Contagious Politics: Tie Strength and the Spread of Political Knowledge

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Abstract

This work explores the influence of social connections on young people's political knowledge. Extending previous research on individual and interpersonal predictors of political learning, the study examines relational characteristics and their role in informed citizenship. Factors expected to affect social contagion in political behavior include conversation content, interaction frequency, relational closeness, mutual communication partners, and shared ideology.

The analyses were based on longitudinal network data from thirteen residential student communities. The study found evidence consistent with social contagion. The political knowledge of participants was predicted by the knowledge of their strong social ties. Political discussants were not as influential as high-frequency general conversation partners. These findings have important implications for research exploring social influence on political behavior. They signal that the contacts we tend to identify as political are not necessarily the ones that matter most in shaping our opinions and attitudes.

Keywords: political knowledge, social influence, social networks, political communication, tie strength, political homogeneity

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Informed citizenry is crucial for the wellbeing of a democratic society. While different models of democracy engender different normative expectations for citizens, a basic understanding of the political process is required for meaningful deliberation and public participation (Stromback, 2005). Political knowledge is consistently associated with key civic outcomes (Delli Carpini & Keeter, 1997). It is a strong and reliable predictor of engagement in politics. Being informed also increases the likelihood that the political choices we make are in our own best interest.

Most people today acquire political information from a mix of mass media and interpersonal sources. Relevant conversations with friends can increase our political knowledge (Eveland & Thomson, 2006). In some cases, our social ties can even compensate for a lack of information due to low news consumption (Andersen & Hopmann, 2018).

Works exploring the network correlates of political knowledge typically focus on the role of political discussion ties. Recent social contagion research, however, highlights the importance of looking at a wider variety of relationships. Both the nature and the structural characteristics of social connections can affect their ability to spread information and change minds (Centola & Macy, 2007). The strength of a relationship as well as its communication content may determine the impact it will have on political and civic behavior. In many cases, stronger ties that only occasionally share relevant information are still more influential than weaker ties who offer more pertinent and novel knowledge (Aral & Van Alstyne, 2011). Strong ties are also more likely to influence our attitudes and behavior (Centola, 2018).

Combining insights from political communication and network science, this study examines the impact of social interaction on informed citizenship in early adulthood. Key properties of social ties examined in this work include their communication *content* (political or general discussion), their *frequency* (the rate of interaction), *capacity* (the volume of information that can be exchanged), *redundancy* (the number of shared connections), and *political homogeneity* (the ideological similarity of the partners).

The analyses reported here are based on longitudinal full-network data from thirteen residential student communities. The study finds evidence of contagion in political knowledge and discusses the critical conditions required for interpersonal influence to take place. Results show that the political knowledge of participants is predicted by the knowledge of their strong social ties. Alternative hypotheses are examined to make sure that network influence is the best explanation for the results presented here. Sensitivity checks provide a test of the model robustness against unmeasured confounding. The paper concludes with a discussion of the theoretical and methodological implications of the findings.

Predictors of Political Knowledge

Research exploring the sources of variation in political knowledge has identified a number of influential personal and social factors. The key predictors include individual characteristics (demographic, political, and psychological traits); news consumption (exposure, attention, comprehension, and retention of information from different news sources); and political discussion (frequency of political talk, as well as number and attributes of the discussants).

While interpersonal discussion is of most relevance to this work, the literature review also includes a brief outline of individual and media predictors of informed citizenship. The following sections highlight key findings of current research in the area before moving on to elaborate on the impact of social ties over and above other predictors of political knowledge.

Individual Factors

At the individual level, a number of demographic characteristics consistently predict factual political and public affairs knowledge. Research typically finds a higher level of political knowledge among better-educated, higher-income, older, whiter respondents (Fraile & Iyengar, 2014; Gil de Zuniga & Diehl, 2019). Work in the knowledge gap tradition has explored the disparity in knowledge among socioeconomic groups and the role that news media play in widening the gap between information haves and have-nots (Eveland & Scheufele, 2000; Tichenor, Donohue, & Olien, 1970). Political content, often tailored for the upper-middle class, is more likely to be selectively consumed and better understood by its intended recipients, perpetuating existing knowledge inequalities.

Research has also uncovered a gender gap in political knowledge with women consistently scoring lower than men, though the differences are smaller among younger and better-educated respondents (Jerit & Barabas, 2017). Factors known to increase that gap include a stronger interest in national politics among men, and a lower tolerance for uncertainty among women, making them more likely to respond *Don't know* (Miller, 2018).

Other key individual-level predictors of knowledge include political variables such as *interest*, *ideology*, *party affiliation*, and *strength of partisanship*, as well as personality traits such as *need for orientation* and *need for cognition* linked to personal motivation for seeking and processing information (Lee & Oh, 2013; Liu & Eveland, 2005).

News Consumption

Since only a few of us have direct access to political figures and events, current affairs and political information is typically obtained through media reports. Research has found mutual influence between political learning and attentive news use (Moeller & de Vreese, 2015).

Scholarship examining the attention, comprehension, and retention of information from the news often focuses on differences across formats. Findings suggest that consuming more print and online news is associated with higher levels of political knowledge (Eveland, Marton, & Seo, 2004; Kenski & Stroud, 2006).

Moving beyond the focus on news exposure, the cognitive mediation model (Eveland, 2001) examines the relationship between motivation, information processing, and political learning. Paying attention to new information and connecting it with previously learned ideas makes it more likely that news exposure will increase knowledge.

Recent social and technological shifts have complicated the way citizens acquire and process political knowledge. In a high-choice media environment, individuals have access to virtually unlimited options for mass and interpersonal communication. The wealth of news sources allows those who are already politically interested to find abundant information, while the uninterested have the option to tune out current affairs and focus on other content.

While attentive online news consumption is expected to increase political knowledge and participation (Boulianne, 2015), passive reliance on digital platforms for information may have the opposite effect. Accidental exposure to occasional news stories on social media can give people the false impression that they are well-informed about current affairs despite not following the news. This "news-finds-me" perception is associated with lower levels of political knowledge and participation (Gil de Zuniga & Diehl, 2019).

Interpersonal Discussion

The discussion of politics is an essential driver of democratic participation. Interpersonal communication networks are expected to transmit information about news stories and political messages that can increase political knowledge. Conversations on civic topics can contribute to political learning (Eveland & Thomson, 2006), compensating for gaps in knowledge experienced by people with lower news consumption (Andersen & Hopmann, 2018). Across news use levels, talking about politics can lead to a better comprehension and retention of information (Scheufele, 2002).

Beyond just exposing us to new information, conversations about politics can improve the storage and retrieval of political knowledge. Building on the cognitive mediation model, Eveland (2004) suggests that discussions affect our motivation and information processing. Anticipating a future discussion can prompt individuals to pay more attention to the news and think about politics. Moreover, talking with others requires accessing already stored knowledge and making new connections between ideas, thus stimulating learning.

Key factors in this area include the size and composition of discussion networks. While discussing politics with a larger number of people is expected to contribute to learning, findings around the political heterogeneity of discussants are less clear-cut (Eveland & Hively, 2009). Having conversations with people who disagree with us can be beneficial and motivate learning (Scheufele, Nisbet, Brossard, & Nisbet, 2004). On the other hand, having diverse social ties with conflicting opinions could be a problem as it increases our uncertainty about political facts and choices (Huckfeldt, Mendez, & Osborn, 2004; Mutz, 2006).

Social Influence on Political Knowledge

Recent experimental studies (Carlson, 2019; Eveland & Schmitt, 2015) have expanded our understanding of the mechanics shaping political discussions and their influence on learning. One thing those experimental efforts do not capture, however, is the long-term, cumulative impact of social relationships. This work contributes to the existing literature by using panel network data to examine the characteristics of potentially influential social ties. The expected effect in this context stems from mechanisms of social contagion: the transmission of information and norms relevant to political knowledge through interpersonal communication.

Research examining predictors of political activity has found that social influence affects a wide variety of attitudes and behaviors, from ideology to voting (Ognyanova, 2019; Rolfe & Chan, 2017; Sinclair, 2012). Our political knowledge is likely also influenced by the expertise of our contacts. Conversations are more likely to contribute to knowledge when our partners are familiar with the subject (McClurg, 2006).

Conversely, ill-informed discussants could introduce false information or create confusion resulting in lower political knowledge.

In addition to sharing information, our interpersonal ties also exert normative influence (Deutsch & Gerard, 1955). We monitor the people around us to learn what opinions and behaviors are considered socially acceptable. Our desire for social approval provides a strong motivation for behavioral conformity. Over time, our social environment can change the way we think about information seeking, learning, and civic participation. If, for example, paying attention to politics is the norm among my peers, I may become more informed in order to fit in. If, on the other hand, conversations in my social circle revolve around speculations and conspiracy theories, I may adjust my information preferences accordingly, becoming less knowledgeable in the process.

While social contagion may be a relevant mechanism affecting political knowledge, not all of our interpersonal contacts are likely to be equally important. Seeking to identify influential social ties, most research in the area focuses on the *content* of interpersonal communication. Having conversations about politics does seem crucial if we are to change someone's political attitudes or behavior. Because of that, the social effects examined in the literature usually focus on the role of political discussants. It is, therefore, reasonable to expect that the social ties respondents identify as *political* would be relevant here:

> **H1 (*Tie content hypothesis*):** Individual political knowledge will be positively predicted by the knowledge of one's *political ties*.

Tie Strength and Homogeneity

While political ties are widely studied in the academic literature, their use in research does suffer from some conceptual and practical shortcomings. For one thing, people vary in their understanding of politics (Fitzgerald, 2013). What counts as a political discussion for some may not be considered relevant by others (Morey & Eveland, 2016). It is also difficult for survey respondents to disentangle political talk from other ordinary conversations. Influential discussions of politics are often embedded in our everyday social interactions (Klofstad, McClurg, & Rolfe, 2009; Minozzi, Song, Lazer, Neblo, & Ognyanova, 2019). Interpersonal relationships that we may not think of as political can still influence our ideology, partisanship, and electoral choices (Sinclair, 2012). Network ties that involve frequent communication on general topics are likely to also exchange political information (Eveland & Hutchens, 2013). Connections with friends, colleagues, or classmates may thus have an impact on political knowledge

(Pietryka et al., 2018).

Network science can assist us in identifying potentially influential social ties. Tie strength is one key factor known to affect both information diffusion and behavioral contagion. In his seminal work on the subject, Granovetter (1973) suggests that we rely on strong, intimate relationships for material and emotional support, while weaker ties are a better source of novel information. Strong ties are expected to be more similar to us, move in the same circles we do, and rely on the same information sources we use. In contrast, weak ties are often seen as more diverse and more likely to connect us to new people and ideas.

Follow-up research finds support for some of Granovetter's insights but paints a more complicated picture. Cohesive networks with strong ties have the capacity to transmit more information faster, and messages get reinforced when they are repeated by multiple contacts (Aral & Van Alstyne, 2011). Weak ties may offer a higher proportion of new information, but they also tend to be slower and less reliable in delivering it. Because of that, in a complex or rapidly changing environment, strong ties do provide more novel information (Aral, 2016; Bruggeman, 2016). They are also in a better position to influence attitudes and affect behavior (Centola, 2018). In less dynamic settings where information is scarce or easily digestible, weak ties are more helpful. Given the complexity and fast pace of U.S. politics, strong ties may be in a better position to deliver information and influence knowledge.

How then do we identify those strong ties? Recent research (Brashears & Quintane, 2018) suggests that tie strength is a multidimensional construct that incorporates three separate factors: *capacity* (the volume of information or resources you can exchange with a person), *frequency* (the rate at which those exchanges occur) and *redundancy* (the extent to which you share other social contacts with that person). Social ties that are emotionally closer to us (relatives, good friends) are expected to have a higher capacity. Such *close ties* can be mobilized to provide information and resources when needed, even if we interact with them infrequently. Conversely, the *intense ties* with people we see often (colleagues, classmates) may not always have a high capacity, but they do have a high communication frequency.

Based on the literature on tie strength, we can expect that:

H2 (*Tie capacity hypothesis*): Individual political knowledge will be positively predicted by the knowledge of one's *close ties*.

H3 (*Tie frequency hypothesis*): Individual political knowledge will be positively predicted by the knowledge of one's *intense ties*.

Tie capacity and frequency characterize the communication (or resource) flow among connected individuals. *Redundancy*, the third dimension of tie strength, is based on the structure of connections (Brashears & Quintane, 2018). Ties high in this dimension connect us to individuals who move in the same social circles we do and with whom we have many shared contacts. We may already know much of the information those redundant ties tell us since we have many overlapping conversation partners. On the other hand, those ties can reinforce learning by repeating ideas we may have heard elsewhere (Centola, 2018). Moreover, because of the shared social context, redundant ties can exercise stronger normative pressure (Krackhardt, 1999). It is, therefore, likely that:

> **H4 (*Tie redundancy hypothesis*)**: Individual political knowledge will be positively predicted by the knowledge of one's *shared ties* (people connected to many of our other contacts).

While homogeneity is not a dimension of tie strength, stronger ties with whom we share more contacts and experiences are also likely to be more similar to us in their choices, attitudes, and demographic characteristics (McPherson, Smith-Lovin, & Cook, 2001). Connections between similar partners are known to enhance social contagion, leading to faster and broader spread of new practices and opinions (Centola, 2011; Rogers, 1995).

Perceived similarity is also a crucial factor in political interactions. The outcomes of public deliberation, for instance, depend on the ideological homogeneity of conversation partners (Wojcieszak, 2011). As party affiliation becomes an increasingly central part of American social identity (Mason, 2018), people tend to favor others who share their political views and distrust those who do not (Iyengar & Westwood, 2015). We are generally more accepting of arguments made by our own side and more resistant to ones coming from members of the opposing party. Given the choice, people prefer to get information from co-partisan ties not only when seeking answers about politics, but also when investigating entirely unrelated matters (Marks, Copland, Loh, Sunstein, & Sharot, 2019). In political discussion experiments, participants have been able to learn more from informants who were not only knowledgeable, but also politically like-minded (Carlson, 2019). The last hypothesis of this study thus suggests that:

> **H5 (*Tie homogeneity hypothesis*)**: Individual political knowledge will be positively predicted by the knowledge of one's *co-partisan ties.*

The five hypotheses of this work are presented on Figure 1.

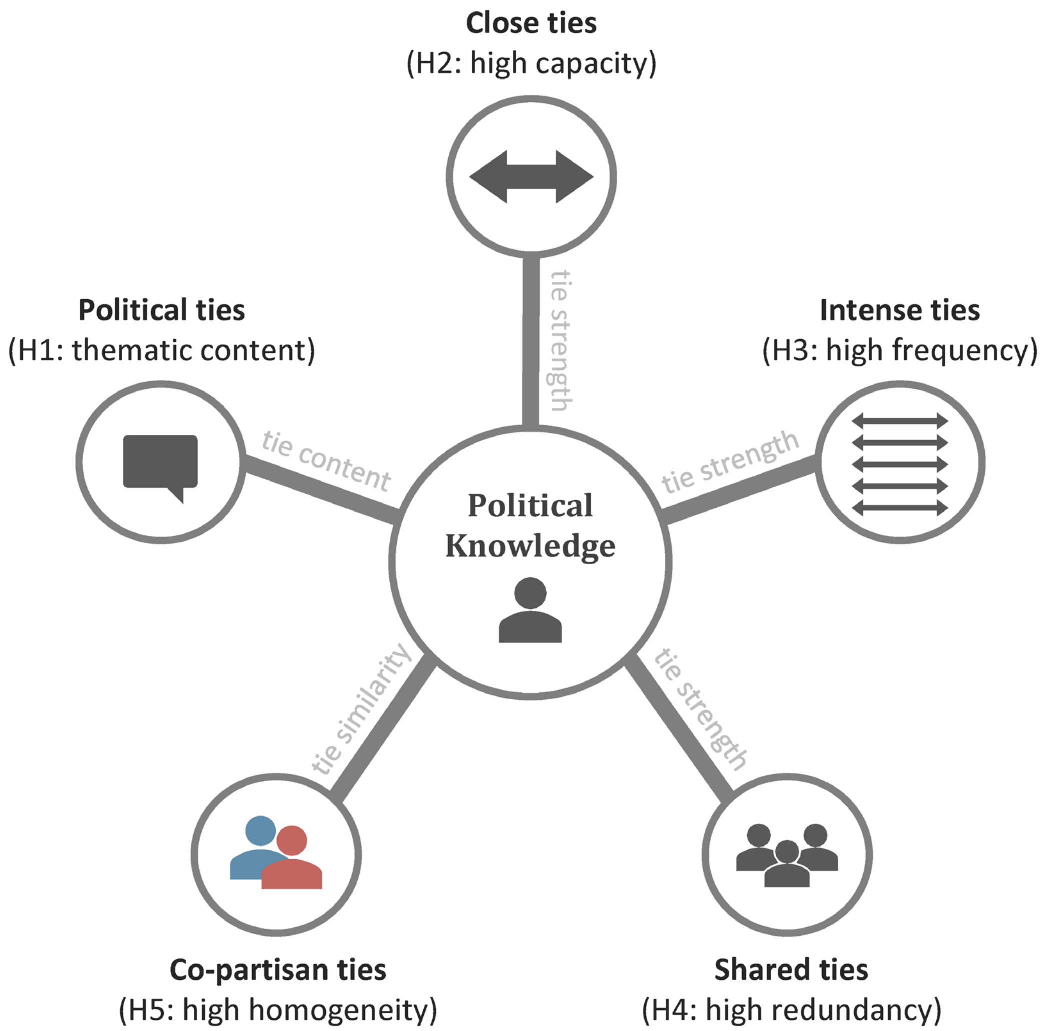

Figure 1. Social influence on political knowledge: hypothesized types of ties.

Method

Study Context

The analyses examined the social networks of 13 residential student communities. The communities were part of a living-learning program operating at a large public university. Each community included students who lived in the same dormitory and took classes together. Each community was based on a distinct academic discipline or interest (business, psychology, pre-medical, French language, etc.). Shared living spaces and collective learning were expected to facilitate the formation of influential and enduring social ties.

The study was based on full-network longitudinal data collection, following in the tradition of previous research on social ties in college (Klofstad, 2010; Sacerdote, 2001). Such datasets can be challenging to collect but they help us identify complex interdependencies between social structure and individual behavior (Eveland, Hutchens, & Morey, 2012; Ognyanova, 2019). In contrast with several earlier studies, however, in this case researchers were not able to randomly assign students to rooms in the dormitory.

A key feature of full-network studies is that they focus on a specific social context and may not always generalize broadly to all types of communities. In this case, the social context is also of substantive interest. College years are a time when people develop attitudes and establish habits that might persist for decades after (Ghitza & Gelman, 2014; Klofstad, 2015). During that period, we also form strong and lasting interpersonal relationships that might influence our behavior throughout our adult lives (Newcomb, 1943). Understanding the informational and normative influence of those ties on political knowledge seems, therefore, particularly relevant and important.

Procedures and Participants

The data used here came from two survey waves completed in the last week of August and first week of December of 2017 (further referred to as W1 and W2). Students received the first survey before entering the living-learning program, while the second survey was sent out at the end of their first semester. The time period between the two waves captured an important transition as students entered a new social environment.

The surveys were distributed to all 390 members of the 13 residential communities. Community size varied from 88 members for the largest to 8 members for the smallest, with a typical size of 20 to 40 community members.

Students received e-mail invites with unique links to an online questionnaire using the Qualtrics platform. Institutional review board (IRB) guidelines for human subject research were followed in the design and administration of the study[1]. As an incentive, participants were included in a drawing for ten $15 Amazon gift cards and one Apple iPad Mini. The response rates were high: 83% (*n* = 325) in Wave 1 and 72% in Wave 2 (*n* = 280). Unless otherwise noted, the analyses conducted in this study were based on a sample of 255 respondents who participated in both survey waves.

[1] Rutgers University, Arts and Sciences IRB protocol #18-037M, continuing review approved 09/2019.

Sensitivity power analysis for this sample size (α = .05, power set to .80) suggests that effect sizes as small as f^2 = .03 could be detected. The demographic characteristics of the respondents are available in Table 1.

Table 1. *Demographic characteristics of the sample*

Variable	Time 1	Time 2
Gender: Female	57%	60%
Race/Ethnicity: White Non-Hispanic	28%	26%
Race/Ethnicity: African American	20%	17%
Race/Ethnicity: Hispanic	20%	19%
Race/Ethnicity: Asian	37%	41%
First generation immigrant	18%	20%
Party ID: Republican	9%	12%
Party ID: Democrat	67%	69%

Table 2. *Key variables - descriptive statistics*

Variable	Time 1 Mean (SD)	Time 2 Mean (SD)
Political knowledge (0-5)	2.88 (1.66)	3.09 (1.59)
Family income (1-8)	4.89 (2.22)	4.80 (2.20)
Parent education (1-7)	5.33 (1.68)	5.36 (1.69)
Interest in politics (1-5)	3.30 (1.15)	3.14 (1.21)
Ideology (Liberal-Conservative, 1-7)	3.08 (1.25)	3.15 (1.32)
Ideology strength (0-3)	1.25 (0.98)	1.20 (0.99)
Political discussion partners (0-25)	NA	1.95 (3.69)
Political discussion frequency (1-7)	NA	3.90 (1.96)
Total news use (1-7)	5.88 (1.52)	5.64 (1.83)
Online news use (1-7)	4.49 (2.07)	4.29 (2.08)
Social media news use (1-7)	4.15 (2.32)	4.16 (2.23)

Measurement

Network variables.

Network variables were recorded in the second survey wave, after the students had spent a semester interacting with each other. In order to capture their social connections, respondents were shown a roster listing all members of their community. Participants were asked to select the names of all individuals with whom they had certain types of relationships. Except in the case of close ties, the respondents were not limited in the number of names they could select.

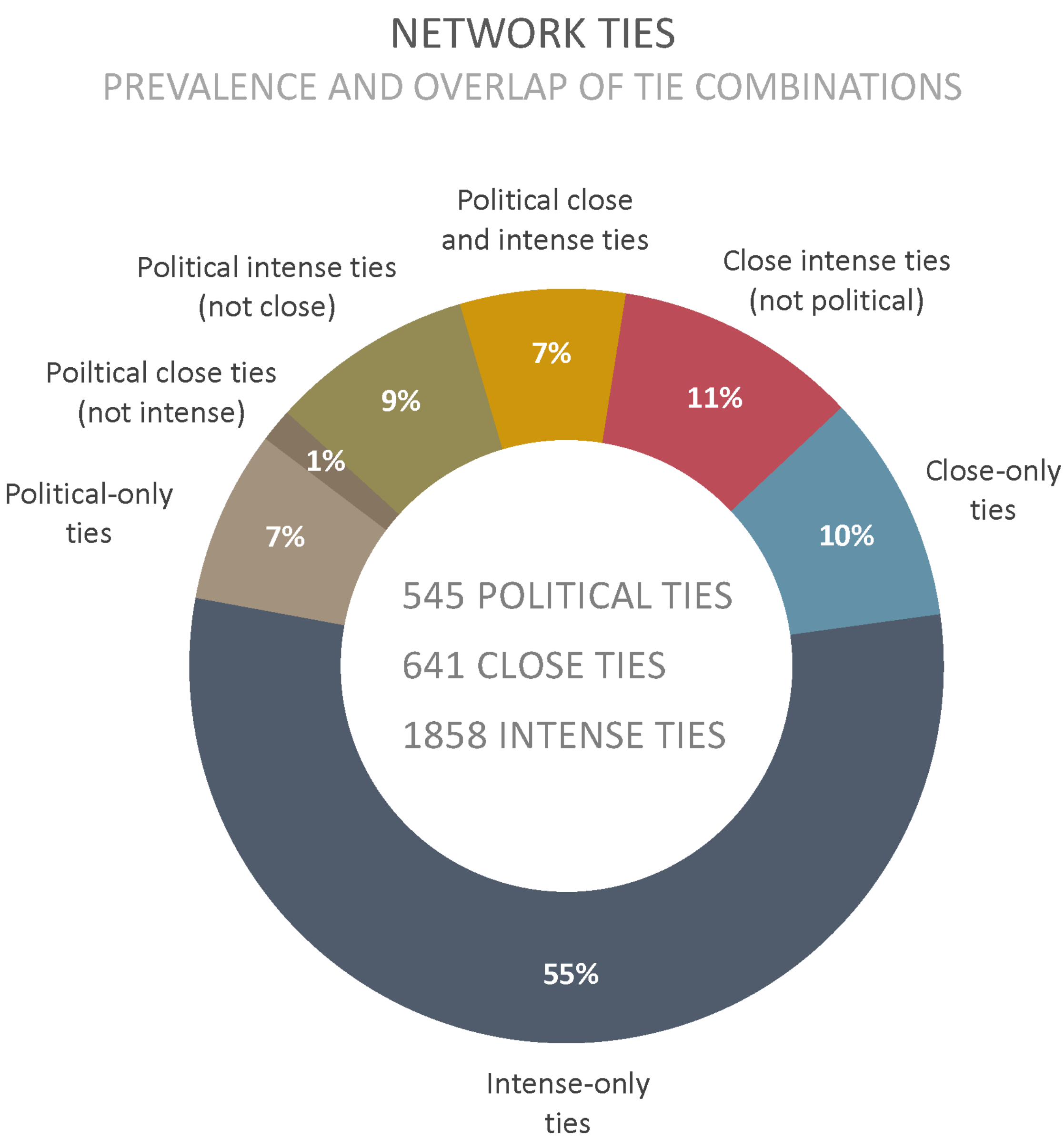

Figure 2. Prevalence and overlap of *political*, *close*, and *intense* ties. The figure shows what percent of all connected dyads that have each possible combination of ties.

The description of *political ties* used here was "I often discuss politics or current events with this person". *Intense ties* were described as "I spend a lot of time with this person". *Close ties* were identified by asking participants to select up to 3 members of their community with whom they felt they had "the closest, strongest relationship".

The responses to the roster questions were used to construct networks for each community as binary matrices indicating whether a directed tie was present (1) or absent (0) in each case. The average density of the networks (ties that were actually present as percent of all possible ties within that community) was 15% for political ties, 10% for close ties, and 34% for intense ties. The average number of ties per participant was 3.9 (*SD* = 4.5) for political ties, 4.6 (*SD* = 2.2) for close ties, and 13.3 (*SD* = 9.7) for intense ties. Figure 2 shows the distribution of ties and the overlap among the three networks.

Political knowledge.

The dependent variable in this study was *factual political knowledge* which captures textbook facts about politics, as well as surveillance information such as the names and roles of political figures (Moeller & de Vreese, 2015). The construct was measured with an adapted version of the well-known scale developed by Delli Carpini and Keeter (1997).

The same five questions were used to measure political knowledge in Waves 1 and 2. Three of the five were open-ended, asking participants to identify the job or political office held at the time by Mike Pence (Vice President) and Neil Gorsuch (Supreme Court Justice), as well as the country led by Angela Merkel (Germany). Those political figures were selected as they were relatively likely to be in the news at the time: Mike Pence as a new VP; Neil Gorsuch as a new and controversial Supreme Court Justice; and Angela Merkel because of the high-stakes federal elections in Germany during the fall of 2017.

The other two questions were multiple-choice, asking respondents which party at the time held the majority of seats in the U.S. Senate (Republican Party) and in the House of Representatives (Republican Party). The knowledge items were scored 1 for a correct response and 0 for an incorrect response or selecting "Don't know". The *political knowledge* index (rage 0-5, M_{W1} = 2.88, SD_{W1} = 1.66 and M_{W2} = 3.1, SD_{W2} = 1.59) was computed by summing all items. Cronbach's alpha was acceptable (α_{W1} = .79, α_{W2} = .77). Confirmatory factor analysis of the knowledge items using tetrachoric correlations also indicated that the index was acceptable: all loadings were significant, and the fit of the model was good for W1 (χ^2 = 4, *p* = .4, *DF* = 4, *CFI* = .99, *TLI* = .99, *RMSEA* = .01, *SRMR* = .03) and W2 (χ^2 = 5.8, *p* = .21, *DF* = 4, *CFI* = .99, *TLI* = .99, *RMSEA* = .04, *SRMR* = .04). A t-test (*t* = 2.45, *DF* = 254, *p* = .01) and a Wilcoxon signed rank test (*p* = .01) indicated that there was a significant increase in the knowledge scores of participants between the two survey waves.

Control variables.

Control variables were selected based on the political knowledge literature reviewed earlier in this work. The means and standard deviations of those variables are presented in Table 1 and Table 2. Demographic controls included *gender*, *race* & *ethnicity*, as well as *immigration status* measured as a binary variable indicating whether a person was a first-generation immigrant to the U.S. or not. This variable was included as new immigrants could be expected to be less familiar with American politics.

Socioeconomic status variables included *annual family income*, measured on a scale ranging from 1 (Under $10,000) to 8 (Over $150,000) and highest achieved parent education level ranging from 1 (Grade 9 or less) to 7 (Graduate degree). Political variables included *ideology* ranging from 1 (Very liberal) to 7 (Very conservative); *strength of ideology*, measured as the distance of ideology scores from the mid-point of the scale (range 0 to 3), *interest in politics* ranging from 1 (Not at all interested) to 5 (Extremely interested), and binary party identification variables for Republicans and Democrats. Models also controlled for the overall frequency of *political discussion* with peers ranging from 1 (Never) to 7 (Daily) and number of *political discussion partners* in the community (ranging from 0 to 25). Media variables included frequency of total *media news use* (getting news about political and current affairs), *online media use* (referring specifically to news websites), and *social media news use,* all ranging from 1 (Never) to 7 (Daily).

Analysis

This work employed the *nascent network* approach proposed by Lazer and colleagues (Lazer, Rubineau, Chetkovich, Katz, & Neblo, 2010). That research design involves surveying individuals at multiple time points, starting at a time before they have entered a social system and formed interpersonal connections. That first measurement allows us to record self-reported data about the respondents before they have any exposure to the social network. The benefit of this design is that initial measurements are clean of any network influence.

The analyses used here were conducted using the R platform for statistical computing version 3.6 (R Core Team, 2015) and RStudio (2020) version 1.1.456. The main analysis used ordinary least squares regressions with cluster-bootstrapped standard errors and p-values to account for the fact that respondents were clustered by community into 13 groups. Shapiro-Wilk tests were conducted to examine model error terms. The results of those tests confirmed that the regression residuals met the normality assumption in each case.

The network influence models regressed individual *political knowledge* (measured in Wave 2) over the average political knowledge of social ties in Wave 1, controlling for one's own political knowledge in Wave 1. This is a version of a widely used network autoregressive model of the form $\boldsymbol{y} = \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X}\beta + \varepsilon$, where $\mathbf{y}$ is the political knowledge vector, $\boldsymbol{W}$ is the row-normalized form of the binary adjacency matrix of the social network, and $\boldsymbol{X}$ includes the controls described above.

H1-H3 suggested that one's political knowledge would be predicted by the political knowledge of their *political*, *close*, and *intense* social ties. To test those hypotheses, network autocorrelation models were estimated for each of those three types of ties.

H4 suggested that political knowledge would also be predicted by *shared ties* (ones with whom the person shares many contacts). To examine the role of such ties, valued matrices were generated for each of the three networks. In those, a tie from A to B would be weighted based on the number of their shared contacts, (the number of other people connected to both A and B). The hypothesis was tested by estimating network autocorrelation models using those weighed matrices.

H5 proposed that political knowledge would be predicted by the knowledge of that person's *co-partisan* ties. Additional network matrices were generated in order to address that question. Those networks included only the social ties where both people in a relationship did (for co-partisan models) or did not (for anti-partisan models) affiliate with the same political party. Autocorrelation models were estimated separately for co-partisan and anti-partisan ties in the *political*, *close,* and the *intense* networks.

The analysis for H5 was conducted using a subsample of 227 W2 participants (209 of whom were also present in W1) who identified as Democrats (84%) or Republicans (16%)[2]. Independents and those who selected the "other" category were excluded from these tests since it was not possible to properly define their co- and anti- partisan connections.

[2] The partisan distribution of the participants was close to the expected for that age group in a Democratic-leaning Northeastern state.

To confirm that social influence was the best available explanation for the findings of the analysis, the study tested several alternative hypotheses. Sensitivity analyses were also used to evaluate the robustness of the models against endogeneity or unmeasured confounding.

Results

To examine H1-H3, network autocorrelation models with cluster-bootstrapped errors were estimated for political knowledge. Only H3 was supported by model results (presented in Figure 3 and Table 3) . Network influence was a significant positive predictor of political knowledge for *intense ties* (β_{intense} = .14, *SE* = .03, $p <$ .001) but not for *political ties* ($\beta_{\text{political}}$ = 0, *SE* = .03, *p* = .91) or *close ties* (β_{close} = .07, *SE* = .04, *p* = .12)[3]. The *intense ties* model predicted that political knowledge would increase by .27 per unit increase in the average knowledge of social ties. The explained variance in knowledge was 60% with an explained variance change for network influence of 2%.

H4 examined the effect of high redundancy through models weighing ties based on the number of contacts shared with the focal person. The results found partial support, with network estimates significant for close ties (β_{close} = .11, *SE* = .02, *p* = .002) but not for *intense ties* (β_{intense} = .07, *SE* = .05, *p* = .21) or *political ties* ($\beta_{\text{political}}$ = .04, *SE* = .04, *p* = .43).

H5 dealt with the effect of co-partisan and anti-partisan social ties. In the models examining co-partisan social ties, the network influence estimate was positive and significant for *intense ties* (β_{intense} = .11, *SE* = .04, *p* = .04) but not for *political ties* ($\beta_{\text{political}}$ = -.01, *SE* = .03, *p* = .85) or *close ties* (β_{close} = .03, *SE* = .04, *p* = .46). In contrast, the estimates based on connections across party lines were not significant for any of the three types of ties[4].

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[3] The magnitude and significance of the network influence did not change in post-hoc tests that excluded political talk variables (political discussion and number of political discussion partners) from the models.

[4] In the analyses described above, partisanship was determined based on self-reported participant data. It is possible that participants did not always know the correct political affiliation of their social contacts. Moreover, as Democrats were a majority in all communities under study, they had more opportunities to form co-partisan ties and fewer opportunities form anti-partisan ties. On average, Republicans had a larger number of cross-cutting ties compared to Democrats. As a minority, right-leaning participants may also have been more reticent to reveal their political identity. To probe for effects from such partisan differences, post-hoc test examined interactions between party affiliations and network influence. No significant interaction effects were found.

Table 3. *Network influence on political knowledge. The predicted variable is political knowledge in Wave 2 of the study. The table includes standardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site.*

Variable	Political Ties	Close Ties	Intense Ties
Network ties: Pol. knowledge (W1)	.00 (.03)	.07 (.04)	.14 (.03)***
Pol. knowledge (W1)	.39 (.08)**	.39 (.08)**	.40 (.08)**
Gender: Female (0-1)	.01 (.04)	.01 (.04)	.00 (.04)
Race/Ethnicity: African American (0-1)	.02 (.04)	.02 (.03)	.04 (.04)
Race/Ethnicity: Hispanic (0-1)	-.03 (.04)	-.01 (.04)	.00 (.03)
Race/Ethnicity: Asian (0-1)	.04 (.04)	.05 (.04)	.04 (.04)
Family income (1-8)	.02 (.05)	.02 (.05)	.04 (.05)
Parent education (1-7)	.05 (.06)	.05 (.06)	.05 (.06)
First generation immigrant (0-1)	.06 (.05)	.06 (.05)	.06 (.05)
Interest in politics (1-5)	.14 (.04)**	.14 (.04)**	.10 (.04)*
Ideology (Liberal-Conservative, 1-7)	.06 (.09)	.05 (.08)	.04 (.08)
Ideology strength (0-3)	.09 (.05)	.09 (.05)	.09 (.05)
Party ID: Republican (0-1)	.08 (.08)	.09 (.08)	.08 (.07)
Party ID: Democrat (0-1)	.14 (.04)*	.14 (.04)*	.13 (.04)*
Political discussion partners (0-25)	-.02 (.03)	-.02 (.03)	-.01 (.04)
Political discussion frequency (1-7)	.11 (.03)*	.11 (.03)*	.11 (.04)*
Offline news use (1-7)	.27 (.05)**	.28 (.05)**	.27 (.05)**
Online news use (1-7)	.10 (.04).	.09 (.03).	.09 (.04)*
Social media news use (1-7)	-.18 (.04)**	-.18 (.03)***	-.17 (.03)***
Observations	255	255	255
R^2 Total	58%	59%	60%
Δ R^2 Network influence	0%	0%	2%

*** p<.001, ** p<.01, * p<.05, • p<.1

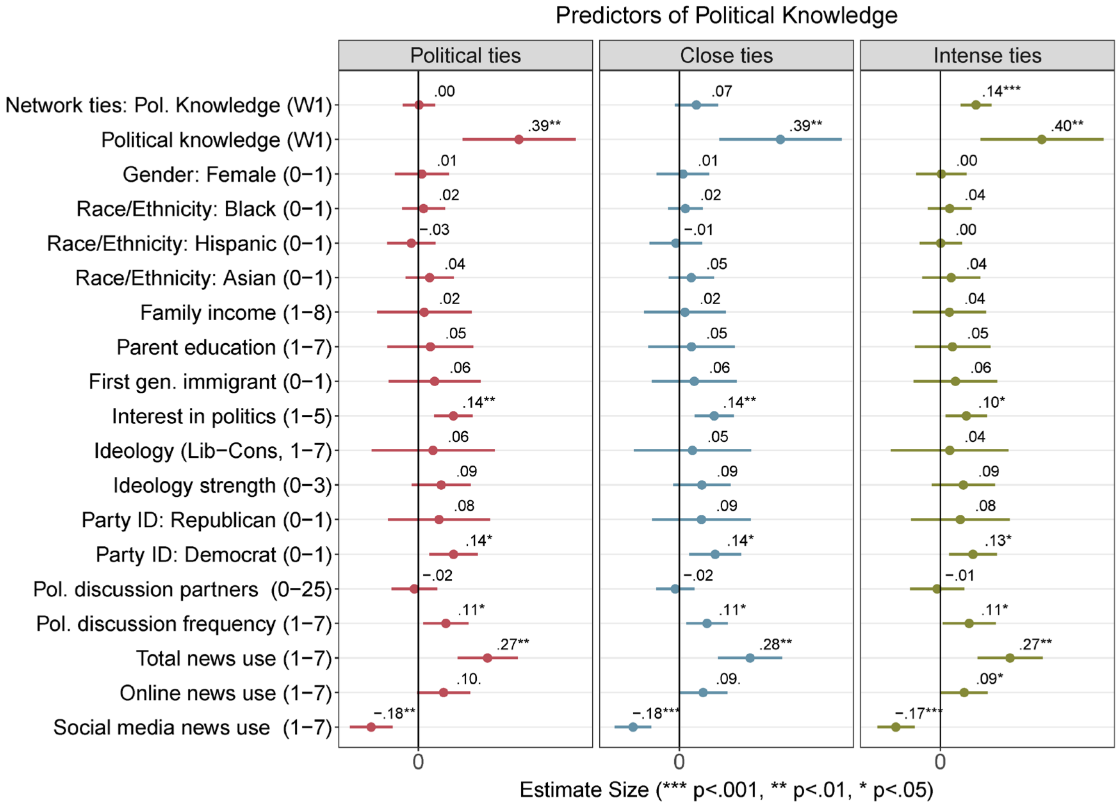

Figure 3. Model results: network influence on political knowledge. Standardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors.

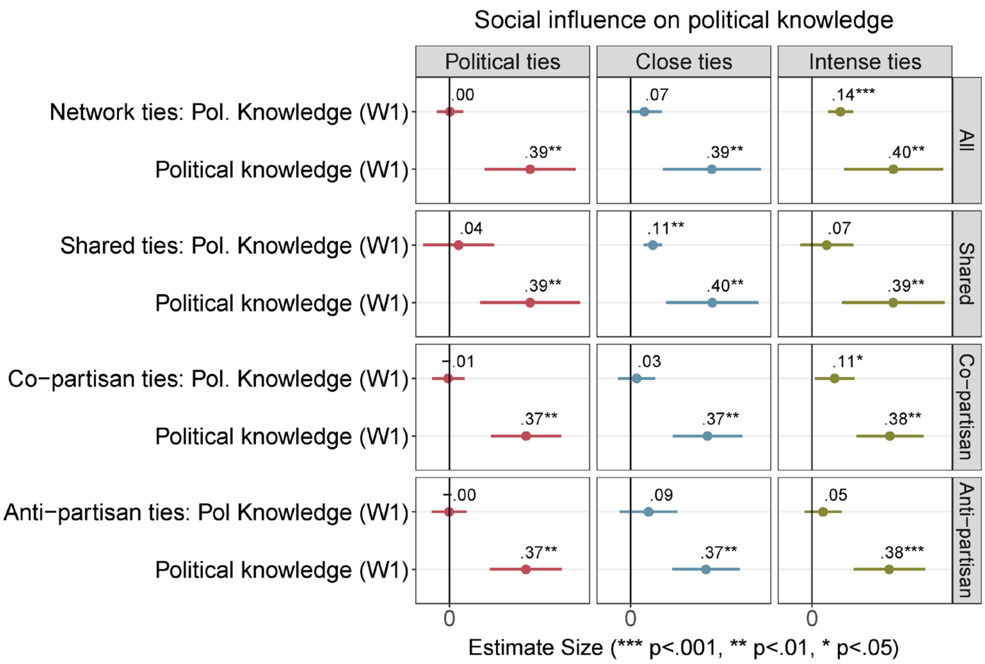

Figure 4. Model results: tie influence on political knowledge. Standardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors. The figure shows estimates for network and own political knowledge from Wave 1.

Summary model results for H1-H5 are presented on Figure 4. Model result tables are also available in online Appendix A.

Social Influence: A Closer Look

Results of the analyses described above suggest that the political knowledge of respondents may be influenced by the people around them. There is, however, a possibility that the findings of the analysis are due to *social selection*. Rather than being affected by their peers, students may simply be choosing to spend more time with people who have similar levels of political knowledge. If that is the case, we should see network autocorrelation in models using data from the first wave of the survey collected before students joined college. Such a finding would mean that even before the network had formed, people had levels of political knowledge similar to those of their future social ties. Any similarities at that point could not be due to influence and would indicate that homophilous social selection was taking place.

In models using Wave 1 data and Wave 2 network structure, estimates were non-significant for all three types of ties: *intense* (β_{intense} = -.03, *SE* = .04, *p* = .58), *political* ($\beta_{\text{political}}$ = .01, *SE* = .05, *p* = .88) and *close* (β_{close} = -.04, *SE* = .05, *p* = .42). The tests found no evidence that social connections were more likely to form between people with similar levels of political knowledge. Social influence was therefore a more likely explanation of the results presented in this study.

Network influence estimates can suffer from unmeasured confounding due not only to social selection, but also to environmental factors affecting some parts of the network (e.g., a political campaign) or reverse causality issues (e.g., the respondent's effect on the political knowledge levels of their social ties). To get an idea about the potential impact of confounders, this work uses parametric sensitivity tests conducted with the R package treatSens (Carnegie, Harada, Dorie, & Hill, 2018). The analyses draw and examine simulated confounders from a distribution conditional on the observed data. The results show that any omitted variables would have to have a very strong effect on political knowledge in order to explain away the network influence estimates. For example, a confounder that is not correlated with the network influence variable would need to have a standardized coefficient of at least β=.47 in a regression predicting political knowledge that also includes all other control variables listed above. In comparison, in that same model, the standardized coefficient for one's own political knowledge in the previous data wave is β=.40. These results indicate that the network influence estimates reported here are robust to a relatively high level of endogeneity and confounding. Sensitivity tables are included in Appendix A.

Another way to evaluate the plausibility of network effects is to consider the theoretical mechanisms of influence and their possible outcomes. If social contagion in political knowledge is taking place, especially if it is driven by normative influence, we might expect other political variables to be affected as well. For example, if intense social ties do affect political knowledge, they should likely also influence political interest. Indeed, network autocorrelation models with political interest as the dependent variable do find a network effect for intense ties (β_{intense} = .16, *SE* = .04, *p* = .03) as well as no pre-exposure similarity in Wave 1 (β_{intense} = .15, *SE* = .11, *p* = .28).

Discussion

A functioning democracy depends on a knowledgeable electorate. The attitudes that shape our political learning develop in childhood and solidify during early adulthood, an important time period when we form lasting habits and opinions (Newcomb, 1943). This study seeks to expand our understanding of the social factors influencing political knowledge among college-age Americans.

The analyses find evidence of contagion in political knowledge – but only for some types of social ties. Contrary to expectations, no significant network influence was found for political discussants. Instead, the contagion effects were limited to strong ties. This finding has important implications for research exploring social influence on political behavior. It suggests that the contacts we identify as political are not necessarily the ones who matter the most in shaping relevant opinions and attitudes. The people with whom we spend the most time, even if a small percent of our conversations deal directly with politics, may have a larger cumulative impact over time.

Those findings are consistent with previous works exploring patterns of political communication. Eveland and Hutchens (2013), for instance, confirm that social ties who communicate frequently are likely to exchange political information. Klofstad and colleagues (2009) find that political discussion is embedded in our everyday social interactions with a core network. Political talk is a commonplace aspect of our daily conversations but its effects on behavior may vary based on tie strength.

Even though numerous studies have established the importance of political communication, evaluating the impact of *political ties* presents theoretical and methodological challenges. Research has demonstrated that people vary considerably in their definitions of political discussion (Fitzgerald, 2013; Morey & Eveland, 2016).

This adds uncertainty to traditional network measures based on political talk. Morey and Eveland (2016), for instance, find that two respondents are less likely to agree on whether they have talked about politics than they are to agree on having other common relationships. A similar pattern was found in this work: agreement among respondents was over 2.5 times higher for close and intense connections compared to that for political ties.

The findings presented here further suggest that careful interpretation of social effects is also needed in research where full network data are not available. For instance, scholars often use political name generators similar to the ones included in ANES surveys (American National Election Studies, 2018). Those items ask respondents to provide information about three to five people with whom they talk about politics. As it turns out, requesting a list of names outside of a specific social context will prompt respondents to list strong ties (Klofstad et al., 2009). It is thus possible that the effects we find when we examine those political discussants are due at least partly to tie strength, a factor that is not always explicitly considered by researchers.

In this study, potentially influential social ties were identified using a conceptualization of tie strength grounded in three key factors: interaction frequency, capacity, and redundancy (Brashears & Quintane, 2018). Intense ties who frequently interacted with the respondent were especially relevant for political knowledge. Those frequent discussants were able to shift the behavior of their peers, likely through a combination of information sharing and normative influence. Post-hoc tests suggested that intense ties may also be able to influence other related attitudes such as political interest.

No significant effect was found for close ties: intimate friends considered to be high-capacity contacts because of their willingness to deliver information and resources when needed. That changed, however, when considering tie redundancy: the number of shared friends between two people. High-redundancy close ties did have an impact on the political knowledge of respondents.

Close ties tend to be friends we trust, talk to more freely and understand more easily (Larson, 2017). They do not have to be frequent contacts: most of us have people we feel close to but do not see very often. In the dataset used for this study, 37% of the close ties were not reported to be frequent communication partners (see Figure 2). As suggested in the literature, infrequent communication with a person can be reinforced when similar messages come to us from multiple sources (Brashears & Quintane, 2018). This happens in network configurations where we have redundant connectivity: people connected to each other who also have a number of shared friends that both of them know. In models where ties were weighed based on shared contacts, heavily redundant close ties were found to affect political knowledge. Thus, while high-frequency intense ties may not need social reinforcement to influence us, the high-capacity close ties do. Important to note, this study only examined the close ties contained within a student residential community. More intimate relationships with family members, childhood friends, or romantic partners may have a higher information capacity and thus have a stronger impact on political behavior.

The study also found support for the importance of tie homogeneity. Intense co-partisan ties who shared the political views of the respondent had an effect on political knowledge, while anti-partisan ties did not. This finding is consistent with contagion research suggesting that we are more likely to be influenced by people who are similar to us (Centola, 2011). It also confirms findings from experimental political research indicating that we prefer to seek information from people who agree with us (Marks et al., 2019) and that we learn better from conversations with like-minded others (Carlson, 2019).

This work has several important limitations. The study design does not capture the specific mechanisms responsible for network effects on political knowledge. Social psychology identifies two major ways in which interpersonal contact causes behavioral change. Informational influence triggers change based on new facts we learn from our peers, while normative influence works by creating pressure to meet social expectations (Deutsch & Gerard, 1955). Both types of influence should certainly operate in this case. Social interactions are known to affect political knowledge by increasing both information exposure and motivation to learn (Eveland, 2004). Future works might evaluate the independent contributions of the two influence mechanisms in the context of social contagion. One way to address this issue in a follow-up study might be to explicitly ask participants about perceived peer norms regarding political behavior.

The operationalization of political knowledge used in this study, while consistent with previous research (Delli Carpini & Keeter, 1997), could not capture the full nuance and complexity of the concept. Respondents were asked to identify basic facts about the U.S. Congress and recall information about the office held by major political figures. The focus on factual information may have constrained the role interpersonal and media sources were found to play in political learning. Different patterns of social influence may emerge in research focusing on structural knowledge which deals with the perceived relationships among facts (Eveland & Hively, 2009).

The analyses reported here examine full-network data from residential student groups. A full-network study design does not rely on random sampling of individuals because it needs to capture an entire connected community. While the response rate for the study was fairly high (83% in Wave 1 and 72% in Wave 2), self-selection biases cannot be ruled out, especially as no data is available for students who opted out of participating in the study.

Full network data provide opportunities for a nuanced analysis of social structure, but they can also raise concerns of generalizability. The specific social environment examined here reflected the experiences of college students. Young adults are an important population as they are going through a period of life when long-term political attitudes and behavior solidify (Klofstad, 2015). Still, one question we might reasonably ask is whether the findings presented here would also apply to other populations. Though that seems plausible, additional research may be needed to explore network contagion in political knowledge across different social groups.

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Appendix A

Table 1a. *Network influence on political knowledge. The predicted variable is political knowledge in Wave 2 of the study. The table includes standardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site.*

Variable	Political Ties	Close Ties	Intense Ties
Network ties: Pol. knowledge (W1)	.00 (.03)	.07 (.04)	.14 (.03)***
Pol. knowledge (W1)	.39 (.08)**	.39 (.08)**	.40 (.08)**
Gender: Female (0-1)	.01 (.04)	.01 (.04)	.00 (.04)
Race/Ethnicity: African American (0-1)	.02 (.04)	.02 (.03)	.04 (.04)
Race/Ethnicity: Hispanic (0-1)	-.03 (.04)	-.01 (.04)	.00 (.03)
Race/Ethnicity: Asian (0-1)	.04 (.04)	.05 (.04)	.04 (.04)
Family income (1-8)	.02 (.05)	.02 (.05)	.04 (.05)
Parent education (1-7)	.05 (.06)	.05 (.06)	.05 (.06)
First generation immigrant (0-1)	.06 (.05)	.06 (.05)	.06 (.05)
Interest in politics (1-5)	.14 (.04)**	.14 (.04)**	.10 (.04)*
Ideology (Liberal-Conservative, 1-7)	.06 (.09)	.05 (.08)	.04 (.08)
Ideology strength (0-3)	.09 (.05)	.09 (.05)	.09 (.05)
Party ID: Republican (0-1)	.08 (.08)	.09 (.08)	.08 (.07)
Party ID: Democrat (0-1)	.14 (.04)*	.14 (.04)*	.13 (.04)*
Political discussion partners (0-25)	-.02 (.03)	-.02 (.03)	-.01 (.04)
Political discussion frequency (1-7)	.11 (.03)*	.11 (.03)*	.11 (.04)*
Offline news use (1-7)	.27 (.05)**	.28 (.05)**	.27 (.05)**
Online news use (1-7)	.10 (.04).	.09 (.03).	.09 (.04)*
Social media news use (1-7)	-.18 (.04)**	-.18 (.03)***	-.17 (.03)***
Observations	255	255	255
R^2 Total	58%	59%	60%
ΔR^2 Network influence	0%	0%	2%

*** p<.001, ** p<.01, * p<.05, • p<.1

Table 1b. *Network influence on political knowledge, model with no controls for political discussion. The predicted variable is political knowledge in Wave 2 of the study. The table includes standardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site.*

Variable	Political Ties	Close Ties	Intense Ties
Network ties: Pol. knowledge (W1)	.00 (.03)	.07 (.04)	.13 (.03)**
Pol. knowledge (W1)	.40 (.08)***	.40 (.08)***	.40 (.08)**
Gender: Female (0-1)	.01 (.04)	.01 (.04)	-.00 (.04)
Race/Ethnicity: African American (0-1)	.02 (.04)	.02 (.03)	.03 (.04)
Race/Ethnicity: Hispanic (0-1)	-.03 (.04)	-.02 (.04)	-.00 (.03)
Race/Ethnicity: Asian (0-1)	.03 (.04)	.03 (.04)	.02 (.04)
Family income (1-8)	.03 (.05)	.02 (.05)	.04 (.05)
Parent education (1-7)	.05 (.07)	.05 (.07)	.05 (.06)
First generation immigrant (0-1)	.07 (.06)	.06 (.05)	.06 (.05)
Interest in politics (1-5)	.18 (.04)**	.18 (.04)**	.15 (.04)**
Ideology (Liberal-Conservative, 1-7)	.06 (.10)	.06 (.09)	.05 (.09)
Ideology strength (0-3)	.09 (.06)	.09 (.05)	.09 (.06)
Party ID: Republican (0-1)	.08 (.08)	.09 (.08)	.08 (.08)
Party ID: Democrat (0-1)	.15 (.04)*	.15 (.04)*	.14 (.05)*
Offline news use (1-7)	.27 (.05)**	.27 (.05)**	.27 (.05)**
Online news use (1-7)	.09 (.04).	.08 (.03).	.08 (.04).
Social media news use (1-7)	-.16 (.04)**	-.16 (.03)**	-.15 (.03)**
Observations	255	255	255
R^2 Total	57%	58%	59%
Δ R^2 Network influence	0%	0%	2%

*** p<.001, ** p<.01, * p<.05, • p<.1

Table 2. *Shared tie influence on political knowledge. The predicted variable is political knowledge in Wave 2 of the study. The table includes standardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site.*

Variable	**Political Ties (# shared)**	**Close Ties (# shared)**	**Intense Ties (# shared)**
Network ties: Pol. knowledge (W1)	.04 (.04)	.11 (.02)**	.07 (.05)
Pol. knowledge (W1)	.39 (.08)**	.40 (.07)**	.39 (.08)**
Gender: Female (0-1)	.01 (.04)	.01 (.04)	.00 (.04)
Race/Ethnicity: African American (0-1)	.02 (.04)	.03 (.03)	.02 (.03)
Race/Ethnicity: Hispanic (0-1)	-.02 (.03)	-.01 (.04)	-.01 (.04)
Race/Ethnicity: Asian (0-1)	.04 (.04)	.04 (.04)	.05 (.04)
Family income (1-8)	.03 (.05)	.03 (.05)	.03 (.05)
Parent education (1-7)	.04 (.06)	.05 (.06)	.04 (.06)
First generation immigrant (0-1)	.06 (.05)	.05 (.05)	.06 (.05)
Interest in politics (1-5)	.14 (.04)**	.12 (.03)**	.12 (.04)**
Ideology (Liberal-Conservative, 1-7)	.05 (.08)	.04 (.08)	.04 (.09)
Ideology strength (0-3)	.09 (.05)	.08 (.05)	.09 (.05)
Party ID: Republican (0-1)	.09 (.07)	.09 (.07)	.09 (.08)
Party ID: Democrat (0-1)	.14 (.04)*	.13 (.04)*	.14 (.04)*
Political discussion partners (0-25)	-.01 (.03)	-.02 (.03)	-.02 (.03)
Political discussion frequency (1-7)	.10 (.03)*	.11 (.03)*	.11 (.03)*
Offline news use (1-7)	.27 (.05)**	.27 (.05)**	.27 (.05)**
Online news use (1-7)	.10 (.04).	.09 (.03)*	.10 (.04)*
Social media news use (1-7)	-.18 (.03)***	-.17 (.04)**	-.17 (.03)**
Observations	255	255	255
R^2 Total	59%	59%	59%
Δ R^2 Network influence	0%	1%	0%

*** p<.001, ** p<.01, * p<.05, • p<.1

Table 3. *Co-partisan tie influence on political knowledge. The predicted variable is political knowledge in Wave 2 of the study. The table includes standardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site.*

Variable	**Co-partisan Political Ties**	**Co-partisan Close Ties**	**Co-partisan Intense Ties**
Network ties: Pol. knowledge (W1)	-.01 (.03)	.03 (.04)	.11 (.04)*
Pol. knowledge (W1)	.37 (.08)**	.37 (.08)**	.38 (.08)**
Gender: Female (0-1)	-.00 (.06)	-.00 (.06)	-.00 (.06)
Race/Ethnicity: African American (0-1)	-.01 (.05)	-.01 (.05)	-.00 (.05)
Race/Ethnicity: Hispanic (0-1)	.02 (.04)	.02 (.04)	.02 (.04)
Race/Ethnicity: Asian (0-1)	.09 (.04).	.09 (.04).	.07 (.04).
Family income (1-8)	.05 (.05)	.05 (.05)	.06 (.04)
Parent education (1-7)	.08 (.05)	.08 (.05)	.08 (.04)
First generation immigrant (0-1)	.03 (.06)	.03 (.06)	.03 (.06)
Interest in politics (1-5)	.19 (.05)**	.18 (.04)**	.17 (.05)**
Ideology (Liberal-Conservative, 1-7)	.02 (.10)	.02 (.10)	.01 (.11)
Ideology strength (0-3)	.06 (.07)	.06 (.08)	.06 (.08)
Party ID: Republican (0-1)	.00 (.11)	.00 (.11)	.03 (.11)
Political discussion partners (0-25)	-.03 (.04)	-.03 (.04)	-.02 (.04)
Political discussion frequency (1-7)	.16 (.04)*	.16 (.05)*	.17 (.05)*
Offline news use (1-7)	.17 (.04)*	.18 (.04)**	.17 (.04)*
Online news use (1-7)	.12 (.06)	.12 (.06)	.12 (.06)
Social media news use (1-7)	-.18 (.04)**	-.18 (.04)**	-.17 (.04)**
Observations	209	209	209
R^2 Total	54%	54%	55%
ΔR^2 Network influence	0%	0%	1%

*** p<.001, ** p<.01, * p<.05, • p<.1

Table 4. *Anti-partisan tie influence on political knowledge. The predicted variable is political knowledge in Wave 2 of the study. The table includes standardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site.*

Variable	**Anti-partisan Political Ties**	**Anti-partisan Close Ties**	**Anti-partisan Intense Ties**
Network ties: Pol. knowledge (W1)	-.00 (.03)	.09 (.04)	.05 (.04)
Pol. knowledge (W1)	.37 (.08)**	.37 (.08)**	.38 (.08)***
Gender: Female (0-1)	.00 (.06)	.00 (.05)	-.00 (.06)
Race/Ethnicity: African American (0-1)	-.01 (.05)	-.01 (.05)	-.01 (.05)
Race/Ethnicity: Hispanic (0-1)	.02 (.04)	.02 (.05)	.03 (.04)
Race/Ethnicity: Asian (0-1)	.09 (.04)*	.09 (.03)*	.09 (.04).
Family income (1-8)	.05 (.05)	.04 (.04)	.05 (.04)
Parent education (1-7)	.08 (.05)	.08 (.05)	.08 (.05)
First generation immigrant (0-1)	.03 (.07)	.03 (.06)	.03 (.06)
Interest in politics (1-5)	.19 (.04)**	.19 (.05)**	.18 (.05)**
Ideology (Liberal-Conservative, 1-7)	.03 (.10)	.01 (.10)	.02 (.10)
Ideology strength (0-3)	.06 (.08)	.05 (.08)	.07 (.07)
Party ID: Republican (0-1)	.00 (.11)	.01 (.11)	-.01 (.11)
Political discussion partners (0-25)	-.03 (.04)	-.03 (.04)	-.03 (.04)
Political discussion frequency (1-7)	.16 (.04)*	.17 (.04)*	.16 (.04)*
Offline news use (1-7)	.18 (.04)**	.18 (.04)**	.17 (.04)**
Online news use (1-7)	.12 (.06)	.12 (.06)	.11 (.06)
Social media news use (1-7)	-.18 (.04)**	-.17 (.04)**	-.17 (.04)***
Observations	209	209	209
R^2 Total	54%	54%	54%
Δ R^2 Network influence	0%	1%	0%

*** p<.001, ** p<.01, * p<.05, • p<.1

Table 5. *Sensitivity analysis - intense ties model.*

Analyses assume that an unobserved confounder U is omitted from the models. Drawing series of simulated confounder values from a distribution conditional on the observed data, we identify ones for which the significance of the network influence parameter is lost. Below, Y is a vector of standardized regression coefficients for the relationship of the confounder with the outcome variable, and Z is a vector of standardized regression coefficients for the relationship of the confounder with the predictor (conditional on the control variables).

Coefficients on U where significance level 0.05 is lost:

Y	**Z**
0.402	-0.869
0.397	-0.666
0.400	-0.463
0.451	-0.318
0.497	-0.463
0.515	-0.495
0.568	-0.463
0.519	-0.261
0.515	-0.241
0.470	-0.058
0.451	-0.027
0.431	0.000
0.402	0.058
0.386	0.172
0.368	0.261
0.383	0.463
0.359	0.666
0.346	0.869

Table 6. *Sensitivity analysis – shared close tie model.*

Analyses assume that an unobserved confounder U is omitted from the models. Drawing series of simulated confounder values from a distribution conditional on the observed data, we identify ones for which the significance of the network influence parameter is lost. Below, Y is a vector of standardized regression coefficients for the relationship of the confounder with the outcome variable, and Z is a vector of standardized regression coefficients for the relationship of the confounder with the predictor (conditional on the control variables).

Coefficients on U where significance level 0.05 is lost:

Y	**Z**
0.355	0.893
0.342	0.752
0.349	0.610
0.338	0.468
0.357	0.326
0.344	0.184
0.349	0.043
0.345	0.000
0.353	-0.043
0.375	-0.183
0.375	-0.184
0.375	-0.189
0.366	-0.326
0.375	-0.380
0.395	-0.468
0.417	-0.595
0.423	-0.610

0.459 -0.671

0.501 -0.721

0.540 -0.752

0.542 -0.753

0.584 -0.777