data. For the context of the present study, respondents are required to report whether they have had political discussions “frequently” with someone using binary indicators. Yet there is at least suggestive evidence that the when the term “frequent” or some equivalent quantifier is used as a cut-point in a political discussion measurement, such measurement is likely to elicit very sparse network ties. For instance, within the context of comparing several egocentric network measurements, Klosfstad et al. (2009) report that the average frequency of political discussion among the general public ranged from .57 to .98 based on a 4-point scale, with the highest value of the frequency representing “often” (for 1992 CNES data and 1996 ISL study) or “almost daily” (for 1988 GSS data). Eveland and Kleinman (2013) have used valued whole network data in comparing general and political discussions from voluntary student organizations, and they found that the mean tie strength of a given political discussion network was .24 based on a 4-point scale, with the highest value representing “almost every day.” Given such a low degree of political discussion frequency across studies, it appears to be the case that the term “frequently” used in this study is also likely to generate many disconnected clusters and limited number of political discussion ties (compared to other types of social ties, as evident in
descriptive statistics in Table 2), which somewhat closely resemble the results from Song (2015).

What are the implications for such measurement quality for inferring social selection and social influence processes? If anything, one possibility is that the use of the term “frequent” with binary indicators of discussion ties may prioritize highly stable and strong political discussion ties, and indeed this relation, if it exists, is more likely to exert strong normative influence on an ego’s political preference. Also from the perspective of identifying social selection, such highly stable and relatively infrequent relationships would leads us to find a few, yet highly discernable, factors that create such social selection dynamics. By contrast, by virtue of reporting only “frequent” political discussion ties, any infrequent and occasional political encounters are likely to be buried and dismissed as “no ties” although occasional and random encounters including political discussions (and likely disagreement that associated with such random encounters), in reality, would be much more frequent than what is measured by such instruments. Scholars have generally suggested that such infrequent and occasional political encounters are much more likely to involve political disagreement (Eveland et al., 2013) and diversity of viewpoints that promote political learning (Valenzuela, Kim, & Gil de Zúñiga, 2012), and therefore would have important implications in social influence processes (but for an opposing claim, see Feldman & Price, 2008). By employing a restrictive definition of political discussion ties (i.e., only “frequent” political discussions

46 Although within a considerably different context, Klofstad et al. (2013) showed that the use of more a expansive (i.e., absence of agreement) vs. restrictive (i.e., perceived “overt” disagreement) definition of “political disagreement” could considerably alter the empirical relationships between political disagreement and many political behaviors.
qualify as a tie), it may have further undermined the preconditions of informational social influence process, which requires a considerable degree of “heterogeneity” among connected alters. That is, if the measurement of the political discussion network tends to elicit very strong dyadic political discussion ties (that are not likely to be representative), then an ego and alters are more likely to be similar in many of the aspects – as suggested in a bulk of egocentric discussion network research (e.g., Marsden, 1987; McPherson, Smith-Lovin, & Brashears, 2006). Therefore the use of the term “frequently” in political discussion network measurement is not likely to be suitable to detect “heterogeneity” among potential interaction partners. It may further imply that normative and informational social influence are not able to be detected simultaneously by a single, monotonically defined tie strength, further suggesting the need for using valued network ties and employing varying cut-points in identifying different social influence processes.

It is also worth mentioning that the measurement of “informational” social influence relied upon a far from ideal measure. As discussed previously, the measurement of informational social influence seems to require very specific and idiosyncratic features: (a) a “topical” relevance of information that each individual possesses in regard to a criterion variable (in this case, presidential approval and party identification), and (b) unequal and heterogeneous distribution of relevant “information” within a given social network. For instance, per approval of presidential performance, an ideal measure of informational social influence would tap (a) various criteria of which individuals bring up during political conversations that are perceived to be relevant to the evaluations of a president, and (b) the uniqueness and the novelty of such information being exchanged within a given dyad. Yet such a measure is rarely available among existing observational
social network studies. This further relates to the overall limitations of previous research examining social network influence without examining the “content” that is being exchanged among social ties. For instance, research within small group settings often suggests that a certain “content” feature of information (i.e., number and quality of arguments that support a particular assertion) could be distinguished from a mere distribution of group members’ opinion positions (which presumably convey normative influences via providing descriptive norms) in dissecting normative and informational social influences (Kaplan & Miller, 1987; Stasson & Davis, 1989; Price et al., 2006).47 This further implies that “detailed assessments of what each person actually says in discussion, including both expressions of preference and arguments that are raised” are needed in determining the locus of social influence processes (Price et al., 2006, p. 51). This presumably requires detailed coding of actual “content” of political discussions that have taken place within social networks – which is often available in online networks or within experimental contexts where researchers unobtrusively obtain such information. However, such questions concerning the actual “content” that is flowing within social ties are largely absent in the literature, at least concerning network-attribute coevolution processes using purely observational, offline social networks. This is an interesting future direction to be explored. For instance, future research might examine the content of the actual political discussion and its implications for social influence processes within whole networks. Another option would be to consider the extent to which structural properties

47 However, under certain conditions, the sheer number of individuals who support a certain position could serve as a persuasive argument itself as the elaboration likelihood model of persuasion predicts (Petty & Cacioppo, 1986).
of online or offline social networks coevolve with the meaning structures of political discourse.

Analytical Issues

Another methodological issue deserving to be mentioned, from the perspective of an analysis of longitudinal data, is the issue of correctly matching the appropriate measurement lags with the “duration” of the hypothesized underlying processes or behavioral consequences (Cohen, 1991; Eveland & Morey, 2011; Selig & Preacher, 2009; Slater, 2007). Within the context of explicating a dynamic autoregressive influence of one’s media use and attribute change, Slater (2007) explicitly states, “the fact that one has longitudinal data is no guarantee that one can detect spiral processes if the measurement lags do not reflect a good understanding of the underlying processes” (p. 286). Within the context of the present study, the sociometric questionnaires for political discussion and time spent together networks do not clearly specify the time windows within which such behaviors has occurred. In such a situation, the measurement instruments are likely to elicit very “habitual” and stable behaviors that existed over time, therefore likely to report a tie that has stable, repeated political discussion and time spent together relationships. In contrast, especially for social influence models, any “changes” in outcome variables (i.e., political preferences) are susceptible to decay over time, with decay as a function of time duration (i.e., measurement lags). Therefore, such a stable and habitual nature of attributes elicited, coupled with a substantially longer duration of measurement lags (e.g., a one year lag for current studies), may not detect substantial variations over time in dependent attribute measures for social influence models,
especially if highly stable autoregressive influences are already taken into account in the models (e.g., Hoffman & Eveland, 2010).

It is also worth noting that the model specifications for the GEE procedures, in particular, make a nontrivial assumption about the possible mechanisms of social influence. First, the GEE model used in this study assumes that there is no unobserved homophily effects beyond what is already observed and controlled for in the analysis, which appears to be a somewhat unrealistic assumption under certain situations (Shalizi & Thomas, 2011). Further, the GEE models of this sort assume that there is no correlation between an ego’s attribute of interest (e.g., party identification or presidential approval) and an alter’s attribute except via dyadic interpersonal influence through direct network ties between a given dyad (Christakis & Fowler, 2013). Therefore it implicitly assumes that the social influence, regardless of whether it is direct person-to-person contagion or other forms of social influence process, exclusively and independently operates within the “dyadic” level, as implied in its model specification as a dyadic-independence model (e.g., only one dyadic relationship between an ego and her alter is considered while conditional on all other model parameters: O’Malley, 2013).

Most previous studies have not investigated social selection models using the same data in their analysis of social influence, yet the present study has triangulated the possible social selection dynamics by employing TERGM analysis. The analyses have found that only gender and religious homophily were significant in social selection models, and they are all controlled for in estimations of the GEE models – in addition to an alter’s political preference at a previous time point (which has been shown to control for homophily effects with respect to the attributes in question: Cacioppo et al., 2009;
Carrington et al., 2005; Fowler & Christakis, 2008b). Therefore it is less likely that the present study would suffer similar limitations. Moreover, previous studies that have employed similar analytical techniques have convincingly demonstrated that this assumption of “no unobserved homophily” is indeed somewhat robust against possible model misspecifications under the presence of true unobserved homophily (e.g., Christakis & Fowler, 2013; Fowler & Christakis, 2008a; 2008b; VanderWeele, 2011; VanderWeele & Arah, 2011).

Yet there still remain some valid concerns. As O’Malley (2013, p. 545) has suggested, the GEE procedures “do not account for the statistical dependence introduced by individuals who play the dual role of ego and alter at the same time,” a scenario of which ordinary GEE procedures do not assume in a typical longitudinal data analysis framework. Further, as noted by O’Malley (2013) and by Christakis and Fowler (2013) themselves, an ego within the Framingham Heart Study dataset overwhelmingly had only one or two alters, which suggests that the dyadic independence model assumption (i.e., the influence of a given dyad is independent across different dyads) is likely to be valid and appropriate. In contrast, the present study has a considerable proportion of individuals who have more than a single alter (and alters themselves are also likely to be connected as well), as evident in network descriptive statistics. A more sensible treatment overcoming such limitations within social influence model specifications is still being developed, and full consideration of such an application is beyond the scope of this dissertation. One of the alternative strategies would involve randomized trials or quasi-experiments that enable researchers to directly manipulate or observe the spread of relevant attributes while establishing firm causality (Bond et al., 2012; Coviello et al.,
2014; Huckfeldt et al., 2014; Kramer, Guillery, & Hancock, 2014), yet such an approach would have its own limitations and strengths – as evident in recent controversies surrounding a social network “experiment” regarding emotional contagions (e.g., Kramer et al., 2014).

Theoretical Implications

Evidence from the current study regarding social selection and social influence dynamics sheds considerable light on the nature and origin of political discussion networks and their political consequences. As Sinclair (2012, p. xv) acknowledges, “social influence completes the democratic process” such that “to the extent that people’s relationships influence their politics, social networks drive behavioral patterns that dictate the quality of representation in a democracy.” Discussion networks therefore are believed to play a crucial role in the democratic processes by providing diverse political perspectives (Eveland & Hively, 2009; Mutz, 2002; Nir, 2011) and to increase various civic capacities (Delli Carpini et al., 2004; Fishkin, 1992; Kim & Kim, 2008). Therefore, the extent to which individuals self-segregate with those who have similar political preferences (e.g., Bennett & Iyengar, 2008; Huckfeldt et al., 2004; Wojcieszak & Mutz, 2009) could have profound democratic implications. However, while individuals do exercise choice in the construction of communication networks, choices are intrinsically constrained by autoregressive influences from one’s communication networks (Huckfeldt et al., 2004; Marsden & Friedkin, 1994). In line with this perspective, the results from the present study (especially from the TERGM analyses) suggest that political preference homophily had a rather limited role in explaining the underlying principles of tie-
formation within political discussion networks, similar to the results observed in Lazer et al. (2010), Bello and Rolfe (2014), and Song (2015).

Most importantly for the purpose of the present study, the limited impact of political preference homophily could further suggest the possibility of “mediation” or even epiphenomenal association. That is, what initially appear to be a result of political preference homophily (as evident in the simple network random permutation test) is in fact partly driven by other factors such as gender or religious homophily effects, or exogenous social relationships. From a methodological perspective, it is indeed possible for political preference homophily within political discussion networks to be nonsignificant if exogenous social relations are already homophilous in terms of political preferences. Yet even after considering the fact that demographic compositions of the sample are relatively homogenous for this sample of respondents (i.e., a majority of respondents were white males that were either Catholic or had no religious affiliation), it is somewhat questionable to assume that one’s political preferences are driving factors of exogenous social relations, since individuals do not appear to consciously self-select with whom they “routinely” interact with based on purely political reasons (Eveland & Kleinman, 2013; Huckfeldt, 1983; 1984; Klofstad et al., 2009). At best, in order for exogenous social relations to be homophilous in terms of political preferences, such exogenous relations should be conditioned upon other democratic dimensions that reasonably overlap with political preferences (similar to Blau’s [1974] notion of the consolidation of social parameters). For instance, white male Republicans may be less likely to talk about politics with black female Democrats, not because they explicitly avoid political interactions across the partisan divide, yet simply because of their gender
or ethnicity differences. Such an explanation is indeed quite plausible, yet the present study does not account for such a possibility by employing a TERGM analysis on exogenous networks. It would be fruitful for future research to provide more decisive answers with the TERGM analysis of exogenous social relations (e.g., close friends and time spent together networks) and provide empirical evidence concerning the possibility of mediation via other demographic dimensions or by exogenous social relationships (for similar discussion of this possibility, see Song, 2015). Nevertheless, the TERGM analyses of a political discussion network suggested that, if anything, explicit “political” selection is not likely to be a decisive factor in creating such observed clustering of political preferences, despite the fact that the network random permutation test suggested a significant degree of clustering of political preferences of individuals.

A nonsignificant (or weak and marginally significant) tendency towards political preference homophily therefore leave us with the following possibility: individuals do not consciously self-select with whom they discuss politics, but rather are “inadvertently” exposed to political discussions based on some external, non-political factors (Downs, 1957) such as demographic selections, close friendships, or time-spent together relationships. This empirical pattern is largely consistent with previous studies (Bello & Rolfe, 2014; Klofstad et al., 2009; Lazer et al., 2010; Song, 2015), which suggested political attitude similarities are not likely to be foundational in the structuring of political discussion networks. In line with this perspective, the results indicated that political discussion is more likely with those one who routinely interact with one another (“time-spent together” network), or with those who have close emotional and relational attachments (“close-friends” network) – therefore suggesting that discussing politics is
essentially a byproduct of everyday routine activities (Downs, 1957; Duneier, 1992; Eveland et al., 2011). In other words, much broader, non-political interactions of individuals have a profound implication in understanding the patterns political discussions (Eveland & Kleinman, 2013; Klofstad et al., 2009; Kim et al., 1999; Small, 2009; Song, 2015). At the same time, the significant and positive estimates for alters’ political interest suggests that individuals, when opportunities arise, are indeed likely to discuss politics with those who closely follow politics, utilizing the social supply of potential political discussants. Coupled with previous findings, this implies that (a) social supplies of one’s alters are fundamentally conditioned by one’s non-political interaction patterns, (b) individuals are not likely to self-segregate themselves from whom they disagree, and (c) this social supply of political interaction partners would continue to contribute to the political diversity of one’s immediate environment (Bello & Rolfe, 2014; Huckfeldt, 2001; Huckfeldt & Sprague, 1995; McClurg, 2006).

Among the factors that shaped social selection dynamics, gender homophily appears to be the only substantially meaningful predictors of political discussion network ties, while race homophily was not. While consistent with Huckfeldt and Sprague’s (1995) results, the significant gender homophily observed in this study partially contradicts Lazer et al.’s (201) and Song’s (2015) results, wherein they reported no significant associations between gender homophily and probabilities of political discussion network ties. Prior studies have indicated that among relatively educated, young, and white people (similar to the sample used in this study), gender homophily is not likely to be very salient (Marsden, 1987; McPherson et al., 2001), or at most it only emerges at the very early stages of relationship development (van Duijn et al., 2003;
Newcomb, 1961). Therefore, a significant degree of gender homophily in this study is indeed quite surprising. Yet most of the prior studies have investigated gender homophily within general publics, in which the “spouse” relationship is highly central for “important matters” or political discussion networks. It is unlikely that one’s spouse would know other-sex friends who frequently discuss “important matters” or political issues. This is especially true for both men and women, according to several previous studies (e.g., Louch, 2000; McPherson et al., 2011), such that they are unlikely to have such opposite sex relationships outside of one’s home, if not from other social or voluntary associations. Therefore among general publics, it appears that gender heterophily as a function of a spousal relationship is more prevalent in political discussions or “important matter” discussion networks. In contrast, within the context of the present study, all respondents lived in a scholarship house and therefore were likely to have a reasonable degree of sex-integrated environments (unlike previous studies that deal with general publics), while the gender composition of respondents is largely biased towards males, unlike Lazer et al.’s (2010) or Song’s (2015) data.48 Considering that one of the proximal factors shaping social relations is availability and accessibility of potential alters within one’s immediate environment (Newcomb, 1961), the significant and substantial degree of gender homophily observed in this study does not appear to contradict this logic.

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48 Lazer et al.’s (2010) or Song’s (2015) data have relatively balanced gender distributions, unlike the data of the present study. For the present study, gender homophily was estimated by a uniform homophily parameter (i.e., male and female are estimated to have an equal degree of homophily) yet such parameter estimates are based on unequal distributions of gender (more males than females). Since same-gender relationships among minorities and cross-gender relationships are naturally limited in this situation (as a function of baseline availability effects), the overall parameter estimates might have been driven by homophily tendencies among males.
The TERGM analyses suggested that political discussion is also likely to be shaped by its own endogenous processes, therefore individuals are more likely to discuss politics with whom they previously have discussed politics or with whom they are indirectly connected by their alters. First, the nonsignificant GWD-out (activity) effects suggest that the emergence of a few extremely centralized actors that dominate the entire political discussion network was unlikely, while the preferential attachment (GWD-in) was significant in all of the political discussion networks (as evident in the significant mean parameter estimate) with slight variations across groups. At the same time, significant GWESP (transitivity) parameter estimates, coupled with significant and negative GWDSP (in-transitivity) estimates, were largely consistent with prior research (e.g., Song, 2015). This empirical pattern suggests that a core-periphery structure based on “localized closure” is likely within political discussion networks, such that several (often interconnected) sub-groups of mutually overlapping social circles are prevalent in political discussion networks (Song, 2015; also see Box-Steffensmeier & Christenson, 2014; Gondal & McLean, 2013 for a similar empirical patterns).

The results of the present study regarding social influence processes did not support the initial hypothesis concerning the mechanisms of normative social influence. Neither closeness centrality nor ego-network density significantly moderated the relationship between an ego’s and his or her alter’s political preference within the political discussion networks. This was also true for informational social influence, such that neither the dyadic differences in information or knowledge nor betweenness centrality significantly interacted with political preferences of an alter in predicting the ego’s political preference. Instead, the present study found significant and robust
unconditional effects of an alter’s political preference on that of an ego, suggesting a much simpler form of person-to-person contagion (or assimilation) is likely responsible for creating observed similarities of political preferences within political discussion networks.

It is also interesting to observe that the negative impact of closeness centrality or ego-network density on the social influence parameter (i.e., the effect of alters’ political preferences on that of an ego’s) within both political discussion and time spent together networks, which was opposite from the initial prediction. It is worth stressing that the conditional GEE model presented in the current study estimates the effect of only one particular alter – that is, how much an ego’s political preference is expected to differ when an alter’s preference increases one unit while all other factors, including all other alters’ preferences, are held constant. Therefore it potentially suggests that the effect of just one particular alter becomes more conditionally limited when an ego could observe (or have access to) alternative information regarding a reference group’s attributes, as implied in an increase in an ego’s closeness centrality. Since an increase in closeness centrality would mean that one can easily (and more accurately) perceive relevant others’ attributes, one particular alter’s preference may need to be more “contextualized” within the distribution of preferences among one’s ego-network. Therefore, it may become less effective in changing an ego’s preference when other alters’ opinions are held constant.49

49 Alternatively, this empirical pattern may be heavily driven by simple degree effects. As one’s closeness increases, an ego tends to report more alters (as tapped by outdegree centrality). The zero-order correlations between an ego’s closeness centrality and outdegree centrality within political discussion networks were: r=.847 (year 2010), r=.885 (2011), r=.838 (2012), and r=.854 (2013). This high correlation between closeness centrality and outdegree centrality was also true for the time-spent together network.
This is indeed consistent with prior research showing that the influence of network alters becomes less influential depending on the residual distribution of political knowledge (Richey, 2008) or distribution of political preferences (McClurg, 2006).

Next, a series of supplementary analyses found that close friend “only” and time spent “only” networks, where dyads with political discussion ties are removed from the original close friend and time spent networks (therefore capturing close friend and time spent together ties that do not discuss politics), produced largely identical empirical patterns regarding similarities of political preferences within the network. This further implies that the significant unconditional person-to-person contagion effects observed from political discussion ties are likely to be confounded with the effects of other types of social relations. There is at least suggestive evidence that non-political interactions may produce (although not strong) political implications (Eveland & Hutchens, 2013; Koch, 2000; Mcdermott, 1998; Riggle et al., 1992; Rule & Ambady, 2010; Song & Eveland, 2015), and the result from the present study was largely consistent with this logic. However, as suggested by prior research (Eliasoph, 1998; Eveland et al., 2011; Walsh, 2004), it is not entirely clear that individuals clearly distinguish non-political discussion topics from political ones. Therefore, it is somewhat ambiguous whether the content of interpersonal interactions for other social relations (e.g., close friendship and time-spent network) truly lack a “political” relevance. Prior research has suggested that one’s networks are not specialized across different topics (Huckfeldt & Sprague, 1995; Klofstad et al., 2009; Walsh, 2004), so therefore it is possible that other types of networks would have a similar impact on political preferences if respondents do not clearly distinguish political discussions from other topics (Klofstad et al., 2009).
The results of the additional analyses suggested that the attributes with better visibility and plasticity (i.e., smoking and happiness) are more likely to play a role in social influence processes, as implied in the research question. Most notably, the conditional effects of an alter’s smoking or happiness were more pronounced for an ego with higher ego-network density, suggesting that the greater embeddedness of an ego (coupled with more observability of others’ attributes) produces effective preconditions for social influence. This empirical pattern is indeed in line with the perspective that “public” activities are more easily affected by social influence processes (Sinclair, 2012; Scheufele & Eveland, 2001; Hayes et al., 2006). Collectively, prior studies generally interpreted similar empirical patterns as evidence of normative social pressure over informational social influence, and this is especially true for observational studies (e.g., Mutz, 2002; Sinclair, 2012; Sokhey & McClurg, 2012). However, it is not uncommon to find evidence for informational social influence within extant studies as well (e.g., Huckfeldt et al., 2004; Ryan, 2011).

All in all, the empirical patterns uncovered in the present study reveal the complex and nuanced nature of social influence within one’s political discussion network. Although the overall patterns were somewhat closer to the normative influence explanation than its alternative (especially findings from the supplementary analysis), the nature of unconditional effects documented across the GEE analyses requires a good deal of caution in interpretation. It is important to note that the simple person-to-person “contagion” effect generally does not clearly specify an underlying theoretical mechanism regarding the nature of social network influences. Such associations between attributes of an ego and alters may be the result of simple assimilation, political learning,
normative pressures, or any combination of these factors. If, for instance, alters primarily provide reasons for or against political candidates within election settings (e.g., Huckfeldt et al., 2004) or provide some sort of signals concerning certain political policy and party performance (e.g., Sokhey & McClurg, 2012), then the unconditional effect is consistent with the interpretation that individuals are more likely to adjust their political opinions by relying on social “shortcuts” (Beck et al., 2002; La Due Lake & Huckfeldt, 1998; Huckfeldt, 2001; McClurg, 2006; Sokhey & McClurg, 2012). However, the same unconditional effect could be viewed as a result of social persuasion (Friedkin, 1984; 1993), cross-pressures and ambivalence (Mutz, 2002; Visser & Mirabile, 2004), conformity (Lazer, 2001; Sinclair, 2012), or some sort of affective assimilation process among socially intimate ties (Lazer et al., 2010). Therefore, it is particularly troublesome to infer the nature of such influence without additionally assuming “what is being exchanged” within the networks.

There is a growing consensus that discussion networks cannot be fully grasped by just focusing on self-selection processes (Eveland & Kleinman, 2013; Huckfeldt et al., 2004; Lazer et al., 2010; Song, 2015). In line with previous research that has emphasized the “discursive” logic of political discussions (e.g., Kim & Kim, 2008; Kim et al., 1999), this study further demonstrated that it is essential to consider the complex mutual interdependencies that shape citizens’ everyday political encounters. In line with this perspective, this dissertation sought to contribute to ongoing discussion regarding mutual interdependencies in human political behaviors. The present study, of course, begs many more questions than definitive answers. However, despite the ultimate lack of support for key hypotheses, this study has revealed a more complex and nuanced picture of
coevolutionary processes concerning political discussions and political attributes. As mentioned earlier, the unconditional effects of political preferences of alters are likely to be contextualized within complex dependency patterns (McClurg, 2006; Richey, 2008), and such influence is embedded within the cumulative effects of every other dyadic social influence (Huckfeldt et al., 2004). Implications for such patterns are rather straightforward: the end-result of the dyadic influence would largely cancel out each other if an ego is surrounded with a diverse set of alters. Previous research consistently indicated that individuals do not appear to actively self-select their political interaction partners solely based on political preferences (Eveland et al., 2011; Huckfeldt et al., 2004; Lazer et al., 2010; Morey et al., 2012). The findings from the current study, especially for the TERGM analyses in particular, provides direct support for such viewpoint in a convincing manner, in that individuals are inadvertently influenced by whom they routinely interact with, and this does not necessarily appear to be driven by purely “political” motives. Rather, individuals’ network constructions are largely shaped by their routine activities and idiosyncratic features in the social supply of potential alters. At the same time, such idiosyncratically driven network constructions give rise to complex, ongoing patterns of political encounters – which constitute the “discursive” foundations in the exchange of political preferences (Conover & Searing, 2005; Eveland & Kleinman, 2013; Huckfeldt et al., 2004; Mutz & Mondak, 2006; Walsh, 2004). Therefore this complex pattern would contribute to the collective dynamics of everyday democratic processes by voluntary citizens (Delli Carpini et al., 2004; Kim et al., 1999; Kim & Kim, 2008; Scheufele et al., 2006).
Directions for Future Research

The present study has uncovered substantial evidence of complex interdependencies in political discussion networks and political attributes. Although the findings from the present study have a number of limitations, such limitations help us identify a few promising future directions for improving this line of research.

First, as previously mentioned, most of the whole network research studying selection and influence is based on a case-study approach. Often, this constraint is inevitable, in that as the sheer number of networks that are being measured increases, the cost to researchers also quickly increases (Borgatti et al., 2013). As a consequence, a bulk of the research concerns convenient student samples from college (e.g., Eveland & Kleinman, 2013; Klofstad, 2009; Levitan & Visser, 2009; Song, 2015; Wang et al., 2013; Wimmer & Lewis, 2010) or from classrooms within primary education settings (e.g., Goodreau et al., 2009; Lubbers & Snijders, 2007; Mercken et al., 2010). As a consequence, research that deals with multiple networks often employs networks from a larger, yet relatively homogenous target population. While such an approach is in many ways an important improvement over the single case-study approach and has its own value, what is relatively unknown is whether, and how, different “contexts” of social networks and relevant network boundary specification criteria affect coevolutionary processes through, for instance, varying demographic compositions of a group or varying degrees of network elasticity implied in such different contexts. For instance, Lazer’s (2001) and de Klepper et al.’s (2010) discussions regarding tie elasticity are largely based on a case-study approach, in that they do not provide formal comparison across different types of networks with differing degree of tie elasticity. Therefore, a seemingly sensible
approach to explore such questions may be to sample sufficiently diverse sets of networks to address the “heterogeneity” of groups across different contexts, which is expected to offer additional insights into how such variations of group contexts affect dynamic network-attribute coevolutionary processes. For instance, researchers may purposefully sample a set of whole network panel data from business firms, civic organizations, and schools with a similar number of unique nodes, therefore inducing systematic variability in certain key demographic compositions and/or network elasticity in ties. Alternatively, researchers may rely on a simulation-based approach to first explore such questions (e.g., Siegel, 2009), and validate tentative conclusions with available real-world data. As Lazer and colleagues (2010, p. 267-268) note, “there exists no ideally generalizable setting for the study of social influence” but “society is made up of many diverse micro settings, which vary along dimensions that affect social influence process.” It is essential for future research to explicitly consider such variability and its theoretical as well as methodological implications in studying coevolution processes between one’s social networks and political attitudes or behaviors.

Future research might explore some of the measurement considerations identified in the current study. As discussed above, it appears to be the case that there exists a considerable ambiguity in how respondents interpret political discussion measurement instruments. A number of prior studies on this topic (e.g., Fitzgerald, 2013; Morey & Eveland, 2015) generally suggest that individuals may have considerably different conceptions of what counts as “political” when answering typical political discussion network questions. Also, available evidence (Eveland & Kleinman, 2013; Klosfstad et al., 2009; Song, 2015) collectively suggests that the use of some quantifiers (e.g.,
“frequently” discuss politics) with binary indicators of ties may elicit very strong yet unrepresentative political discussion ties, which may have contributed to the less than optimal quality of the political discussion measurement.

A seemingly useful remedy to this problem was recently suggested by Morey and Eveland (2015), in that they propose that researchers ask multiple, separate questions regarding each aspect of politics, and then construct an index of “political discussion.” For instance, researchers may ask a series of questions regarding (a) tax cuts, (b) unemployment, (c) foreign affairs, (d) campaigns and political candidates running for office, (e) environmental and science issues, (f) social issues such as abortion or gay marriage, and so forth. Such an approach also naturally creates “valued” network ties that can capture multi-layer or “multiplexity” of social relations that leads to the emergence of structural properties in the aggregated “political” discussions (Cardillo et al., 2013; Menichetti et al., 2014). This may further differentiate issue-specific knowledge or information levels among respondents, which would have important implications in identifying informational social influence processes. Researchers may explore, for instance, whether normative and informational social influence are associated with different tie strength in political discussion networks when employing an index-based political discussion network measurement (e.g., normative influence is more

50 This approach has much in common with recently proposed methods of measuring televised exposure to politics (Dilliplane, Goldman, & Mutz, 2013). Presumably, such an approach would likely tap “breadth” of political discussions that one may have with their potential discussion partners, while the conventional approach of asking “frequency” of discussion (e.g., how “often” do you discuss politics) may reveal the “depth” of interactions with the same alter.
pronounced among network ties with higher scale values, whereas informational social influence is more pronounced among network ties with lower scale values).

Another interesting avenue for future research is the possibility of conducting a survey experiment validating a frequency-based discussion network measure using an index-based political discussion measure. For instance, by conducting a small scale survey experiment, one may further explore whether such an “index of political discussion” approach may elicit a different nature of political discussion ties in terms of topologies of networks (such as overall degree distribution, number of components, or transitive triads) from the simple frequency based approach. From a measurement development perspective, it would be fruitful for future research to systematically compare various cutoff values from the simple frequency-based discussion measurement (e.g., “once a week” vs. “couple of times a week” vs. “almost everyday”) with the varying index values from the index-based measurement approach. For instance, does a cutoff value using “a couple of times a week” as a quantifier yield a roughly equivalent result from the index-based measurement approach? Presumably, the index-based measurement approach requires repeating multiple questions per alter, which may not be feasible for a network with a large number of nodes due to respondent fatigue. By systematically comparing the frequency-based measurement with the index-based approach, researchers may establish a reasonably justifiable ground regarding the use of specific measurement approaches.

Another measurement consideration that future research should investigate is the issue of appropriate time lag (or delay) between waves of measurement (Cohen, 1991; Eveland & Morey, 2011; Selig & Preacher, 2009; Slater, 2007). Generally speaking,
more measurement occasions allow researchers to gain more insight about the temporal evolution of networks and associated changes in individuals’ attitudes or behaviors. Moreover, there are two additional considerations: (a) minimizing the possibility of network composition changes (due to early panel exit and late panel entries) between measurement lags, and (b) correctly matching the timing of any effects to be unfolded with measurement lags. Although little is known about how to appropriately identify the measurement lags in longitudinal network measurements, it appears to be the case, at least for the bulk of studies that have been conducted within school contexts, year-based or semester-based observations seems to be common (e.g., Lazer et al., 2010; Mercken et al., 2012; Steglich et al., 2010). Although it seems a sensible approach to take, the chance of introducing exogenous network structural changes due to early panel exit and late panel entries may be minimized by employing much shorter measurement lags (e.g., three month intervals: Knecht et al., 2010) than naturally occurring or seasonal changes (e.g., year-to-year changes due to a new school year). Also, researchers may conduct exploratory analysis by gathering network panel data with much shorter measurement lags, and take the lag as moderator (LAM) approach (Selig, Preacher, & Little, 2012) to explicitly consider the effect of measurement lag itself in identifying how long any effects in dependent variables may take to manifest and how long any effects might take to dissipate. Although the specific theory and prior evidence should ultimately inform decisions regarding measurement lags, such initial exploration using the LAM approach using shorter measurement lags may additionally help researchers to identify reasonably appropriate measurement intervals.
Another area of future research as a logical next step is to combine a content analysis and longitudinal network panel data to better understand the detailed account of actual “content” of political discussion that has taken place within social networks, including expressions of preferences and arguments that are raised during political discussions. There has been substantial scholarly attention to the use of content analysis, especially in political discussion research in general (e.g., Cappella et al., 2002; Himelboim, Gleave, & Smith, 2009; Price et al., 2006; Stromer-Galley & Muhlberger, 2009). To date, however, the use of content analysis has not been explicitly considered at least within the context of studying coevolution between networks and political attributes using longitudinal network modeling techniques. The closest of its kind to date comes from “The Electronic Dialogue Project” conducted by Price and colleagues (2002; also see Cappella et al., 2002; Price & Cappella, 2002; Price et al., 2006), where the project involved a multi-wave, real-time electronic group deliberation about political issues and a presidential campaign that were unobtrusively recoded and included pre- and follow-up surveys of respondents. Future research might employ similar observational strategies, such as those that unobtrusively record all textual data and interaction patterns among participants of online political discussion groups to construct longitudinal whole networks. Message-level content analyses then can be conducted on the content of the actual political discussions, such as the number of arguments (argument repertoire) that support a given claim (Cappella et al., 2002; Price et al., 2006), types of evidence provided by each discussant (Streenbergen, Bächiger, Spörndli, & Steiner, 2003), or actual expression of political disagreement (Eveland et al., 2011; Stromer-Galley, 2007). Recent developments of automated textual data analysis (Grimmer & Stewart, 2013;
Hopkins & King, 2010) and the content-analytic approach to small group deliberations (Black, Burkhalter, Gastil, & Stromer-Galley, 2011; Stromer-Galley, 2007) would able to offer new theoretical and methodological insights when coupled with the statistical modeling of longitudinal network dynamics. Such theoretical and methodological development could be a useful advance for the literature in uncovering the coevolutionary dynamic of social networks and mutual interdependencies of human political behaviors.

Conclusion

Political discussions have long been heralded as the way citizens come to the “core” of modern representative democracies. While the existing line of research on this topic does a good job establishing a strong relationship between political discussions and their outcomes, however, relatively scant attention has been paid in treating political discussions in a way that aligns with its fundamental nature – being “interdependent” and “social.” The purpose of this dissertation, motivated by the recent development in studies of coevolutionary dynamics, was to uncover mutual interdependencies in political attitudes and the causal role of which informal political discussion networks play in shaping such patterns. This study therefore sought to contribute to the ongoing attempts to disentangle social selection and influence processes, and their dynamic relationships over time. The prominent stream of thought in this literature suggests that, while individuals do exercise choice in their construction of social relationships, such choices are inherently constrained by recursive influences from one’s networks. The results suggest that individuals do not consciously organize their political discussion networks solely based on political criteria. Rather, individuals are inadvertently exposed to political
discussions based on some external, non-political causal forces. At the same time, such exposure is likely to be contextualized within a complex, cumulative intersection of every other dyadic political discussion. It appears that neither selection nor influence completely dominate the way in which individuals are exposed to political preferences of others. Therefore, such multifaceted interdependency patterns, as results of this study suggest, give rise to complex, ongoing patterns of political encounters – which contribute to the collective dynamics of voluntary citizens in producing a healthy democracy.
References


Zuckerman, A. (2005). Returning to the social logic of politics. In A. Zuckerman (Eds.), *The social logic of politics: Personal networks as contexts for political behavior* (pp. 3–20).
Appendix A: Survey Instruments and Question Wordings

**Gender.** What is your gender?

1. Male
2. Female

**School year.** What year are you in school?

1. Freshman
2. Sophomore
3. Junior
4. Senior

**Network batteries** (Respondents were provided each of group member’s name. Responses were anchored on a dichotomized scale, with 1 or any non-missing positive integer = “yes”, and 0 for otherwise)

1. *Chapter evaluation:* “Please provide chapter evaluation for each scholar”
2. *Time-spent together network:* “I spend a lot of time around this Scholar”
3. *Esteem network:* “I hold this Scholar in especially high esteem”
4. *Academic network:* “This scholar has assisted me with my academics”
5. *Negative tie:* “Sometimes I do not find it easy to get along with this Scholar”
6. *Close friends network:* “This scholar is a close friend”
7. *Political discussion network:* “I frequently discuss politics, social issues, or current events with this Scholar”

**Race.** What racial or ethnic group best describes you?

1. White
2. Black
3. Hispanic
4. Asian
5. Native American
6. Middle Eastern
7. Mixed
8. Other
Religion. What is your religion?

1. Baptist – any denomination
2. Catholic
3. Mormon
4. Jewish
5. Muslim
6. Hindu
7. Buddhist
8. Pentecostal
9. Eastern Orthodox
10. Other Christian
11. Other non-Christian
12. None

Political party identification. (Responses were gauged on a 7-point scale, from “Strong Republican” (1) to “Strong Democrat” (7), with “Independent/Some other party” (4) being the middle point of the scale).

Generally speaking, do you think of yourself as a….?

1. Strong Republican
2. Democrat
3. Independent
4. Another party

Would you call yourself a Strong Republican?

1. Strong Republican
2. Not very Strong Republican

Would you call yourself a Strong Democrat?

1. Strong Democrat
2. Not very Strong Democrat

Do you think of yourself as closer to the…?

1. Republican party
2. Democratic party
3. Neither

Interest in politics. In general, how interested are you in politics and public affairs?

1. Very interested
2. Somewhat interested
3. Slightly interested
4. Not at all interested
Ideology. In general, do you think of yourself as…?

1. Extremely liberal
2. Liberal
3. Slightly liberal
4. Moderate
5. Slightly conservative
6. Conservative
7. Extremely conservative

Political knowledge.

1. Do you happen to know what job or political office is now held by Dick Cheney? (since 2012: held by Joe Biden?)
2. Whose responsibility is it to determine whether a law is constitutional or not?
3. How much of a majority is required for the US House and Senate to override a Presidential Veto?
4. Which party currently holds a majority of seats in the House of Representatives?
5. Which of the two major political parties is generally considered more conservative?

Big-5 personality. Here are a number of personality traits that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement.

1. (Extraversion) Extraverted, enthusiastic
2. (Agreeableness) Critical, quarrelsome
3. (Conscientiousness) Dependable, self-disciplined
4. (Emotional stability) Anxious, easily upset
5. (Openness) Open to new experience, complex
6. (Extraversion) Reserved, quiet
7. (Agreeableness) Sympathetic, warm
8. (Conscientiousness) Disorganized, careless
9. (Emotional stability) Calm, emotionally stable
10. (Openness) Conventional, uncreative

Presidential approval. Do you approve or disapprove of the way Barack Obama is handling his job as president?

1. Strongly disapprove
2. Disapprove
3. Neither approve or disapprove
4. Approve
5. Strongly approve
Appendix B: Descriptive statistics for TERGM and GEE datasets

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Table 16. Descriptive statistics from sparse matrices for TERGM analyses.

*Note:* (1) Number of nodes from concurrent networks (year 2011 to 2013). (2) Average degree in each sparse matrices. (3) Graph density of sparse matrices. (4) Number of weak components in sparse matrices. (5) Average path distance. (6) Number of isolates in sparse matrices.
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Table 17. Descriptive statistics for GEE models, political discussion network.
Table 17 continued

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Note. Variables with single asterisk were not imputed by multiple imputation. Variables with double asterisks were derived from network data, therefore do not have variability across datasets.