The social context of media trust: A network influence model

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Abstract

Concerns about the low public trust in U.S. media institutions have recently deepened amid increasing partisan polarization, large-scale digital disinformation campaigns, and frequent attacks on the press from political elites. This study explores the social factors that shape our trust in mainstream news sources. An examination of longitudinal network data from thirteen residential student communities highlights the importance of interpersonal influence on views about the media. The results show that the media trust of participants is predicted by the trust scores of their online and offline social contacts. The most robust and consistent effect comes from face-to-face interaction with politically like-minded conversation partners. Among online social ties, the analysis finds effects from contact with others who distrust the media but not from communication with people who report high levels of media trust.

Keywords: media trust, social influence, social contagion, social network, tie strength, mass communication, political communication

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The social context of media trust: A network influence model

The decline of citizen trust in major social and political institutions has troubled scholars in a wide range of academic fields (Citrin & Stoker, 2018). Mainstream news organizations are among the institutions experiencing the most significant and consequential loss of public confidence. Recent technological, social, and political trends have contributed to the decline of trust in journalism. The financial problems of the media industry have reduced the volume of high-quality accountability reporting (McChesney & Nichols, 2010). Digital technology fundamentally changed the news business. Widely available user-generated content and countless niche news outlets now compete with traditional media. The increasing use of alternative sources is associated with a tendency to question mainstream news and doubt political authority (Fletcher & Park, 2017; Tsfati & Cappella, 2003).

Changing consumption patterns have also increased our reliance on social media and search engines for relevant information (Gil de Zuniga, Weeks, & Ardevol-Abreu, 2017). On those platforms, mainstream news is often displayed alongside commentary, personal stories, rumors, jokes, and deliberate misinformation. Consuming this stream of content with various sources, intent, and credibility could plausibly affect the public trust in the quality, accuracy, and objectivity of news (Flanagin & Metzger, 2017).

Beyond the impact of technological shifts and industry trends, our social environment also shapes our views of the media. Based on longitudinal network data from 13 residential student communities, this study identifies interpersonal drivers of media trust. The findings suggest that the people arounds us can influence our perceptions of journalism. A series of analyses evaluate the key characteristics of connections that affect our opinion of the media. The results show that the impact of social contacts varies depending on communication mode, relationship strength, and shared political affiliation.

Conceptualizing media trust

Trust is an abstract concept central to our understanding of all social systems. It describes a relationship in which an actor accepts vulnerability to the actions of the trusted party (Mayer, Davis, & Schoorman, 1995). A core aspect of trust is the willingness to take a risk based on expected but uncertain positive outcomes (Rousseau, Sitkin, Burt, & Camerer, 1998).

Kohring and Matthes (2007) link the element of risk inherent in the concept of media trust to the ability of journalists to selectively cover and frame events. We rely on news media to provide us with the information we need to navigate a complex political, financial, and social environment. Trusting journalism means that we are likely to base consequential actions on the news we consume. Building on that idea, Kohring and Matthes (2007) identify four key dimensions of media trust. The four factors correspond to our confidence that journalists will cover the important topics, focus on the appropriate facts, present those facts accurately, and provide well-founded commentary, critique, or guidance.

An added layer of complexity emerges when we consider the potential *objects* of media trust. Individuals may have varying levels of trust in news content, trust in journalists or editors, trust in a news organization or a medium, and trust in the media system as a whole (Blobaum, 2016). Studies exploring the objects of trust have found that our attitudes towards different referents are interdependent. In other words, our propensity to trust a message is linked to our trust in its source and its distribution medium (Lucassen & Schraagen, 2012). News credibility scholarship similarly examines the interconnected credibility of messages, their source, and the medium of delivery (Metzger, Flanagin, Eyal, Lemus, & Mccann, 2003).

The key outcome variable examined in this study is individual trust in the media system. This idea is captured by the concept of *generalized media trust* which measures broad attitudes towards journalistic institutions. The existence of abstract confidence in journalism explains consistent findings that audience perceptions of different media channels are correlated (Kiousis, 2001). The operationalization of this construct varies across studies, with some survey items asking about *trust* while others mention *confidence* in media. Comparative research, however, has shown that responses to both types of questions are highly correlated (Ladd, 2012). Given the similar results across different wordings and the fact that media trust is stable when measured repeatedly over time, Ladd and Podkul (2019) note that there is indeed evidence of a common underlying generalized media trust concept.

While this study focuses on generalized trust in journalistic institutions, it should be noted that scholars have also pointed out the benefits of using more specific constructs. Daniller et al. (2017), for instance, recommend measuring trust in the respondent's own news sources, or in sources that participants perceive as popular among the broader public.

Predictors of media trust

Communication scholarship has examined a wide range of factors known to predict generalized media trust. Tsfati and Cohen (2012) broadly organize the key predictors in two categories: audience features and media characteristics. The first category deals with the effect of *individual* background, attitudes, and behavior, while the second refers to *media* content, format, workforce, and other attributes.

Although less prominent in empirical research, there is also evidence that characteristics of the social and political environment can affect media trust (Blobaum, 2016). Relevant *contextual* predictors include macro-level political and economic factors (Tsfati & Ariely, 2014). As discussed later in this work, social context also plays an important role in the way journalistic institutions are perceived.

Individual factors

Much of the communication scholarship dealing with citizen attitudes towards the media explores individual-level correlates of trust. Demographic characteristics, personality traits, and political ideology are associated with perceptions of media fairness and credibility (Tsfati & Cohen, 2012). In an examination of survey data from 44 countries, Tsfati and Ariely (2014) find that trust in the media is associated with political interest, interpersonal trust, and education levels.

In the United States, political partisanship is a particularly influential factor, with Democrats consistently reporting higher generalized media trust compared to Republicans (Newman, Fletcher, Kalogeropoulos, Levy, & Nielsen, 2018). People with strongly held political opinions are also more likely to experience *hostile media effects*: the perception that a neutrally worded news article is biased against their view (Feldman, 2017).

Individual media exposure has been variously examined as a cause or an outcome of media trust. In a longitudinal study, Hopmann et al. (2015) found that over time, audience members gain more confidence in the media types they use the most. Other works have suggested that the inverse relationship may hold, with distrust or perceived media bias leading to lower news consumption (Ardevol-Abreu & Gil de Zuniga, 2017). Although people do still consume media they do not trust (Tsfati & Cappella, 2005), their goals in doing so and the effects they experience from it are different compared to those of trusted sources (Tsfati & Cohen, 2012).

Media factors

Our perception of journalism is also naturally shaped by the characteristics of news content, media organizations, and distribution channels. Public trust may be influenced by the affiliations, financial interests, and ownership structure of news outlets, the level of negativity in news coverage, or the preoccupation of media with scandal or celebrity. The perceived political leanings and ideological agendas of news organizations are also a key concern for audience members (Newman et al., 2018).

Hopmann et al. (2015) found evidence that cynical news coverage focusing on the "strategic game" aspect of political elections in Sweden led to a decrease in media trust. In an earlier experimental study in a U.S. context, however, Ladd (2012) only found effects of horserace political coverage for college-educated Republicans. His experimental study suggested that tabloid-style coverage of celebrities and scandals is a more consistent driver of public distrust in media.

A series of works have also compared the perceived credibility of different media formats. While initial efforts focused on print and television, recent research has included comparisons with digital sources and social media platforms (Flanagin & Metzger, 2017).

Contextual factors

Factors related to political actors and institutions are among the key contextual predictors of media trust. Scholars have examined environmental determinants including the political culture and democratic stability of a country, or the perceived success of its government in protecting the economic interests of its citizens (Tsfati & Ariely, 2014). Such macro-level political factors have been extensively studied in the context of political trust (Newton, Stolle, & Zmerli, 2018). Predictors of political trust may matter for media trust since public confidence in media and political institutions are strongly connected, especially in politically polarized societies (Hanitzsch, Van Dalen, & Steindl, 2018).

Media trust is also sensitive to influence from celebrities and elites. Condemnations of journalism coming from political actors, for instance, can erode public confidence in the news (Ladd, 2012).

Exploring predictors of perceived credibility for online information, Metzger and colleagues (2010) emphasize the importance of personal interactions and peer ratings. The social context of media trust is of particular interest here as this study examines interpersonal influences on our views of the press. The next section of this work builds on existing research by exploring the role of network ties as a contextual predictor of media trust.

The role of social influence

The social context of media trust has received relatively little attention in communication scholarship. Yet, it seems likely that our friends and acquaintances not only assist us in finding and evaluating specific information, but also influence how much we trust news sources.

Being influenced by others does not necessarily require that they set out deliberately to persuade us. Our opinions can shift through *learning*: we update our views based on new information shared by our conversation partners. We may also be swayed by *normative influence* as we tend to view our social ties as a benchmark that tells us what opinions and actions are socially acceptable and approved by those around us (Deutsch & Gerard, 1955).

Interpersonal factors also contribute to perceptions of media fairness and objectivity. Eveland and Shah (2003) show that discussions with like-minded others are associated with stronger perceptions of hostile media bias. We assess what is fair or biased based on personal experience grounded in our social environment and network connections. If we are surrounded by people who agree with us, our ideas of a fair news story may become skewed.

Political science research has examined a variety of attitudes and behaviors susceptible to network effects, from political ideology to voting in elections (Lazer, Ognyanova, Neblo, Minozzi, & Rubineau, 2015; Rolfe & Chan, 2017). Studies of that kind demonstrate that influential discussions about politics, news, and current affairs are embedded in our everyday social interactions (McClurg, 2003; Minozzi, Song, Lazer, Neblo, & Ognyanova, forthcoming).

The processes of generating and destroying trust are deeply rooted in social relationships (Newton, 2001). People place more trust in members of their own network and have more confidence in products, companies, and institutions recommended by their social contacts. This transitive property of trust allows us to make up our mind about people and organizations without necessarily having personal interactions with them.

In times of risk and uncertainty, our levels of trust are especially strongly influenced by our social network (Cook, Santana, & Uslaner, 2018). Periods of political or economic instability, for instance, promote increased reliance on networks and decreased trust in institutions. This may apply to the conditions in the United States during and after the 2016 presidential campaign. As wide-spread concerns about misinformation and fake news have added uncertainty to the political and media environment, Americans can be expected to rely even more heavily on their social contacts to decide whether institutions can be trusted. Accordingly, the central hypothesis of this work is:

> **H1**: Individual media trust will be positively predicted by the media trust of a person's *offline* social ties.

While much of the early research on social influence has focused on face-to-face discussions, there is also evidence that influence can take place in a digital space. Social contagion in online platforms affects our mood (Ferrara & Yang, 2015), health behavior (Centola, 2011), and product adoption (Aral & Walker, 2014). Perhaps the most striking evidence of social influence channeled through digital platforms comes from two large-scale social experiments of political mobilization on Facebook (Bond et al., 2012; Jones, Bond, Bakshy, Eckles, & Fowler, 2017). Those large randomized online trials demonstrate that social media ties can affect our electoral behavior.

In the context of the present study, social connections are embedded in an offline residential community. Still, participants do report different primary communication modes with their local social ties. Some dyads interact primarily offline, others tend to communicate online, and many report that they connect both on the Internet and face to face.

One question explored in this work is whether social connections can affect media trust through *online* interactions. Social ties can confer credibility to specific online content: people may trust a social media post more or less depending on who has posted it (Pew Research Center, 2017). Social media users are also more likely to click on a link to a news story if it is posted by a close friend (Kaiser, Keller, & Kleinen-von Konigslow, 2018). The following research hypothesis suggests that the impact of our social ties on the Web extends beyond specific posts to generalized trust in media institutions:

> **H2**: Individual media trust will be positively predicted by the media trust of a person's *online* social ties.

Characteristics of influential ties

A number of factors affect the ability of social ties to influence us. Diffusion and contagion models predict that our probability of adopting a behavior will increase as more of our contacts exhibit that behavior (Rogers, 1995). Persuasion research claims that we are more susceptible to appeals by those we like and respect (Cialdini, 2001). Network scholarship further suggests that strong ties have more influence on our behavior while weak ties can be more helpful in providing previously unknown information (Granovetter, 1973). Later works show that close, cohesive connections can also deliver novel information through a higher volume and frequency of information exchanges (Aral & Van Alstyne, 2011).

We have more opportunities and more reasons to communicate with our strong social ties. They are often trusted contacts that we can speak to more openly and understand more easily (Larson, 2017). Strong ties are considered especially important for the transfer of complex ideas or unspoken norms and practices (Hansen, 1999).

Having multiple strong ties with redundant opinions plays a critical role in convincing people to adopt and spread new ideas or behaviors (Centola, 2018). On social media, for instance, users are considerably more likely to repeat news coming from close contacts than share posts from acquaintances (Bakshy, Rosenn, Marlow, & Adamic, 2012).

S*trong ties* are typically defined as closer, more intimate relationships and operationalized by identifying contacts who communicate frequently and exchange a lot of information (Granovetter, 1973). Grounded in previous scholarship, this study predicts that strong ties, whether defined through intimacy or communication intensity, would be especially influential in the context of media trust:

> **H3**: Individual media trust will be positively predicted by the media trust of a person's *strong* social ties.

In addition to trust and interaction frequency, shared social identity plays a key role in the process of social influence. We are prone to be more influenced by people who share our background, interests, and experiences. Research has demonstrated that ties between similar partners enhance social contagion, increasing the spread and adoption of new behaviors or technologies (Centola, 2011; Rogers, 1995).

Conversations with others who share our political views are similarly likely to be more persuasive. In polarized western societies, social identity is increasingly bound with political affiliation (Mason, 2018). Partisan identities make Americans more likely to favor their own tribe, as well as to dislike and distrust the other side (Iyengar & Westwood, 2015). People are more resistant to arguments from members of the opposing party when those are perceived as a social identity threat.

In the context of views about media, Eveland and Shah (2003) offer evidence that conversations with ideologically similar others may be particularly important. Their study demonstrates that people who have more discussions with like-minded partners are more likely to perceive the media as biased. While studies have found that we are more comfortable expressing disagreement with our strong ties (Morey, Eveland, & Hutchens, 2012), research also suggests that conversations with co-partisans can make our views more extreme (Schkade, Sunstein, & Hastie, 2007). If that is the case, our understanding of what constitutes fair media coverage may shift as well. Thus, exposure to like-minded co-partisan ties may have a stronger impact than exposure to anti-partisan ones. Accordingly, the fourth hypothesis put forward here is:

> **H4**: Individual media trust will be positively predicted by the media trust of a person's *co-partisan* social ties.

Finally, this study examines the possibility that there may be a difference in the impact of social ties depending on their level of media trust. Because trust is easier to destroy than it is to build (Slovic, 1993), people with more cynical views of the media may be in a better position to change minds.

Humans, furthermore, have a consistent negativity bias in information selection, processing, and recall (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Rozin & Royzman, 2001). We pay more attention to negative signals in the environment, we think about them more often and remember them better. Voters preferentially select to read negative information about political candidates (Meffert, Chung, Joiner, Waks, & Garst, 2006). Negative news stories elicit stronger psychophysiological reactions in experimental subjects (Soroka & McAdams, 2015). Given that psychological bias, it is plausible that negative opinions shared by people skeptical of the media could have a stronger impact than positive ones shared by those who trust news outlets. The last hypothesis of this study reflects those considerations:

> **H5**: Individual media trust will be positively predicted by the media trust of a person's *low-trust* social ties.

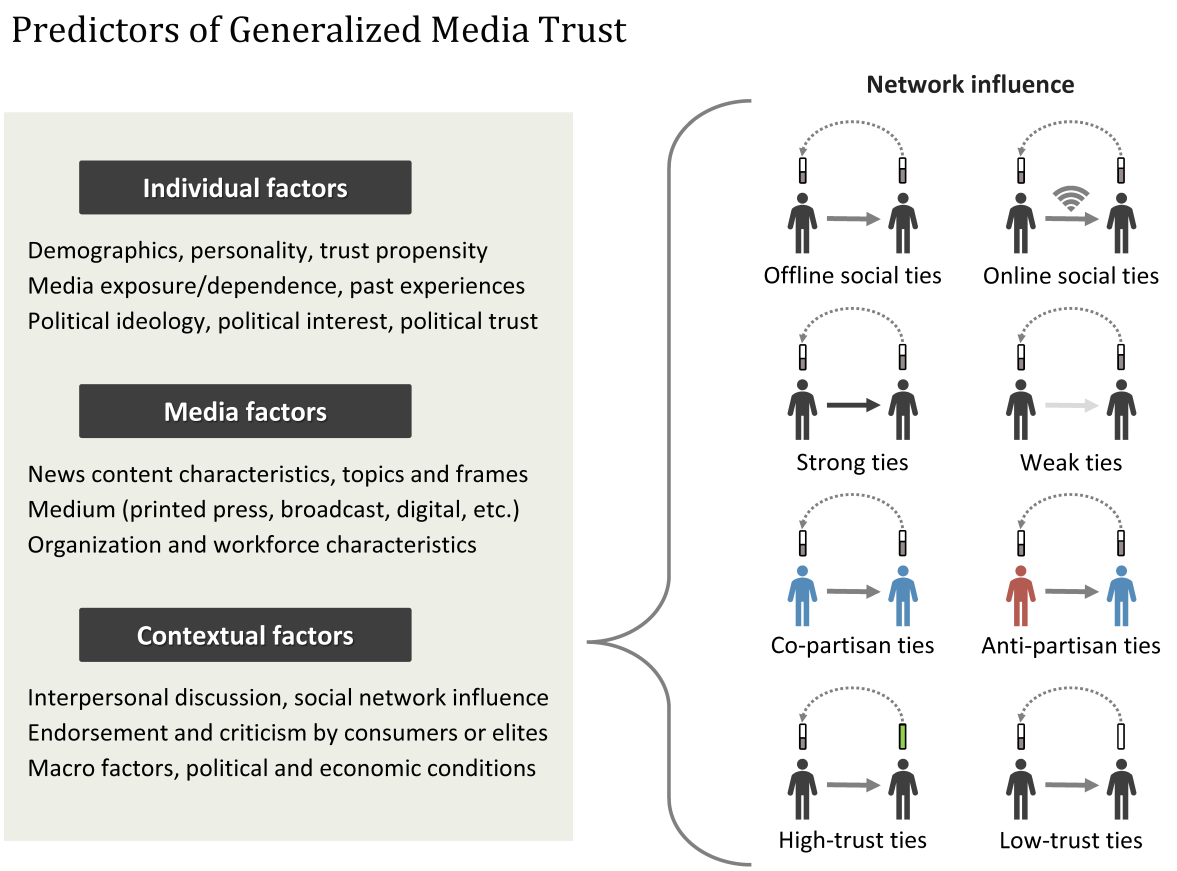

Figure 1. Predictors of media trust.

Understanding network effects

Measuring social influence presents a number of conceptual and methodological challenges. One important issue emerges at the stage of data collection. Full-network longitudinal datasets are best suited to track changes in network structure and individual behavior (Pietryka et al., 2018). Data of that kind describe the relationships among all members of a group, community, or organization. The participants typically report on their own social ties and provide information about their own actions and opinions.

Beyond data collection, a major challenge in studying network effects is establishing the causal relationships between social structure and individual behavior. Social influence is only one of several mechanisms that lead to network autocorrelation (the clustering of people with similar attributes in a network). To confirm that social influence is taking place, we need to rule out alternative explanations including social selection, contextual effects, and confounding variables causing spurious correlations (Shalizi & Thomas, 2011).

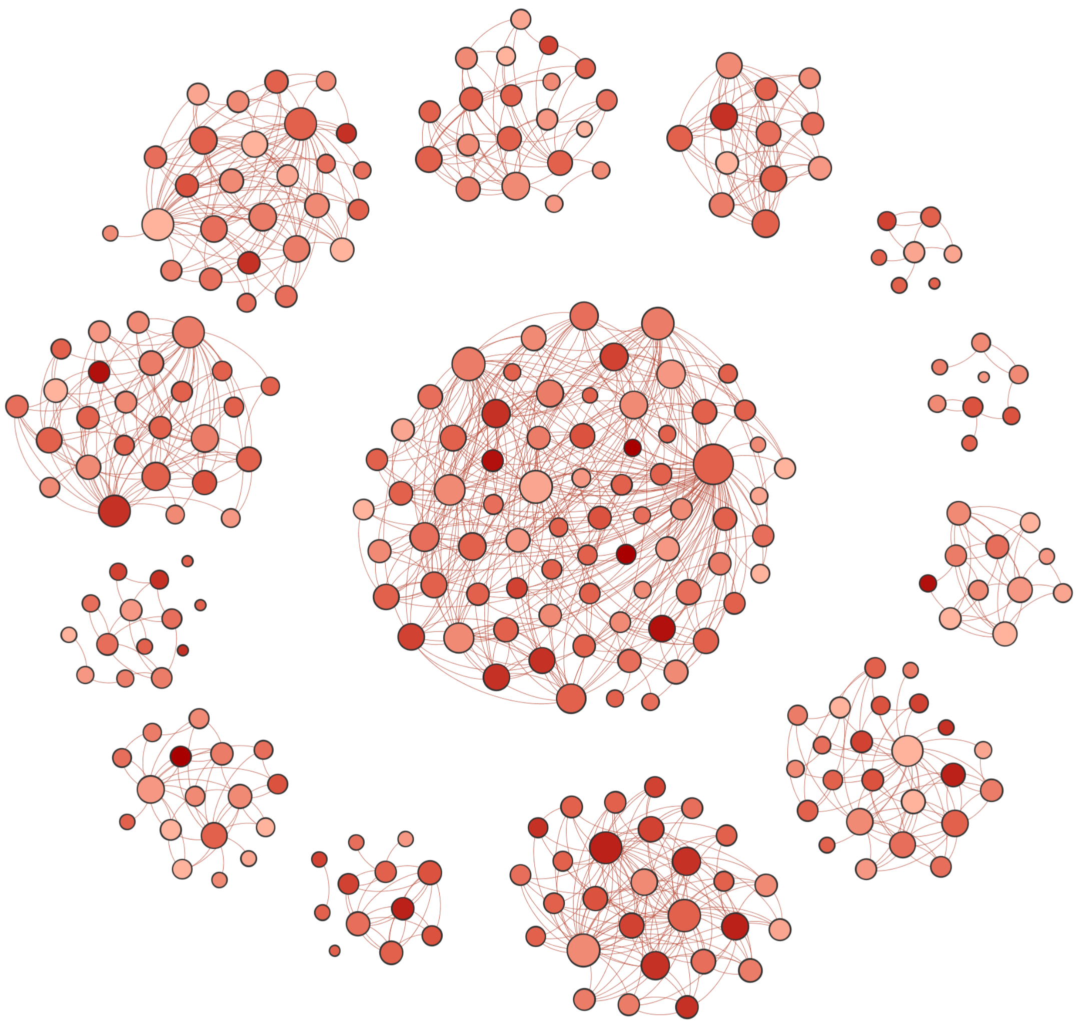

Figure 2. Social networks of the 13 communities included in the analysis. Node size based on number of social connections; color intensity based on generalized media trust in Wave 2.

The approach selected here was to examine full network data from residential student communities in a large public university. Student communities provide one of the most commonly studied social contexts for network research (Lazer, Rubineau, Chetkovich, Katz, & Neblo, 2010; Newcomb, 1943). This is not just because they are convenient for researchers: student networks offer important advantages that go beyond simple availability. One opportunity this context presents is access to a well-defined social system with clear boundaries. Students who both live and study together quickly develop strong and often lasting relationships which serve as conduits for social influence. This social context is also of substantive interest as college years are a period in which people establish attitudes, habits, and interpersonal ties likely to persist throughout their adult life (Klofstad, 2015).

The present work adopts the *nascent network* research design introduced by Lazer and colleagues (Lazer et al., 2015, 2010). That approach involves surveying individuals at multiple time points, starting at a time before they have entered a social system and formed interpersonal connections. In this first measurement, we can record the self-reported characteristics of subjects who have no prior exposure to the social network. The benefit of this design is that initial measurements are clean of any network influence.

Method

Procedures and participants

The analysis examines the social networks of 13 residential student communities. The communities are part of a living-learning program operating at a large public university. Each community consists of students who live in the same dormitory and take classes together. Each community is based on a distinct academic discipline or interest (e.g., business, psychology, pre-medical, Latin culture, French language, etc.) The shared living spaces and collective learning facilitate the formation of the robust and influential social relationships.

The data used here come from two survey waves completed in August and December of 2017. The first wave was distributed before the start of the school year when students would join the university and their residential communities. The second wave was collected after the students had lived in their community for a semester. The surveys were sent to all 390 members of the 13 residential communities. Community size varied from 88 members for the largest to eight members for the smallest, with a typical size of 20 to 40 members.

The surveys were distributed over e-mail using the Qualtrics platform. As an incentive, participants were included in a drawing for ten $15 Amazon gift cards and one Apple iPad Mini. Thanks to the cooperation of the community administrators, 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 are based on a sample of 255 respondents who participated in both survey waves. 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.

Measurement

Mean scores for the variables described below are available in Table 1 and Table 2. Item non-response for the questions used in the analyses was relatively low, with 1%-6% missing data. Those values were imputed though it should be noted that the results of the analyses conducted here do not substantively change with listwise deletion of missing data.

Network variables.

To capture their social connections, participants were shown a roster that listed all members of their community. The respondents were asked to select the names of all individuals with whom they had certain types of relationship. The description of offline social ties used here was "I spend a lot of time with this person". Online social ties were described as "I often talk to this person online". 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 the *offline network*, *online network,* and *close ties network* 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 present as percent of all possible ties within that community) was 34% for offline ties, 19% for online ties, and 10% for close ties.

Media trust.

Following the practice to measure generalized trust in media using items adapted from the General Social Survey, this study asked participants how much confidence they had in *Newspapers*, *TV News*, and *Online News*. Responses were measured on a scale ranging from 1 (None at all) to 5 (A great deal). The generalized media trust was computed by combining the three items. Cronbach's alpha was acceptable (α = .82). Principal component analysis suggested a single component which would explain 72% of the variance. The standardized factor loadings were high and similar in size (.84, .92, and .80). The *media trust* variable was computed by summing the three items weighted by their factor loadings (range 3 to 15; weighted range 2.5 to 12.8, M = 6.7, SD = 2.2).

Participant scores on media trust changed considerably between the first and second wave of the study. The zero-order correlation of trust in the two waves was relatively low at r = .48. The autocorrelation was similarly low for other news and information variables in the data. Those patterns can be explained by the major life shift experienced by students who moved to college after the first survey wave and spent a semester there before completing the second survey.

Control variables.

Control variables included in the model were selected based on the media trust literature discussed above. The means and standard deviations of control variables are available in Table

1 and Table 2. Demographic controls included *gender*, *race* and *ethnicity*, as well as *immigration status* measured as a binary variable indicating whether a person was a first-generation immigrant to the US or not. Models also controlled for *annual family income*, measured on a scale ranging from 1 (Under $10,000) to 8 (Over $150,000); *ideology* ranging from 1 (Very liberal) to 7 (Very conservative); *interest in politics* ranging from 1 (Not at all interested) to 5 (Extremely interested); frequency of *political discussion* and frequency of *media use* for news and information, both ranging from 1 (Never) to 7 (Daily).

Table 1. *Demographic characteristics of the sample*

Variable	Wave 1	Wave 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%

Table 2. *Key variables - descriptive statistics*

Variable	Wave 1 Mean (SD)	Wave 2 Mean (SD)
Confidence in US media (3-15)	7.07 (2.26)	6.69 (2.23)
Confidence in newspapers (1-5)	2.87 (1.02)	2.63 (1.02)
Confidence in television news (1-5)	2.71 (1.05)	2.59 (1.04)
Confidence in online news (1-5)	2.70 (1.06)	2.62 (0.99)
Family income (1-8)	4.89 (2.22)	4.80 (2.20)
Interest in politics (1-5)	3.30 (1.15)	3.14 (1.21)
Political discussion (1-7)	5.04 (1.66)	4.43 (1.86)
Ideology (Liberal-Conservative, 1-7)	3.08 (1.25)	3.15 (1.32)
Frequency of poitical discussion(1-7)	5.04 (1.66)	4.43 (1.86)
Frequency of media use (1-7)	5.98 (1.40)	5.76 (1.73)

Additional theoretically grounded control variables were tested but not included in the final model as all resulting parameters were small in size and non-significant. Those variables included community size, as well as the raw and normalized network sizes of the participants (the incoming, outgoing, and total ties for each respondent in each network).

Analysis

The analyses were conducted using the R platform for statistical computing version 3.6 (R Core Team, 2015) and RStudio (2019) version 1.2.1335. The analysis used ordinary least squares regressions with cluster-bootstrapped standard errors and p-values to account for the fact that respondents in the data were clustered by community into 13 groups.

The network influence models used here regress individual *media trust* (measured in Wave 2) over the average media trust of social ties in Wave 1, controlling for one's own media trust in Wave 1. This is a variant of a network autoregressive model of the form $\boldsymbol{y} = \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X}\beta + \varepsilon$, $\varepsilon \sim (N, \sigma^2 I)$, where **y** is the media trust 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 suggested that one's media trust could be predicted by the media trust of their offline social ties, while H2 proposed the same would be true of online social connections. To address both, network autocorrelation models were estimated for the online and offline social networks reported by participants.

According to H3, strong ties would influence media trust. To evaluate the hypothesis, the analysis used two different operationalizations of tie strength. The first metric, *tie closeness*, aimed to capture relationship intimacy. It used the network generated by asking respondents to identify the three people in their community to whom they felt the closest. Those close ties varied in their mode of communication: 63% were also selected as offline ties, 40% were selected as online ties, 36% were both, and 34% were none.

The second metric, *tie intensity*, was based on the online and offline connections of the respondents. Multiple modes of communication were used as an indicator of a stronger connection that was grounded in several shared social contexts. Here, dyads were assigned 0 if they had no connection, 1 if they had only an offline or an online tie, and 2 if they had both an offline and an online tie[1]. Network autocorrelation models were used to test the hypothesis.

H4 predicted that co-partisan social ties would have an impact on media trust. 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) share the same political party. That resulted in four new networks:

[1] Analyses were also conducted with an alternative operationalization of *tie intensity* that assumed offline ties were stronger than online ones (1 was assigned to dyads with online only ties, 2 to dyads with offline only ties, 3 to dyads with both ties). The two *intensity* measures were highly correlated, and the results of both models were practically identical.

co-partisan offline ties, co-partisan online ties, anti-partisan offline ties, and anti-partisan online ties. Network autocorrelation models were estimated for each of those networks.

H5 suggested that low-trust social ties may influence media trust. The sample was split into quartiles based on media trust scores, with the top 25% deemed to be high-trust, and the lowest 25% deemed to be low-trust. The network influence term used to answer this question was computed as the percent of a respondent's social ties who had low (high) trust.

Results

To test H1, a network autocorrelation model with cluster-bootstrapped errors was estimated for media trust. Model results are available in Figure 3 and Table 3. Network influence was a large and significant positive predictor of media trust (b = .31, SE = .07, p < .01), suggesting that we could expect a .3 increase in generalized media trust per unit increase in the average trust of offline social ties. The explained variance in that model was 29% with an explained variance change for the network predictor of 3%.

Table 3. Network influence on media trust. The predicted variable is generalized media trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .90 for offline ties, .77 for online ties.

Variable	Offline Ties	Online Ties
Network influence: Media trust (W1)	.31 (.07)**	.30 (.10)*
Media trust (W1)	.42 (.05)***	.42 (.05)***
Gender: Female	.08 (.34)	.04 (.32)
Race/Ethnicity: African American	-.21 (.27)	-.01 (.21)
Race/Ethnicity: Hispanic	.14 (.36)	.28 (.35)
Race/Ethnicity: Asian	.46 (.21)	.64 (.19)*
Family income (1-8)	-.02 (.04)	.00 (.04)
First generation immigrant (0-1)	.01 (.30)	-.04 (.32)
Ideology (Liberal-Conservative, 1-7)	-.09 (.08)	-.07 (.08)
Interest in politics (1-5)	-.11 (.17)	-.11 (.18)
Political Discussion (1-7)	.10 (.06)	.10 (.07)
Media use (1-7)	.16 (.07)	.16 (.08)
Observations	255	255
R^2	0.29	0.28
ΔR^2 Network influence	0.03	0.02

• p < .1, * p < .05, ** p < .01 ***p < .001

H2 was tested using a similar model based on the online social network reported by respondents. The online network influence parameter was positive and significant (b = .30, SE = .10, p < .05). The variance in media trust explained by the online model was 28% with a 2% ΔR^2 for the network variable. While the explained variance contributed by network factors is small, it does emerge consistently across analyses and is notable especially because this study examines only one of the social contexts of the participants.

To provide a more comprehensive understanding of the dynamics of media trust, this work also includes separate models in which the predicted outcome variables are *confidence in newspapers*, *confidence in TV news*, and *confidence in online news.* Results are presented on Figure 3, with full model results included in Appendix A.

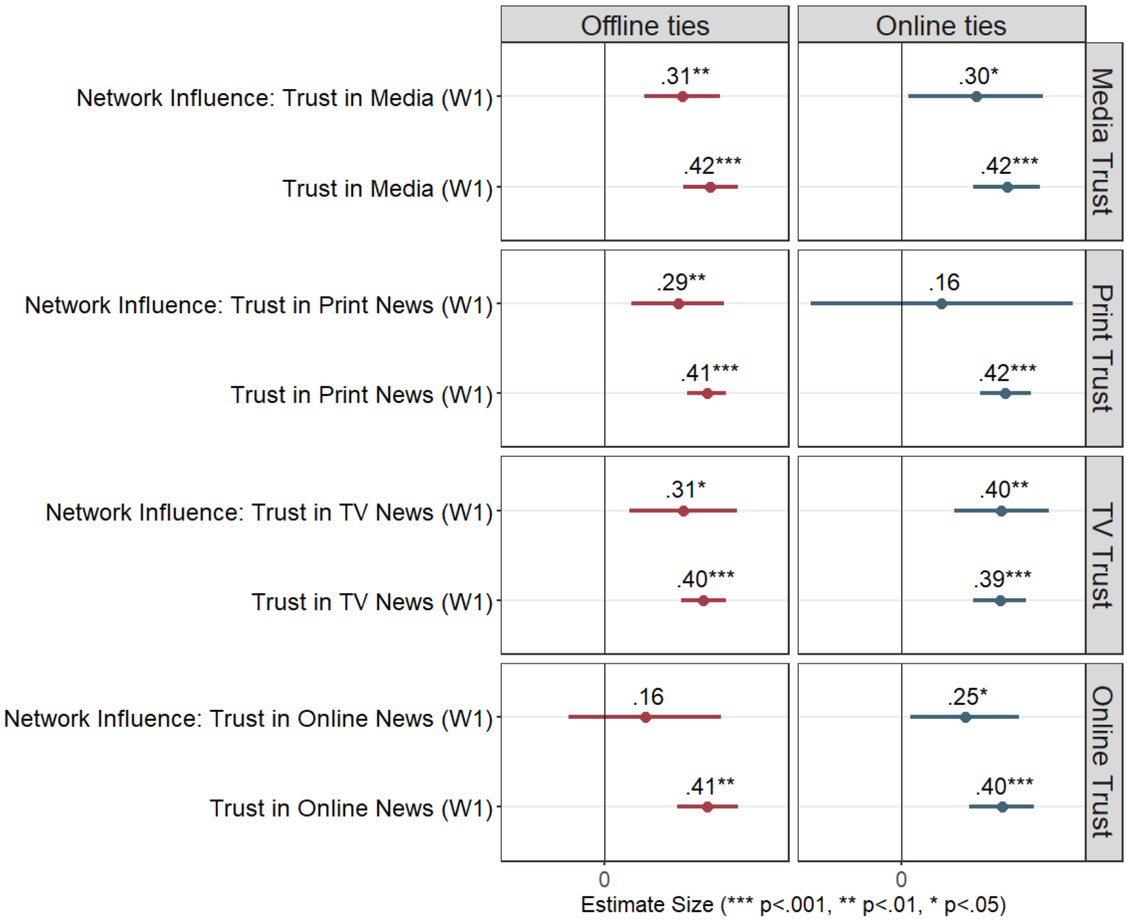

Figure 3. Model results: network influence on media trust. The figure presents unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors. The results show network influence estimates for generalized media trust and trust in specific media. The coefficients for one's own score on the variable in the first survey wave (measured on the same scale) are also included for comparison.

In the data examined here, there was unsurprisingly a considerable overlap between online ties and offline ties (see Fig.4). The participants talked online to 33% of the people with whom they spent time offline. The participants also spent offline time with 55% of their reported online ties. One way to better understand the independent influence of the offline and online channels of communication was to run models that included only unimodal ties.

Figure 4. Online and offline network overlap. Overlapping ties represent dyads of people who communicate both offline and online.

A model was estimated to examine the network influence of offline-only ties: those social connections that people had offline but did not contact online. Similarly, an online-only network influence model was estimated for social ties to whom people talked online, but not offline. While the average media trust of the offline-only ties did significantly positively predict media trust (b = .27, SE = .08, p < .05), this was not true of the online-only ties (b = .19, SE = .18, p > .05). These results suggest that offline interaction may be the main pathway for social influence, while online communication is relevant to the extent that it involves offline ties. The full results for these and all following models are available in Appendix A.

H3 proposed that strong ties mattered for media trust. The results provided partial support for that hypothesis. The network influence estimate was positive and significant in the *tie intensity* model (b = .33, SE = .04, p < .001) but not in the *tie closeness* model (b = .18, SE = .11, p > .05).

H4 referred to the effect of co-partisan social ties. The analysis was conducted using a subsample of 227 participants (209 also present in the first data wave) who identified as Democrats (84%) or Republicans (16%), excluding independents or those who selected the "other" category. In the resulting offline network, 74% of all ties were co-partisan, meaning they connected two people with the same political affiliation, and 26% were anti-partisan, connecting people across party lines. In the online network, 76% of the ties were co-partisan, and 24% were anti-partisan.

In the model examining co-partisan offline social ties, the network influence estimate was positive, large in size, and significant (b = .41, SE = .10, p < .001). The explained variance for this model was 31%. In contrast, the estimate focusing on connection between people across party lines was small in size and not significant (b = .03, SE = .10, p > .05) with an explained variance of 27%. For online ties, neither the co-partisan (b = .23, SE = .12, p > .05), nor the anti-partisan ties (b = .03, SE = .09, p > .05) were independently significant.

H5 addressed the network influence estimates of social ties with low media trust. In the low-trust model, the network influence estimate was based on the proportion of each person's ties that fell in the top quartile for media trust. The estimates for both offline ties (b = -1.7, SE = .62, p < .05) and online ties (b = -2.1, SE = .67, p < .05) were large, negative, and statistically significant. Note that these unstandardized estimates are relatively larger in absolute size compared to the ones above due to the nature of the network influence variable here. In this case, the estimates reflect the decrease in media trust we expect to see as people with low media trust go from making up 0% of our social ties to making up 100% of our social ties. In high-trust models, the estimate for network influence was positive and significant for offline ties (b = 1.33, SE = .35, p < .01), but non-significant for online ties (b = .59, SE = .44, p > .05).

Testing alternative explanations

Social influence provides one explanation for the findings presented here. It is also possible, however, that results are partly due to social selection. Individuals may select friends who have similar levels of media trust, or who are similar in other unobserved ways that affect trust. One way to test for that possibility is to examine the levels of media trust for connected participants during the first wave of data collection. Wave 1 of the survey was conducted prior to the start of the school year, before students were exposed to their future residential communities. Thus, any similarities found between an individual and his or her future social ties could be attributed to homophilous social selection: the tendency to form ties with similar others. If, on the other hand, we find no similarities between participants and their network ties at that point in time, homophilous selection is unlikely. The analyses conducted to examine these patterns are presented in Appendix A, Section A2. The results confirm that social ties were *not* more likely to form between people with similar levels of media trust. Social influence is therefore a more likely explanation for the results of this study.

Robustness checks

Network influence estimates are potentially susceptible to a number of unmeasured confounders: social selection (as discussed above), environmental factors that affect parts of the network (e.g., exposure to a media campaign or political elite messages), or reverse causality issues (the respondent's own effect on the media trust levels of their social ties). Sensitivity analyses give us an idea about the magnitude of a potential confounder that would be required in order to render the network influence findings non-significant. The sensitivity tests conducted to evaluate the robustness of the results of this study to unmeasured confounding are presented in Appendix A, section A3 Appendix A, section A3. Overall, the results suggest that network influence estimates are robust to fairly high levels of endogeneity and confounding. Additional checks were conducted to examine the robustness of the main results to outliers. No individuals or communities in the data were found to skew the study results.

Discussion

While low public trust in the media is not new, it has recently come to the forefront against a backdrop of large-scale misinformation and propaganda campaigns across the globe. Scholars have identified dwindling audience trust as a symptom of a problematic erosion in journalistic legitimacy (Broersma, 2019) or a sign of an institutional decline of the news industry (Reese, 2019).

The erosion of trust in the media has far-reaching consequences going beyond its implications for the business model of journalism. Confidence in mainstream sources can influence citizen exposure to information, potentially shaping the way social and political realities are perceived. Media trust is associated with confidence in political actors and institutions (Ariely, 2015; Gronke & Cook, 2007; Hanitzsch et al., 2018) and related to political efficacy (Coleman, 2012). Distrust in journalism can also lead to increased political polarization (Ladd, 2010), especially as people who do not trust media institutions are more likely to discount political news and rely heavily on their partisan predispositions when making electoral decisions (Ladd, 2012).

This study contributes to our understanding of media trust by examining its social component. The findings suggest that our views of the news industry may be shaped not only by our own predispositions and experiences but also by those of the people around us. Perceptions of media reverberate in interpersonal networks causing opinions to shift over time. Along with micro- and macro-level factors, the network structure of social groups plays a critical role in promoting and suppressing confidence in journalism. This is especially true in times of higher uncertainty, political or economic instability, when we rely more heavily on our social networks to decide whom and what to trust (Cook, Santana, et al., 2018).

In the analyses reported above, the media trust of participants was consistently predicted by the media trust of the people with whom they interacted face to face. There was some evidence suggesting that online communication can influence media trust, although the effect could be limited to strong ties who were also offline friends. Bond and colleagues (2012) found a similar pattern in their experiments examining online social influence on voting. Their online intervention affected not only the people who were subjected to it, but also a subset of their online contacts: close friends with face-to-face relationships. Bond et al. concluded that those strong ties are essential for behavioral contagion, and their influence can be channeled through both offline and digital interactions.

To further illuminate the effects of tie strength, this study examined the role of social connections high in communication intensity and perceived relational closeness. *Intense ties* who frequently interacted with respondents both online and offline did affect media trust. Somewhat surprisingly, no effect was found for *close ties*: contacts perceived as emotionally closer and more intimate. While we may perceive relational closeness even without frequent contact with the other person (as is the case with a third of the close ties in the data), a more intense information exchange may be required for opinion change.

The results also suggest that political identity affects the ability of face-to-face interactions to influence views about the media. For respondents in the sample who identified as Democrats or Republicans, like-minded co-partisan ties predicted media trust, while anti-partisan ties did not. This finding is not surprising given that ties between similar partners generally enhance social contagion (Centola, 2011). Furthermore, co-partisan conversations may shift the way participants perceive whether news coverage is fair or biased (Eveland & Shah, 2003), changing their levels of media trust.

Finally, this study examined the possibility that exposure to cynical views about the media may have a stronger impact than exposure to more trusting social ties. In an offline context, the media trust of a respondent was predicted both by exposure to low-trust and to high-trust ties. For online connections, however, only exposure to low-trust ties had a strong significant effect. The models predicted that changing an individual's online network from having no low-trust contacts at all to having only low-trust contacts would decrease their media trust score by 20%.

One possible explanation for this difference between online and offline networks is that digital platforms allow for more selectivity in exposure to content. Combined with a negativity bias (Rozin & Royzman, 2001), that may mean more cynical or critical content gets more attention on social media, making posts from low-trust ties more influential.

There are several limitations of the analyses conducted here, some of which are also discussed earlier in this work. Establishing a causal link between network structure and individual attributes is methodologically challenging (Shalizi & Thomas, 2011). This work relies on a nascent network *a*pproach and tests of alternative hypotheses to confirm that influence is the most plausible explanation. Those analyses show that there is no tendency for individuals in the sample to select social ties with similar levels of media trust or to cluster on other unobserved variables that affect trust. Sensitivity analyses also demonstrate that the network influence estimates are robust to fairly high levels of endogeneity and confounding.

A question that often arises with full-network studies concerns the generalizability of their findings. Since this study explores a particular type of social network, it is not unreasonable to ask if the patterns uncovered here will hold across different social groups. This is a challenge that stems not simply from methodological choices, but from the way social systems function. Interpersonal networks are always part of a specific social context that requires physical proximity, shared organizational settings, or collective participation in a virtual community. Still, based on the considerations outlined in this work, it is plausible that the effects found here would carry to other settings and populations.

Missing data are another potential limitation of the study. While the participant response rate is high (83% and 72%), full network studies are more sensitive to non-response compared to analyses that use random sampling. Previous research has indicated that many network measures can be reasonably estimated even with relatively high level of missingness, as long as network members are missing at random (Smith & Moody, 2013). Examining the network nominations of survey non-respondents in the data does not reveal problematic self-selection biases, though that possibility cannot be entirely ruled out.

Overall, this study provides support for the key role that social structure plays in shaping our views of journalism. Future work should examine ways of productively harnessing interpersonal influence to curb the spread of misinformation in digital spaces. Another fruitful line of research might include a broader look at the way social connections affect confidence in key social institutions.

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Appendix A

A1 Full model results

Table 1. *Network influence on media trust. The predicted variable is generalized media trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .90 for offline ties, .77 for online ties.*

Variable	Offline Ties	Online Ties
Network influence: Media trust (W1)	.31 (.07)**	.30 (.10)*
Media trust (W1)	.42 (.05)***	.42 (.05)***
Gender: Female	.08 (.34)	.04 (.32)
Race/Ethnicity: African American	-.21 (.27)	-.01 (.21)
Race/Ethnicity: Hispanic	.14 (.36)	.28 (.35)
Race/Ethnicity: Asian	.46 (.21)	.64 (.19)*
Family income (1-8)	-.02 (.04)	.00 (.04)
First generation immigrant (0-1)	.01 (.30)	-.04 (.32)
Ideology (Liberal-Conservative, 1-7)	-.09 (.08)	-.07 (.08)
Interest in politics (1-5)	-.11 (.17)	-.11 (.18)
Political Discussion (1-7)	.10 (.06)	.10 (.07)
Media use (1-7)	.16 (.07)	.16 (.08)
Observations	255	255
R^2	0.29	0.28
ΔR^2 Network influence	0.03	0.02

• $p < .1$, * $p < .05$, ** $p < .01$ ***$p < .001$

Table 2. *Network influence on media trust. The predicted variable is generalized media trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .80 for offline ties, .46 for online ties.*

Variable	**Offline-only (not online) Ties**	**Online-only (not offline) Ties**
Network influence: Media trust (W1)	.27 (.08)*	.19 (.18)
Media trust (W1)	.43 (.05)***	.44 (.06)***
Gender: Female	.03 (.35)	.04 (.33)
Race/Ethnicity: African American	-.15 (.28)	-.05 (.20)
Race/Ethnicity: Hispanic	.12 (.39)	.22 (.33)
Race/Ethnicity: Asian	.50 (.22)	.62 (.17)*
Family income (1-8)	-.01 (.04)	.00 (.04)
First generation immigrant (0-1)	-.02 (.33)	-.06 (.32)
Ideology (Liberal-Conservative, 1-7)	-.11 (.16)	-.12 (.18)
Interest in politics (1-5)	.12 (.06)*	.12 (.06)•
Political Discussion (1-7)	-.09 (.07)	-.07 (.07)
Media use (1-7)	.16 (.07)	.15 (.08)
Observations	255	255
R^2	0.28	0.27
ΔR^2 Network influence	0.02	0.01

• $p < .1$, * $p < .05$, ** $p < .01$ *** $p < .001$

Table 3. *Network influence on* *<u>newspaper</u>* *trust. The predicted variable is newspaper trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .76 for offline ties, .46 for online ties.*

Variable	**Offline Ties**	**Online Ties**
Network influence: Media trust (W1)	.29 (.08)**	.16 (.17)
Media trust (W1)	.41 (.04)***	.42 (.04)***
Gender: Female	-.01 (.16)	-.03 (.15)
Race/Ethnicity: African American	-.05 (.12)	.00 (.10)
Race/Ethnicity: Hispanic	.09 (.14)	.12 (.12)
Race/Ethnicity: Asian	.31 (.07)**	.38 (.07)**
Family income (1-8)	-.00 (.03)	.00 (.03)
First generation immigrant (0-1)	-.07 (.11)	-.10 (.13)
Ideology (Liberal-Conservative, 1-7)	-.04 (.08)	-.03 (.08)
Interest in politics (1-5)	.03 (.02)•	.03 (.02)
Political Discussion (1-7)	-.07 (.05)	-.06 (.05)
Media use (1-7)	.10 (.05)	.10 (.05)
Observations	255	255
R^2	0.28	0.27
ΔR^2 Network influence	0.02	0.01

• p < .1, * p < .05, ** p < .01 ***p < .001

Table 4. *Network influence on* *<u>TV news</u>* *trust. The predicted variable is TV news trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .79 for offline ties, .92 for online ties.*

Variable	**Offline Ties**	**Online Ties**
Network influence: Media trust (W1)	.31 (.08)*	.40 (.08)**
Media trust (W1)	.40 (.04)***	.39 (.05)***
Gender: Female	.02 (.13)	.03 (.11)
Race/Ethnicity: African American	-.12 (.14)	.00 (.14)
Race/Ethnicity: Hispanic	.14 (.17)	.24 (.18)
Race/Ethnicity: Asian	.22 (.15)	.31 (.14)
Family income (1-8)	-.01 (.02)	.01 (.02)
First generation immigrant (0-1)	.01 (.13)	.01 (.12)
Ideology (Liberal-Conservative, 1-7)	-.04 (.08)	-.04 (.09)
Interest in politics (1-5)	.04 (.03)	.05 (.03)
Political Discussion (1-7)	-.03 (.03)	-.02 (.03)
Media use (1-7)	.06 (.03)	.06 (.04)
Observations	255	255
R^2	0.23	0.24
ΔR^2 Network influence	0.02	0.03

• $p < .1$, * $p < .05$, ** $p < .01$ *** $p < .001$

Table 5. *Network influence on <u>online news</u> trust. The predicted variable is online news trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .44 for offline ties, .73 for online ties.*

Variable	**Offline Ties**	**Online Ties**
Network influence: Media trust (W1)	.16 (.11)	.25 (.09)*
Media trust (W1)	.41 (.05)***	.40 (.05)***
Gender: Female	.07 (.15)	.05 (.15)
Race/Ethnicity: African American	-.07 (.16)	-.02 (.15)
Race/Ethnicity: Hispanic	-.08 (.16)	-.05 (.15)
Race/Ethnicity: Asian	.03 (.11)	.06 (.10)
Family income (1-8)	-.01 (.02)	-.01 (.02)
First generation immigrant (0-1)	.06 (.17)	.05 (.18)
Ideology (Liberal-Conservative, 1-7)	-.05 (.07)	-.05 (.08)
Interest in politics (1-5)	.05 (.04)	.05 (.04)
Political Discussion (1-7)	.00 (.03)	.01 (.04)
Media use (1-7)	.03 (.02)	.03 (.03)
Observations	255	255
R^2	0.22	0.23
ΔR^2 Network influence	0.01	0.02

• p < .1, * p < .05, ** p < .01 ***p < .001

Table 6. <u>Strong tie</u> *influence on media trust. The predicted variable is generalized media trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .76 for close ties, .90 for intense ties.*

Variable	**Strong Ties (Tie closeness)**	**Strong Ties (Tie intensity)**
Network influence: Media trust (W1)	.18 (.11)	.33 (.04)***
Media trust (W1)	.43 (.05)***	.42 (.05)***
Gender: Female	.06 (.32)	.08 (.33)
Race/Ethnicity: African American	-.11 (.24)	-.18 (.27)
Race/Ethnicity: Hispanic	.19 (.39)	.15 (.36)
Race/Ethnicity: Asian	.55 (.20).	.46 (.20)
Family income (1-8)	-.01 (.04)	-.02 (.04)
First generation immigrant (0-1)	-.10 (.33)	.00 (.30)
Ideology (Liberal-Conservative, 1-7)	-.07 (.17)	-.13 (.18)
Interest in politics (1-5)	.10 (.06)	.10 (.07)•
Political Discussion (1-7)	-.08 (.08)	-.09 (.08)
Media use (1-7)	.14 (.07)	.16 (.07)
Observations	255	255
R^2	0.28	0.29
ΔR^2 Network influence	0.02	0.03

• $p < .1$, * $p < .05$, ** $p < .01$ *** $p < .001$

Table 7. *Co-partisan influence on media trust. The predicted variable is generalized media trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .97 for offline ties, .56 for online ties.*

Variable	**Co-partisan Offline Ties**	**Co-partisan Online Ties**
Network influence: Media trust (W1)	.41 (.10)***	.23 (.12)
Media trust (W1)	.44 (.05)***	.45 (.06)***
Gender: Female	.04 (.26)	-.05 (.28)
Race/Ethnicity: African American	.01 (.35)	.04 (.34)
Race/Ethnicity: Hispanic	.34 (.29)	.44 (.33)
Race/Ethnicity: Asian	.72 (.21)**	.80 (.19)***
Family income (1-8)	.00 (.05)	.02 (.05)
First generation immigrant (0-1)	-.47 (.25)•	-.57 (.25)•
Ideology (Liberal-Conservative, 1-7)	-.16 (.11)	-.20 (.14)
Interest in politics (1-5)	.17 (.08).	.16 (.09)
Political Discussion (1-7)	-.03 (.08)	-.03 (.08)
Media use (1-7)	.08 (.06)	.10 (.06)s•
Observations	209	209
R^2	0.31	0.28
ΔR^2 Network influence	0.04	0.01

• $p < .1$, * $p < .05$, ** $p < .01$ ***$p < .001$

Table 8. <u>*Anti-partisan*</u> *influence on media trust. The predicted variable is generalized media trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .12 for offline ties, .10 for online ties.*

Variable	Anti-partisan Offline Ties	Anti-partisan Online Ties
Network influence: Media trust (W1)	.03 (.10)	.03 (.09)
Media trust (W1)	.46 (.06)***	.46 (.07)***
Gender: Female	-.10 (.31)	-.09 (.31)
Race/Ethnicity: African American	-.00 (.34)	.00 (.32)
Race/Ethnicity: Hispanic	.34 (.34)	.33 (.32)
Race/Ethnicity: Asian	.73 (.19)*	.72 (.17)**
Family income (1-8)	.02 (.05)	.02 (.05)
First generation immigrant (0-1)	-.52 (.26).	-.52 (.28)
Ideology (Liberal-Conservative, 1-7)	-.17 (.13)	-.17 (.13)
Interest in politics (1-5)	.17 (.09).	.17 (.09)
Political Discussion (1-7)	-.03 (.08)	-.02 (.08)
Media use (1-7)	.09 (.05)	.09 (.05)
Observations	209	209
R^2	0.27	0.27
ΔR^2 Network influence	0.00	0.00

• $p < .1$, * $p < .05$, ** $p < .01$ ***$p < .001$

Table 9. *Low-trust tie influence on media trust. The predicted variable is generalized media trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .76 for offline ties, .80 for online ties.*

Variable	**Low-trust Offline Ties**	**Low-trust Online Ties**
Network influence: Media trust (W1)	-1.70 (.62)*	-2.06 (.67)*
Media trust (W1)	.44 (.05)***	.44 (.05)***
Gender: Female	.03 (.35)	-.01 (.33)
Race/Ethnicity: African American	-.16 (.26)	-.03 (.20)
Race/Ethnicity: Hispanic	.11 (.38)	.28 (.31)
Race/Ethnicity: Asian	.50 (.21).	.60 (.17)*
Family income (1-8)	-.02 (.04)	-.01 (.04)
First generation immigrant (0-1)	.01 (.33)	-.04 (.30)
Ideology (Liberal-Conservative, 1-7)	-.11 (.15)	-.09 (.18)
Interest in politics (1-5)	.12 (.06).	.12 (.07).
Political Discussion (1-7)	-.06 (.08)	-.05 (.07)
Media use (1-7)	.15 (.07)	.16 (.07)
Observations	255	255
R^2	0.28	0.28
ΔR^2 Network influence	0.02	0.02

• p < .1, * p < .05, ** p < .01 ***p < .001

Table 10. *<u>High-trust</u> tie influence on media trust. The predicted variable is generalized media trust in Wave 2 of the study. The table includes unstandardized estimates from network autocorrelation models using OLS regression with cluster-bootstrapped errors to account for clustering by study site. Observed power: .83 for offline ties, .22 for online ties.*

Variable	**High-trust Offline Ties**	**High-trust Online Ties**
Network influence: Media trust (W1)	1.33 (.35)**	.59 (.44)
Media trust (W1)	.43 (.05)***	.44 (.05)***
Gender: Female	.15 (.31)	.04 (.33)
Race/Ethnicity: African American	-.05 (.24)	-.06 (.25)
Race/Ethnicity: Hispanic	.17 (.35)	.19 (.38)
Race/Ethnicity: Asian	.48 (.17)*	.58 (.19)*
Family income (1-8)	.00 (.04)	-.00 (.04)
First generation immigrant (0-1)	-.01 (.29)	-.05 (.32)
Ideology (Liberal-Conservative, 1-7)	-.13 (.19)	-.12 (.18)
Interest in politics (1-5)	.12 (.06).	.11 (.07)
Political Discussion (1-7)	-.09 (.08)	-.07 (.08)
Media use (1-7)	.15 (.08)	.16 (.08)
Observations	255	255
R^2	0.29	0.27
ΔR^2 Network influence	0.02	0.00

• $p < .1$, * $p < .05$, ** $p < .01$ *** $p < .001$

A2 Testing alternative explanations

Social influence provides one explanation for the findings presented in this work. It is also possible, however, that results are partly due to social selection. Individuals may select friends who have similar levels of media trust, or who are similar in other unobserved ways that affect trust. One way to test for that possibility is to examine the levels of media trust for connected participants during the first wave of data collection. Wave 1 of the survey was conducted prior to the start of the school year, before students were exposed to their future residential communities. Thus, similarities between an individual and his or her future social ties can be attributed to homophilous social selection: the tendency to form ties with similar others. If, on the other hand, we find no similarities between participants and their network ties at that point in time, homophilous selection is unlikely.

The network autocorrelation models used to evaluate this alternative explanation predict participant media trust in Wave 1 using as treatment the trust of their future social contacts from the same wave. In those models, the estimates are not significant for either offline ties ($b = .26$, $SE = .19$, $p > .05$) or online ties ($b = .30$, $SE = .15$, $p > .05$).

Another way to examine the data for homophily (preference for similar others) is through quadratic assignment procedure (QAP) tests (Krackhardt, 1988). The procedure uses permutation tests to examine the graph correlations between the respondents' social network and the matrix of their dyadic differences in media trust as measured in Wave 1. QAP tests were conducted individually for the 13 residential communities since each of them formed a separate local network, unconnected to the rest. The QAP correlations for both online and offline ties were small and mostly non-significant (the exception was one community which had a small significant negative relationship between online ties and media trust levels). The coefficients did not have a consistent direction, as 7 of the 13 offline network graph correlations and 6 of the 13 online network ones were negative.

These results confirm that social connections were not more likely to form between people with similar levels of media trust. Social influence is therefore a more likely explanation for the results presented in this study compared to social selection. The next section examines the sensitivity of the analysis to unobserved confounding variables.

A3 Robustness checks

Network influence estimates are potentially susceptible to a number of unmeasured confounders: social selection (as discussed above), environmental factors that affect parts of the network (e.g., exposure to a media campaign or political elite messages), or reverse causality issues (the respondent's own effect on the media trust levels of their social ties). Sensitivity analyses give us an idea about the magnitude of a potential confounder that would be required in order to render the network influence findings non-significant.

The sensitivity tests conducted here evaluated the two main models of network influence for offline and online ties. Prior to the analysis, variables in those models were standardized so that the sizes of the coefficients could be compared and examined on a common scale. Parametric sensitivity analyses were conducted using the R package treatSens version 2.1.3 (Carnegie, Harada, Dorie, & Hill, 2018). For the purposes of these tests, we assume that an unmeasured confounder U was omitted from the models. The reported analysis draws a series of simulated potential confounder values from a distribution conditional on the observed data. The reported sensitivity parameters are the standardized regression coefficients for the relationship of the confounder with the outcome variable (conditional on the predictor and control variables); and the relationship of the confounder with the predictor (conditional on the control variables). The results show that omitted variables would have to have a very strong effect on media trust in order to explain away the network influence estimates. For example, the influence from offline ties can be rendered non-significant by a confounder with an effect of .49 on media trust and .48 on the network influence variable. In comparison, the standardized effect of one's own media trust in the previous wave in the same model is .43. While the trust autocorrelation in this dataset is not high, the parameter importance is considerable and it explains close to 20% of the variance in the dependent variable. Tables 11 and 12 below list confounder coefficients for which the significance of network influence in the models is lost. Overall, the analysis suggests that the network influence estimates are robust to fairly high levels of endogeneity and confounding.

Additional checks were conducted to examine the robustness of the main results with regard to differences among the data collection sites. The data for this study came from thirteen separate communities so it would be possible for some sites to be outliers skewing the overall model results. A *leave-one-out* analysis was conducted to rule out the presence of such outliers. The network autocorrelation models were re-estimated on 13 subsets of the data, each of which excluded one of the communities in the sample. All models for offline ties had positive network influence estimates that were statistically significant at the .05 level, ranging in size from .27 to .36, with standard errors ranging from .05 to .09. The network influence estimates in models for online ties ranged in size from .23 to .30 with standard errors from .09 to .12. They were significant in seven cases, and marginally significant with cluster-bootstrapped p value lower than .10 in the other six cases.

Table 11. *Sensitivity analysis - offline ties model.*

Coefficients on U where significance level 0.05 is lost:

Y	Z
0.480	0.895
0.480	0.816
0.474	0.736
0.483	0.657
0.470	0.587
0.467	0.578
0.458	0.499
0.470	0.441
0.474	0.420
0.470	0.386
0.464	0.341
0.469	0.262
0.466	0.183
0.470	0.160
0.478	0.104
0.485	0.025
0.480	0.000
0.481	-0.025
0.504	-0.094
0.508	-0.104
0.504	-0.116
0.487	-0.183
0.497	-0.262
0.504	-0.303
0.525	-0.341
0.537	-0.400
0.541	-0.420
0.541	-0.499
0.571	-0.516
0.603	-0.578
0.605	-0.582
0.638	-0.624
0.662	-0.657
0.672	-0.670
0.705	-0.699
0.739	-0.717
0.769	-0.736
0.773	-0.738
0.806	-0.751

Table 12. *Sensitivity analysis - online ties model.*

Coefficients on U where significance level 0.05 is lost:

Y	Z
0.504	0.895
0.506	0.881
0.515	0.816
0.506	0.737
0.512	0.658
0.517	0.579
0.533	0.500
0.526	0.421
0.538	0.341
0.539	0.262
0.540	0.254
0.545	0.183
0.557	0.104
0.562	0.025
0.573	0.016
0.586	0.000
0.595	-0.025
0.607	-0.066
0.620	-0.104
0.628	-0.183
0.641	-0.219
0.660	-0.262
0.675	-0.301
0.692	-0.341
0.708	-0.379
0.737	-0.421
0.742	-0.427
0.776	-0.474
0.795	-0.500
0.809	-0.519

Appendix References

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