Political Behavior
https://doi.org/10.1007/s11109-026-10188-x

ORIGINAL PAPER

Do Political Discussion Partners Share Policy Priorities and Policy Frames?

Matthew T. Pietryka[1] · **Amber E. Boydstun**[2] · **Taylor N. Carlson**[3]

Accepted: 9 July 2026
© The Author(s) 2026

Abstract

To understand politics, people often rely on political discussion. Among the many ways that discussion may shape political perceptions, one possible mechanism is by promoting a shared sense of priorities—*which* issues are important. A second mechanism is by framing *how* people think about important issues. We examine these potential mechanisms by answering the descriptive question: Do policy priorities and policy frames tend to co-occur within political discussion networks? We answer this question by reanalyzing the 1996 Indianapolis-St. Louis Study in which participants—and their discussion partners—described the most important problem facing the United States in their own words. We show that the modal outcome is for people to hold both different priorities *and* different frames than their discussion partners. This finding stands in contrast to network scholarship suggesting that homophily is so often the norm. Yet we also show that people disproportionately share the *same* policy priorities as their discussion partners, and adopt the same frames in thinking about policy topics, especially when their policy priorities match. This finding suggests that some policy priorities are so embedded in certain frames of thinking that the topic and frame stay linked even as the topic may diffuse through a social network.

Keywords Social networks · Policy frames · Policy priorities · Political discussion

Social networks powerfully influence the way we think about and engage in politics (e.g., Bond et al. 2012; Cramer Walsh 2004; Huckfeldt and Sprague 1995; Sinclair 2012). Both qualitative and quantitative research suggests that people within a network typically have similar preferences. They tend to prefer the same political candidates, political parties, and policy solutions to a wide range of problems (Huckfeldt and Sprague 1995). A large literature has focused on understanding the mechanisms

Extended author information available on the last page of the article

Published online: 17 September 2026

explaining why people within a network have similar political preferences. These proposed mechanisms include (1) social influence via interpersonal communication, persuasion, or conformity (Huckfeldt et al. 2004; Sinclair 2012), and (2) homophily, including both intentional (Settle and Carlson 2019) and incidental selection (Minozzi et al. 2020) into networks of people with shared political perspectives.

Identifying the mechanisms that explain shared policy preferences (e.g., support for a tax policy) within networks is important, but it overlooks other features of public opinion that might also be shaped within social networks. In particular, the extent to which policy *priorities* and policy *frames* co-occur within social networks merits greater attention. Both policy priorities (e.g., thinking that tax policy is an important issue) and policy frames (e.g., conceptualizing tax policy in terms of economics vs. in terms of fairness) have been shown to shape policy preferences (Berinsky and Kinder 2006; Kinder and Sanders 1996; Nelson and Kinder 1996; Vidigal and Jerit 2022). Therefore, examining the similarity of priorities and frames across network ties will help us better understand how individual attitudes aggregate into widespread preferences. That is, we can better understand how *personal* thoughts become *public* opinion (Herbst 1998).

Policy priorities and frames are particularly important to understand within the context of social networks. Political discussion arising in social networks acts as a key mechanism driving homophily in political *preferences* (Butters and Hare 2022; Lazer et al. 2010). While it is possible to discuss policies and candidates without communicating an opinion about them that could thereby shape another person's preferences, it is difficult to imagine a situation in which discussing a topic is completely unrelated to priorities and frames. There is a general assumption in social networks and discussion research that "people talk about matters important to them with people important to them" (Bearman and Parigi 2004, 537), and that the more people hear about given topics, the more likely they are to consider them important policy priorities (Barberá et al. 2019). Therefore, the amount of discussion a topic receives is a signal of whether it should be a priority. Similarly, it is difficult to discuss a topic without using a frame to contextualize it. Nelson and Kinder (1996) call framing "a ubiquitous feature of political discourse" (p. 1058), noting that "citizens are bombarded with suggestions about how issues should be understood. These suggestions come in coherent packages, and at the heart of each package is a frame" (p. 1057). Consequently, frames and priorities are likely to be central components of political discussion, meaning that they could be influenced by social networks in ways that scholarship has yet to examine.

We consider first policy priorities, which are the topics or issues that someone considers to be most important for the government to address. Previous work has demonstrated that policy priorities are crucial in affecting downstream political choices (Dunaway et al. 2010; McCombs and Shaw 2005; Tan and Weaver 2007; but see also Walgrave and Van Aelst 2006). Yet despite the importance of policy priorities in shaping political preferences and even political campaigns (Bevan and Krewel 2015), we have little understanding of the extent to which policy priorities co-occur within social networks in a way similar to the way policy preferences do. Just as peers can shape policy preferences, so too could they shape policy priorities.

In addition to policy priorities, policy *frames*—the way in which people think about policies—also affect downstream political choices (Chong and Druckman 2007; Feezell et al. 2019; Glazier and Boydstun 2012; Iyengar 1991; Iyengar and Simon 1993). Most evidence on framing focuses on policy frames as communicated by mass media. However, social networks are an important context in which policy frames could also be communicated. For example, in her ethnographic study, Cramer Walsh (2004) found that in political discussions, people do not simply adopt the frames or considerations emphasized by news media's coverage of a given topic, but rather filter the topic through their own personal frames of reference. Compared to the frames used in news coverage, these personal frames are more likely to rely on first-hand experience with an issue and tend to draw heavily from the salient social identities within one's personal network. Similarly, recent experimental evidence suggests that some types of frames (Aarøe and Petersen 2020) and information (Carlson 2018, 2019) are more likely to transmit from one person to the next. If media frames can affect the ways people think about a topic, the way people talk about a topic could shape how their peers think about it. Some frames in thought may even produce a spillover effect, such that when someone discusses a policy topic using a certain frame, peers will also adopt that frame in how they think about other policy topics (Hopkins and Mummolo 2016). It is important to understand the extent to which policy frames co-occur within social networks because it could also help explain the homophily observed in policy preferences (i.e., the tendency for people to hold the same preferences as others in their network). Although this question is an important one to consider across a range of distinct types of frames (e.g., loss vs. gain, episodic vs. thematic), here we focus on emphasis frames (e.g., framing an issue in terms of economic vs. fairness considerations; see Nelson [2019] for a discussion).

In this paper, we argue that both policy topic priorities *and* policy frames tend to disproportionately co-occur within social networks. Moreover, we argue that the similarity in network members' priorities is inexorably intertwined with the similarity of their frames; when people discuss politics, we expect they rarely do so in a way that isolates topic priorities (e.g., education) from ways of framing those topics (e.g., fairness and equality), and instead talk about their beliefs and concerns in the form of complete concepts, or topics nested within frames (e.g., children should have equal access to quality education). If our arguments are correct, we should observe that policy priorities and policy frames tend to co-occur within social networks. That is, people should gravitate toward the same policy priorities as their network ties and they should do so while relying on the same frames for thinking about those policies. This diffusion process is essential to understand because what begins at the micro-level within voters' social networks could expand by diffusing to legislators and on through political institutions (Zelizer 2019).

Indeed, previous work has documented the ways in which frames used by political elites can trickle through to voters; and how voter priorities may spread to legislators (e.g., Barberá et al. 2019; Stier et al. 2018). However, these patterns are generally identified in the aggregate, allowing for a limited understanding of how policy frames and priorities spread within social networks. By demonstrating how peers share the same policy frames and priorities, as well as the extent to which they might diverge, we can better understand policy cycles.

We test our expectations by analyzing the 1996 Indianapolis-St. Louis Study in which a random sample of main respondents—and a supplementary sample of people in the main respondents' social networks—described the most important problem facing the United States in their own words. This dataset uniquely includes individual-level data on people's policy priorities, the frames they use to contextualize them, and the same information about their social ties, primarily drawn from face-to-face interactions. While social media data has allowed researchers to understand policy priorities and agenda setting in users' own words too, and directly observe their online networks (e.g., Barberá et al. 2019; Hemphill & Roback 2014; O'Connor et al. 2010), researchers are left making assumptions about whether discussing a topic online necessarily means that the user considers it important, even if they correlate in the aggregate. We use hand-coded content analysis of these most important problem descriptions to identify the topic and frame used by each respondent and their network ties. We then examine the similarity of political discussion partners' policy priorities and policy frames. Our analysis thereby complements recent work leveraging social media data to examine how individuals talk about political issues, by examining how issue priorities and frames co-occur within offline networks, with greater individual-level precision in measuring policy priorities.

We find that, across the entire dataset, the most common outcome was for people to have *different* policy priorities and think about them with *different* frames than their network ties. With so many potential issues to prioritize, and so many frames from which to draw, it makes sense that many discussion partners differ in their priorities and frames. Yet we also find that discussion partners disproportionately *share* both policy topic priorities and frames beyond what we would expect by chance, and that this tendency is stronger for some policy topics and frames than for others. About 36 percent of dyads—two people socially connected to each other—share the same policy topic priority, which is about seven percentage points more than what we would expect by random chance. Similarly, dyads were about five percentage points more likely than we would expect by chance to share the same policy frames. Importantly, we find that people are especially likely to adopt the same frames in thinking about policy topics when their policy priorities match. Together, these two findings—that the modal outcome between discussion partners is different priorities and different frames, but also that discussion partners share both priorities and frames more strongly than we would expect by chance—complicate the dominant narrative about political homophily in the political networks literature, suggesting that in terms of the topics and frames discussed, we need to account for the possibility that network ties in which there is agreement on priorities and frames might operate differently from those in which priorities and frames differ. Although our design cannot identify the causes behind these two types of network ties, we provide guidance for future work by examining the covariates that best distinguish these two types of dyads in our study.

In sum, by analyzing priorities and frames of political discussion partners, rather than only focusing on preferences, we make two key contributions. First, we show that homophily is far from the norm and yet more common than expected by chance; discussion partners are more likely than chance to share the same policy priorities, and they also tend to think about those priorities using the same frames. This compli-

cated finding is notable, given that past scholarship suggests that network homophily is common. Yet, we document different conclusions depending upon whether researchers are speaking in absolute terms, in which case we might conclude that homophily is uncommon, or relative terms comparing to random chance, in which case we might conclude that homophily is common. Second, our analysis reveals that the patterns of similarity within networks are strongest in cases in which discussion partners each prioritize the same policy topic or the same frame. That is, when people agree on which topics are most important, they are more likely to share the same frame compared to when they disagree about which topics are most important. And when people rely on the same frame, they are more likely to agree on which topics are most important, compared to when they rely on different frames. While these expectations may sound intuitive, they suggest that some policy priorities and frames go together so closely that even social influence might not be able to break their connection. As we discuss in the conclusion, this finding has important implications for practitioners considering how different frames (and topics) might be received by the public and spread through social networks.

A *Social* Theory of Policy Priorities and Frames

Both policy priorities and frames have been shown to shape policy preferences, making them important to understand within the context of social networks. To develop our argument about the relationship between social networks, policy priorities, and policy frames, we discuss how previous research has investigated each without consideration of social networks, highlighting our arguments about why social networks are a crucial piece to the puzzle. We examine policy priorities and frames in turn.

Policy Priorities

Policy priorities, as measured by the "most important problem" question, generally capture the issues that the public thinks are important problems, rather than simply representing salient issues (Heffington et al. 2019; Jennings and Wlezien 2015; Wlezien 2005). Policy priorities are important because they shape downstream outcomes. For example, the relationship between policy performance and support for incumbent candidates is stronger for policy topics that people think are important, especially if the policy topics are personally important or stem from personal experience (Krosnick 1988). The public's policy priorities therefore play a vital role in the electoral connection and representation. Because there is competition over which policy topics take priority in the public (McCombs 2004), understanding what shapes policy priorities is essential.

Despite the importance of policy topic priorities and the public agenda, we know little about what shapes one's policy priorities. Previous research has primarily focused on the media and elite communication as the central drivers of policy priorities in the public. For example, people who regularly watch the news possess a stronger consensus on policy topic priorities than do people who do not watch the news (Lopez-Escobar et al. 1998). This consensus among news consumers suggests

that the agenda set by mass media shapes the policy priorities of the public, too. However, an increasingly fragmented media environment has weakened this relationship, leading to a more diverse, but polarized, public agenda in terms of policy priorities (e.g., Stroud 2011).

The general theoretical idea behind the media's ability to shape policy topic priorities stems from cognitive psychology. Whether through priming or repetition, the more exposure individuals have to a given topic, the more likely they are to think that topic is important (Claibourn 2008; Tesler 2015). The news is a primary pathway through which people are exposed to policy topics, which suggests that the more the news covers a given issue, the more accessible it will be in memory to people who consume the news. And with greater accessibility in memory, the topic is more likely to be perceived as important by more people.

Adding to this foundational understanding, we argue that social networks can also shape policy priorities. If we consider the content of a political discussion within a social network to have similar effects on political preferences as content communicated by mass media, then similar mechanisms could be at play. People do not discuss everything that they read in the news (Carlson 2018), and it is likely that they focus on the topics they consider most important. Just as a topic's perceived importance is likely to increase with greater media attention, so too should it increase with greater attention in discussions within a social network. This elevated importance could happen as a consequence of social influence, where one person directly influences another, and/or via reinforcement of preexisting shared preferences. Regardless of the underlying mechanisms, which we leave to future research to unpack, we expect a tendency for policy priorities to co-occur within social networks.

Our first theoretical expectation is that network ties will disproportionately tend to report the same policy topic when asked what they view as the most important problem facing the country. Specifically, we evaluate the following hypothesis:

H1 *Both members of a dyad will prioritize the same policy topic at a rate greater than what we would expect by chance.*

Policy Frames

Policy frames are important because they also shape downstream outcomes. Previous research has shown that subtle, but logically equivalent, changes in the way in which a policy is described can dramatically change the extent to which the public supports it (e.g., Chong and Druckman 2007; Druckman 2001; Sniderman and Theriault 2004; Tversky and Kahneman 1981). The way in which a policy is framed shifts the considerations people focus on while forming their opinions. Policy frames can affect public opinion by making some considerations more accessible (Iyengar 1991) or by shifting which considerations are more important (Nelson et al. 1997). Although framing effects identified in experiments can be short-lived or dampened by competing frames (Chong and Druckman 2007), certain types of frames can be "sticky" and difficult to reconceptualize (Ledgerwood and Boydstun 2014), making it plausible that not only policy priorities but also frames can move through social networks. In

short, *any* discussion of policy includes one or more frames, and these frames often exert a strong influence on the conclusions people draw about the policy.

Given the importance of policy frames for understanding public opinion, it is essential that we understand where these frames come from. Policy frames are typically studied within the context of mass media or candidate communication (e.g., Druckman 2001). Indeed, some scholars have even expressed concern over the ability for the media and political elites to "manipulate" public opinion through framing (e.g., Kinder and Herzog 1993). We leave that important normative discussion to other research, but reconsider here whether the media and political elites are the only source of framing. We posit that peers within social networks can also steer public opinion via framing, just as political elites can. We arrive at this expectation based on a wide range of previous scholarship. Cramer Walsh (2004) identified this pattern in her impressive ethnographic study, showing that people filter the news through their political conversations, coming to use certain frames as a lens through which to think about politics and develop their preferences. Cramer's work focuses on communication within real social networks, giving us a firm understanding of how frames diffuse through discussion between people who know each other personally.

Frames could also spread within social networks via the two-step flow (Katz 1957), whereby opinion leaders who are interested in the news transmit the frames they are exposed to from elites to the rest of their social ties. There is some quantitative evidence that frames can be transmitted socially. For example, Aarøe and Petersen (2020) find that, compared to thematic frames, episodic frames spread more easily from person to person. A similar study found that the frames used in partisan media tend to propagate through social transmission (Carlson 2024). Specifically, when participants read an article that framed marijuana legalization in terms of economic growth, as opposed to in terms of social and economic costs, they were more likely to frame the issue in terms of its economic benefits. Without examining frames specifically, Carlson (2018, 2019) demonstrates that people tend to pass on information that is biased in favor of their partisan preferences, which could shape the frames people use to discuss issues. On social media, evidence suggests that distinct frames can spread from political elite actors, such as political activists, NGOs, and politicians, to constituents (e.g., Stier et al. 2018). This quantitative work suggests that there is variation in the way people transmit information they consume from the news, which highlights the importance of understanding whether frames propagate from one person to the next within networks. However, this work is limited in that it does not examine organic conversations within real social networks.

While there is much we still need to learn about frame diffusion within social networks, there is good reason to expect that policy frames *can* spread within networks, just as they have been shown to spread from political elites. Altogether, our second theoretical expectation is that political discussion partners will tend to rely on the same policy frames. This co-reliance on specific frames could arise through several mechanisms. First, opinion leaders within the network may transmit the frames they consume in the media, thereby leading their peers to adopt the same frames. Second, people who consume the same media or already think about politics through the same frameworks may seek each other as friends or political discussants. Third, people may select into environments where others are more likely to share similar frameworks.

Regardless of the mechanism (social influence or selection), it is important to evaluate the similarity of policy frames between network ties because frames shape one's openness to persuasion. Therefore, examining the co-occurrence of frames within networks allows us to better understand the portions of the electorate that are more susceptible to—or insulated from—opinion change. If peers think about their policy priorities through the same lens (i.e., using the same frames), we should observe that dyads tend to describe the most important problem facing the United States using the same frame. More formally, we test the following hypothesis:

H2 *Both members of a dyad will rely on the same frame at a rate greater than what we would expect by chance.*

Bridging Priorities and Frames

We argue that policy priorities and policy frames tend to co-occur within networks, but we also expect that policy priorities and frames could co-occur *together*. That is, policy topics and policy frames are not orthogonal to each other: some policy frames map more neatly onto some topics than others. For instance, we expect that discussions on a topic like health care will tend toward economic frames rather than other potential frames, such as security and defense. More generally, when people discuss politics, they do so in the form of packaged concepts (policy priorities framed in a certain way) rather than in the form of policy priorities untethered from frames, or frames untethered from policy priorities. In line with this intuition, competing political parties tend to use *different* frames when discussing the *same* policy topics (Arbour 2014; Lefevere et al. 2019).

Understanding the extent to which policy topic priorities and policy frames co-occur together is important for three key reasons. First, it can help us understand how the dyadic similarity that we observe in testing Hypotheses 1 and 2 arises from an inherent connection between the frames and topics themselves. Second, there are important methodological implications of identifying patterns in frame-topic co-occurrence. Many survey experiments on framing effects simply randomize a frame for a given topic of interest, without much consideration for whether that frame "goes with" that topic. Demonstrating how the public maps frames and topics together—without prompting from a survey experiment—can guide the selection of topics *and* frames for future research on framing effects. Third, from a theoretical standpoint, networks in which people share topics and frames, one but not the other, or neither, could be distinct.

In networks where people prioritize the same topics and use the same policy frames to think about them, we generally would expect people to ultimately have similar policy preferences, too. Because frames can be so influential for shaping policy preferences, when people agree on the topics that are most important, as well as how to think about them, it is likely that they think about the same policy solutions. In these cases, policy frames and priorities could be a key component driving the policy preference homogeneity we observe in social networks.

Another possible network composition involves people who have different policy topic priorities *and* use different frames to consider them. Such social ties share

neither policy frames nor topic priorities. These dyads are important because they contradict the norm of homophily in social networks. People embedded in these heterogeneous networks could be exposed to a wider range of conversation topics and frames through which to think about political issues, which could result in less preference homogeneity. However, if certain topics and frames co-occur together, this type of network might be more common than we would otherwise think. If people within a network vary on their topic priority, they probably also vary on the frame they use to think about that topic.

In summary, we expect some topics are inherently intertwined with specific frames. And therefore we expect a tendency *against* networks in which people share the same topic priority but use different frames and likewise a tendency *against* networks that use the same frame to think about different priorities. We therefore evaluate the following hypothesis:

H3 *Both members of a dyad will report the same policy topic and the same frame at a rate greater than what we would expect by chance.*

Research Design

In this paper, we take a step back to ask and answer a relatively simple descriptive question: How similar are political discussion partners' policy priorities and policy frames? Each hypothesis focuses on a distinct form of dyadic similarity: H1 focuses on policy topic priorities; H2 on frames; and H3 on the combination of both topics *and* frames. The nature of our hypotheses leads us to analyze our data in several contexts, including (1) the entire sample; (2) dyads that prioritize the same policy topic; (3) dyads that use the same frame; and (4) dyads that differ on both policy topic and policy frame.

Note that the hypothesis tests we offer below can demonstrate evidence suggestive of, but not exclusive to, social influence. If one person's policy priorities cause another person to also adopt those priorities, we would indeed observe a tendency toward dyadic similarity in policy topics. The same goes for frames. However, as noted above, this pattern may arise instead if people had similar policy priorities (and/or frameworks through which they tend to view issues) to begin with and chose to socialize with each other because of those shared priorities (frames), or for another reason incidentally correlated with those priorities (frames). If we observe similarity within dyads there *could be* social influence; if we do not observe a tendency toward dyadic similarity, then social influence is likely to be rare or inconsequential. In other words, support for at least one of our hypotheses is a necessary condition for us to infer causal influence within social networks, but not a sufficient one.

To test our argument, we return to the 1996 Indianapolis-St. Louis (ISL) Study. This dataset has been used in countless applications aimed at understanding network effects (e.g., Djupe et al. 2018; Huckfeldt et al. 2004; Klofstad et al. 2009; McClurg 2006; Osborn and Morehouse Mendez 2011; Ryan 2011). Our analysis most closely resembles Morehouse Mendez (2008), who pairs the ISL Study with a content analysis of news media. She finds a positive association between media coverage and respon-

dents' most important problem responses, demonstrating evidence for the first step in the two-step flow of communication (Katz 1957). We build on this work by examining the second step: the association between individuals and their discussion partners. Further, we focus not only on the topic of their most important problem, but also its frame.

The ISL Study combines an initial sample of main respondents with a supplemental sample of discussants—people in the communities who talk frequently with the main respondents. The initial sample was drawn randomly from voter registration lists in the metropolitan areas of Indianapolis and St. Louis. The supplemental sample comes from a list of up to five people that each main respondent named when asked for a list of people with whom they typically discuss important matters or politics. The data contain 1,740 dyads for which a main respondent and their named discussant responded to the survey. Our analysis focuses on the N = 1,625 dyads in which both the main respondent and their discussant provided an answer to the most important problem item. Our outcome variables are based on respondents' beliefs about the "most important problem" (MIP) facing the United States, transcribed from open-ended responses.[1] The verbatim transcripts allow us to directly examine not only *which* topics respondents considered most important (i.e., their policy priorities), but also *how* they conceptualize those topics (i.e., their policy frames). By mapping the congruence of policy priorities and policy frames between main respondents and their discussants, we can reliably measure the extent to which policy priorities and policy frames co-occur within social networks.

Previous research has examined text to understand policy priorities. Some research has examined free-response descriptions of the MIP in survey data by hand-coding them into topics (Eissler and Jones 2019) or using structural topic models to sort them into topics with an unsupervised approach (Roberts et al. 2014). Other work has examined posts on social media generated by everyday users to try to measure public opinion or policy congruence with political elites (Barberá et al. 2019). The structure of our data is well-suited to hand-coded analyses because the responses are relatively short, making it difficult for unsupervised topic models to perform well (Roberts et al. 2014). Moreover, the size of the data is manageable for hand-coding. A supervised approach would require us to hand-label a subset of the data and withhold a sample for validation, leaving a relatively small sample for both training and classification. Although it was a significant time investment to hand-label the full corpus, the end result has less measurement error than we likely would have obtained using a machine learning approach.

To categorize people's self-identified policy priorities from their MIP open-ended responses, we use the Comparative Agendas Codebook, utilized by scholars for more than three decades as a consistent coding scheme for tracking policy topics on different agendas (e.g., legislative, executive, media) across time and across countries (Baumgartner and Jones 2009).[2] We use this codebook to categorize respondents' policy topics at

[1] The survey's most important problem data were gathered in two steps. First, respondents were asked, "What do you think is the most important problem facing this country?" Second, after providing an answer, respondents were asked, "Would you like to add anything else?" To categorize topics and frames, we rely on a respondent's answers to both items. Combining each respondent's answers to both items into a single string, the length of the answers was right skewed with a median of 11 words, mean of 18 words, and a standard deviation of 19 words.

[2] https://www.comparativeagendas.net/

the major topic level (macroeconomic issues, civil rights issues, health issues, etc.). To categorize the frames people use to describe their policy priorities, we use the Policy Frames Codebook, developed as a frame-level companion for the Comparative Agendas Codebook and now used widely (Boydstun et al. 2020).[3] Just as the Comparative Agendas Codebook takes a consistent approach to coding topics across policy agendas and over time, the Policy Frames Codebook takes a consistent approach to coding frames across topics and over time. We use this codebook to categorize respondents' framing of their policy priorities (economic frames, fairness frames, morality frames, etc.). Because this Policy Frames Codebook categorizes *emphasis* frames, by design there are conceptual links between many of the topics from the Comparative Agendas Codebook and specific frames from this codebook (e.g., Macroeconomics as a topic and Economics as a frame, Defense as a topic and Security & Defense as a frame). Aware that these intrinsic correlations between topics and frames might skew our results, we repeat our analyses below excluding those topics that have clear frame matches.

For the content analysis, our unit of analysis is the respondent. This notably stands in contrast to work utilizing social media data to examine agenda setting and policy priorities, which is primarily centered on (1) aggregate analyses to demonstrate that aggregate trends in public opinion correlate with the frequency with which topics are discussed in social media posts (O'Connor et al. 2010), or (2) elite communication where individual-level data about political elites can be collected (Hemphill et al. 2021).

As the examples shown in appendix Table 3 illustrate, some responses have clear topics and frames, others less so. In particular, some respondents (565 out of 4,144 total respondents) articulated their MIP using a single word. Although we have made the argument, in line with past research, that it is difficult to *discuss* a topic without using a frame to contextualize it, these responses identify a topic without an explicit frame. Yet many topics have implicit emphasis frames, which we can capture using the frame that is conceptually linked with a topic. For example, if someone identifies their MIP as "economics" (which we code as "Macroeconomics" using the Policy Agendas Codebook), the lack of additional language suggests an implicit economic framing (which we thus code as "Economics" using the Policy Frames Codebook). Recognizing that this approach to treating one-word answers as containing both a policy priority and a frame might skew our results, in our analyses we test our hypotheses with and without these observations.

Since respondents sometimes listed more than one topic (and/or framed a given topic in more than one way), each respondent's answer could receive more than one topic code and/or more than one frame code.[4] For example, consider the following MIP response: "increasing desparity [*sic*] between the rich and poor and lack of univer [*sic*] health coverage." This response includes two topics (macroeconomics and health care) framed in different ways (macroeconomics framed in terms of fairness and economics; health care framed in terms of fairness and health). Thus, the response was coded for two topics (macroeconomics and health) and three frames

[3] https://www.amber-boydstun.com/policy-frames-codebook.html

[4] In total, 56% of responses received a single topic code, 31% received two topic codes, and the remaining 13% received three or more topic codes. Likewise, 51% of responses received a single frame code, 30% received two frame codes, and the remaining 19% received three or more frame codes.

(fairness & equality, economics, and health & safety). Again, we should not expect all frames to be equally applicable to all topics and vice versa. The topic of the environment, for example, is probably more easily framed in terms of *capacity & resources* than in terms of *fairness & equality*. Yet the Policy Frames Codebook was developed around frames that could, at least in theory, be used to discuss *any* policy topic. Therefore, the extent of dyadic similarity of topics and frames remains an open question rather than a foregone conclusion.

Note also that agreement between two people on which topics to prioritize and how to frame them does not necessarily indicate agreement on a particular policy *preference* regarding that topic (for the distinction between MIP responses and policy preferences, see Jennings and Wlezien 2015). We leave this question for future research, although anecdotally we could find few instances in which people who share a policy priority and a frame seemed to express different preferences (e.g., in favor of vs. opposition to universal health coverage), noting that in many cases a respondent's policy preference was not evident in their MIP response.

As in any content analysis data collection process—and especially given the complexities of coding the MIP responses as discussed above—consistency is key. After multiple rounds of practice coding and discussion with one of the authors, a trained undergraduate research assistant who had worked extensively with both the Comparative Agendas Codebook and the Policy Frames Codebook in past projects conducted all the coding. To validate coding consistency, a second research assistant who was trained on both the Comparative Agendas Codebook and the Policy Frames Codebook independently coded a random sample of 219 respondents' answers by topic and by frame.[5] We selected the size of this random sample because 219 respondents represented more than 5% of the full dataset (of 4,144 responses), thus satisfying both the numeric and percentage sample size thresholds for reliable estimates of intercoder reliability (e.g., Kaid and Wadsworth 1989; Lacy and Riffe 1996). For the topic coding, coder agreement was 83% (Cohen's Kappa and Krippendorff's Alpha = 0.80). For the frame coding, coder agreement was 94% (Cohen's Kappa and Krippendorff's Alpha = 0.93).

Results

Our analysis proceeds in three stages. We first describe the extent of policy priority similarity between network ties. Next, we examine policy frame similarity for these ties. Finally, we apply randomization inference to provide formal tests of our hypotheses.

[5] To account for zero inflation within each topic and frame category, the topic and frame with the highest numbering according to the codebook were then used to calculate intercoder reliability (Krippendorff 2019), following best practices by the Comparative Agendas coding protocols (Jones et al. 2023). For example, if one coder classified an item as Macroeconomics (Topic 1) but the other coder classified the item as both Macroeconomics (Topic 1) and Health (Topic 3), for the purposes of the intercoder reliability analysis, only the coders' highest codes would be compared (in this case Topic 1 and Topic 3). This approach thus addresses the problem of zero inflation in the data but also underestimates the consistency of the two coders (e.g., ignoring the fact that both coders in our example agreed on Topic 1).

Do Network Ties Tend to Share Policy Priorities?

We begin our analysis by examining the dyadic similarity of policy priorities. For this analysis, we examine the complete dyads in the data—pairs of main respondents and their named discussants who both responded to the MIP item. Following the terminology of egocentric network analysis (Marsden 2002), we refer to each main respondent in a dyad as *ego* and we refer to each discussant as *alter*. Due to the snowball sampling approach, ego's most important problem (MIP) is always recorded prior to alter's MIP. Therefore, we focus on the likelihood of alter identifying the same topic as ego did for their MIP. If alter has a higher chance of identifying a topic as most important in cases where ego also identified that topic as most important, it indicates a tendency toward dyadic similarity of policy priorities. The grey dots in Fig. 1 show the overall proportion of alters that identified a topic as most important. In addition, the white dots show the proportion of alters who identified a topic as most important, conditional on the ego identifying the topic as most important.[6] The plot suggests that the most pressing problems to respondents included family values, the economy, crime, education, government operations, social welfare, health, international affairs, and civil rights. For each of these topics, alters were more likely to identify a topic as their MIP if the ego

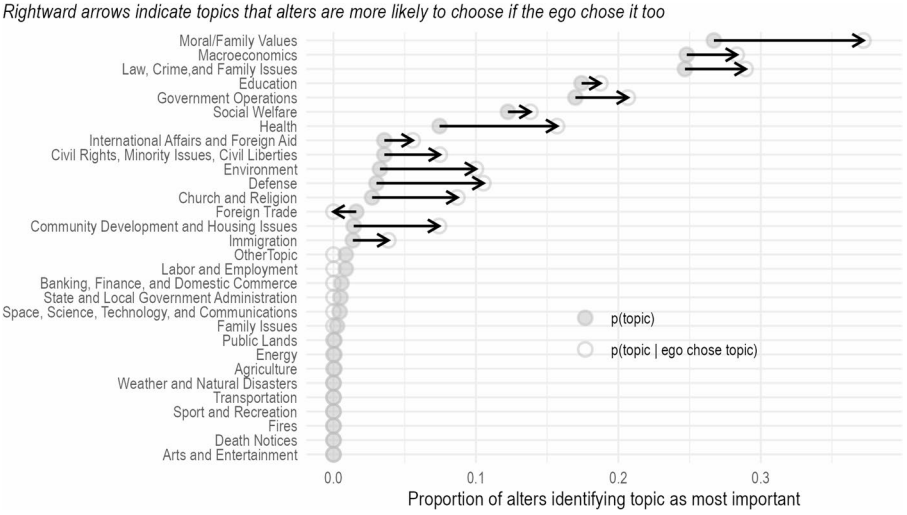


Fig. 1 The co-occurrence of policy topic priorities. The start of each arrow represents the proportion of alters that identified a topic as most important. The end of each arrow represents the proportion of alters that identified a topic as most important, conditional on the ego identifying the topic as most important.

[6] Recall that both ego and alter could identify more than one topic, meaning that these white dots show, given the condition of an ego identifying a topic, the proportion of alters who also identified that topic as (one of) their MIP topic(s).

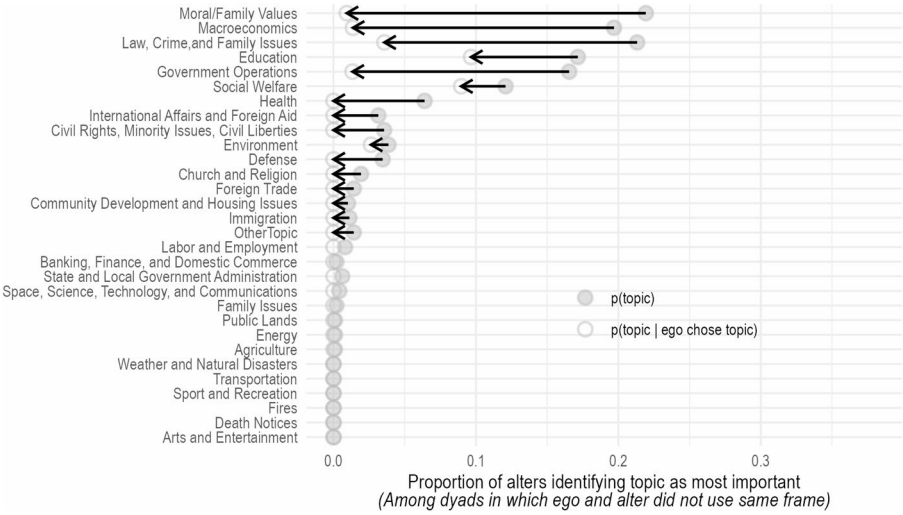


Fig. 2 The co-occurrence of policy priorities when policy frames do not match. The plot includes only ego-alter dyads in which ego and alter did not use the same frame in their response to the most important problem item. The start of each arrow represents the proportion of alters in this subset that identified a topic as most important. The end of each arrow represents the proportion of alters in this subset that identified a topic as most important, conditional on the ego identifying the topic as most important.

also identified the same topic as most important. In other words, the plot suggests a strong tendency toward dyadic similarity of policy priorities, providing preliminary support for Hypothesis 1.

Figure 1 shows that people are more likely to identify a policy topic as important if their social ties do too. This first analysis ignores the frames that people use to describe their most important problems, raising the question of whether this pattern holds if people do *not* think about topics through the same lens. Figure 2 replicates the analysis shown in Fig. 1, but subsets the data to dyads in which ego and alter did not rely on the same frame in their response. In this case, the pattern is reversed. Among the dyads who used different frames, alters are *less* likely to identify a topic as most important if egos identified that topic as most important. This result implies that frames and topics often go hand-in-hand, as we show in Figures 8 and 9 in the appendix. If the dyadic topic similarity shown in Fig. 1 is driven by social influence, Fig. 2 suggests that when a topic's priority arises within the network, so too do the frames with which it is discussed. That is, rather than social networks serving to transmit concerns about a given problem untethered to any framework, ideas tend to co-occur in networks following a packaged way of thinking about a policy problem, in line with Hypothesis 3.[7] Altogether, we conclude that prioritized policy topics tend

[7] We are not suggesting that this explanation alone accounts for the patterns in Figs. 1 and 2. In particular, dyads that adopt the same frame are likely to be distinct in several ways from dyads that choose different frames. For instance, they may communicate more frequently, have more similar socioeconomic backgrounds, or hold each other in higher esteem.

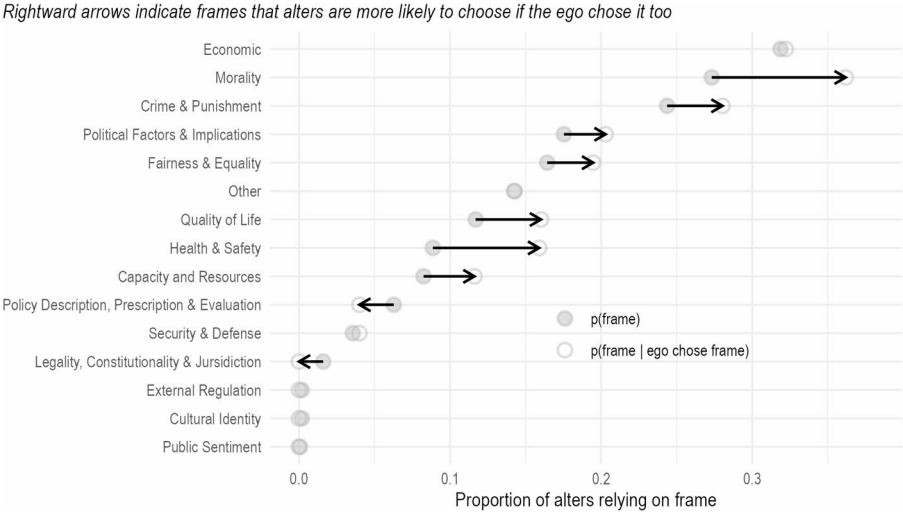


Fig. 3 The co-occurrence of policy frames. The start of each arrow represents the proportion of alters that relied on a frame. The end of each arrow represents the proportion of alters that relied on a frame, conditional on the ego relying on the frame.

to co-occur within networks, especially when egos and alters think about these topics with the same frame.

Do Network Ties Tend to Share Policy Frames?

Turning to dyadic similarity on topic *framing*, Fig. 3 compares the overall (grey) and conditional proportions (white) with which alters employed each frame. The plot suggests that alters are more likely to rely on a given frame if the ego also relied on the same frame, much like Fig. 1 suggested for policy priorities. Figure 4 subsets the data to dyads in which the ego and alter did *not* identify the same topic as most important. The plot suggests that when the ego and alter do not share the same topic, alters are *less* likely to rely on a frame if the ego relied on that frame, akin to the results for policy topic congruence shown in Fig. 2. Together, Figs. 3 and 4 demonstrate that frames tend to co-occur within dyads (in preliminary support of Hypothesis 2), particularly when egos and alters prioritize the same policies (again, in line with Hypothesis 3).

Statistical Inference

The analysis above suggests a general tendency toward dyadic similarity on both topics and frames. To formally evaluate our hypotheses, however, we must examine whether our dyads are more alike than we would expect by chance. If the survey observations were independent, we might examine whether the correlation is greater

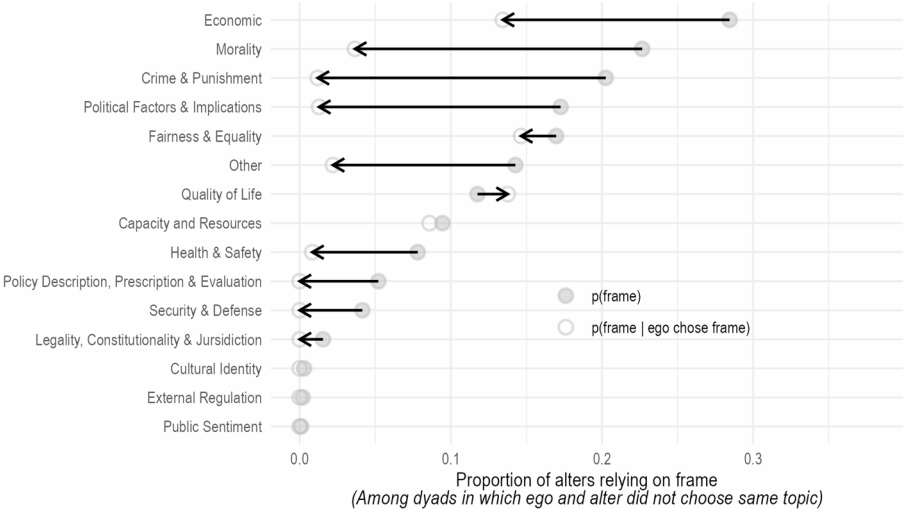


Fig. 4 The co-occurrence of policy frames when policy priorities do not match. In the plot, the data include only ego-alter dyads in which ego and alter did not identify the same topic as most important. The start of each arrow represents the proportion of alters in this subset relied on a frame. The end of each arrow represents the proportion of alters in this subset that relied on a frame, conditional on the ego relying on the frame.

than zero between the policies or frames ego and alter identify. But since our observations are interdependent in complex and unmeasured ways (e.g., social networks, neighborhoods, and media markets), we might observe positive correlations between units even in the absence of social influence.

Thinking about the context of Indianapolis and St. Louis in 1996, for instance, we might expect some topics and frames to pervade across social networks even if our argument about social influence is incorrect. In such cases, scholars often rely on randomization inference (e.g., Goel et al. 2010; Minozzi et al. 2020), which can flexibly accommodate complex error structures without strong assumptions about independence (Erikson et al. 2017). In our analysis, we compare the observed dyadic similarity between ego and alter to a null distribution we generate by randomly permuting the vector of alters 1,000 times. The permutations thus break the dependence between ego and alter while retaining the sample-level distribution of topics and frames. We compare the dyadic similarity in the observed data of egos paired with their real alters to the distribution of dyadic similarity across the 1,000 permutations. See Appendix B for more details and Figure 10 in the appendix for a summary of the randomization inference procedure.[8]

[8] An alternative approach would be to randomly select two responses from a combined pool of egos and alters. But since only the egos are part of the initial random sample, combining the two groups would not account for the variation induced by differences between the timing of the surveys (e.g., changes in news cycles) or differences between main respondents and discussants (e.g., levels of political knowledge or interest).

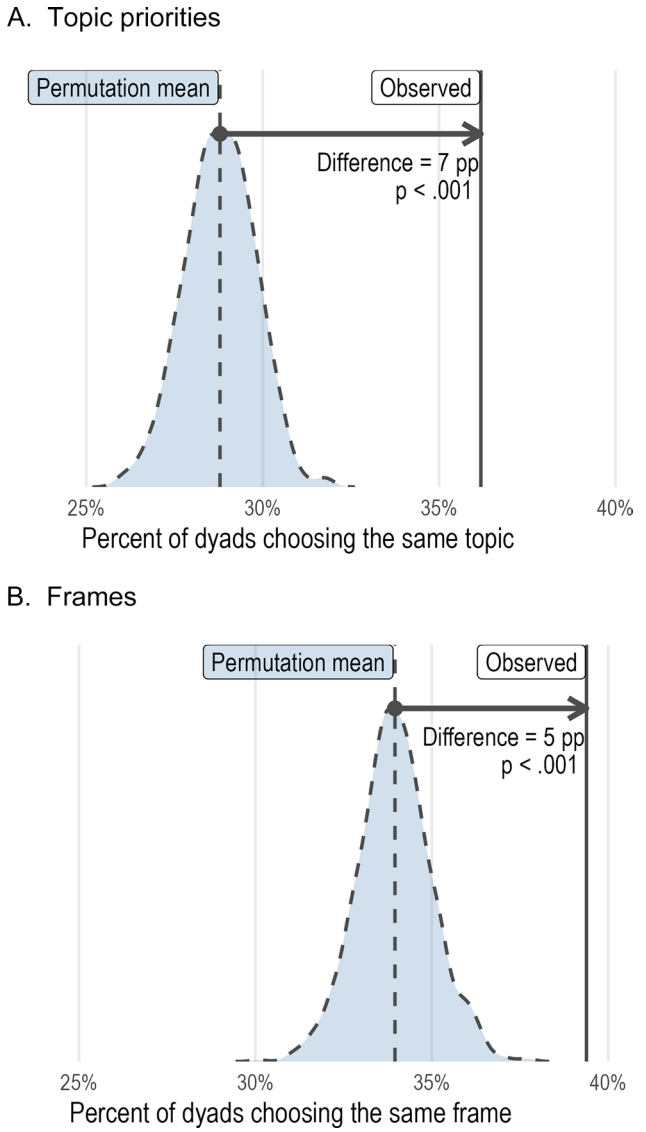


Fig. 5 Percent of dyads who chose the same policy topic priority (Panel A) or used the same frame to characterize their most important problem (Panel B). The solid line indicates the observed value in the data. The dotted line shows the mean of the permutations. The density plot shows the distribution of permuted values.

Figure 5A demonstrates our approach, comparing the observed co-occurrence of policy topic priorities within dyads to the null distribution of policy priority co-occurrence from the permutations. In the plot, the solid vertical line indicates the observed

dyadic similarity, as a percentage. In this case, the line indicates that in 36% of the dyads (95% confidence interval=[33.8%, 38.5%]), both ego and alter identified the same policy topic as a priority.[9] This value is seven percentage points greater than the mean percentage of similar dyads over the 1,000 permutations, marked by the vertical dashed line (29%). Since the observed similarity exceeded the mean in every permutation, it yields an exact *p*-value of 0. Consistent with Hypothesis 1, dyads in our data prioritize the same policy topic at a rate greater than what we would expect by chance.

Figure 5B repeats this analysis for dyadic similarity on frames rather than topics. In this case, the dyadic similarity is five percentage points greater than we would expect by chance, again with an exact *p*-value equal to 0. As Hypothesis 2 predicted, dyads in our data report the same policy frames at a rate greater than what we would expect by chance.

Together, the permutation tests underlying Fig. 5 confirm what we inferred descriptively from Figs. 1 and 3: policy priorities (Fig. 5A) and frames (Fig. 5B) both tend to co-occur within dyads.

Finally, we use the permuted data to more formally evaluate Hypothesis 3, that dyads will describe their policy priorities with the same frame at a rate greater than what we would expect by chance. Figure 6 examines the joint distribution of dyadic topic and frame similarity. The plot reveals an asymmetry. Dyads in our data are 21 percentage points *more likely* to rely on the same frame and same topic than we would expect by chance ($p<0.01$). And dyads are 14 percentage points *less likely* than chance to identify the same topic while using different frames ($p<0.01$). Likewise, they are 16 percentage points *less likely* than chance to identify different topics while both using the same frame ($p<0.01$). Finally, dyads are nine percentage points *more likely* than we would expect by chance to rely on different topics *and* different frames ($p<0.01$). Together, these findings suggest that policy priorities map onto social networks in two main ways: same-topics-same-frames networks, shown in the top panel, where people share the same policy priorities framed the same way, and different-topics-different-frames networks, shown in the bottom panel, where people have no overlap in their policy priorities or their frames in thought.[10]

[9] For each observed value in Figs. 5–6, we report standard errors and 95% confidence intervals in Appendix Table 1.

[10] Relying on a single coder to assign both topic and frame codes for each response may artificially inflate the congruence between specific topics and frames. If so, it would bias our results in favor of Hypothesis 3, which posits that both members of a dyad will disproportionately identify the same topics and the same frames. To guard against this possibility, Figure 11 in the appendix replicates our analysis, but replaces our topic codes with those assigned by Huckfeldt and Sprague (2007). The patterns in Figure 11 echo those found above. Though the differences are attenuated, they all remain statistically significant.

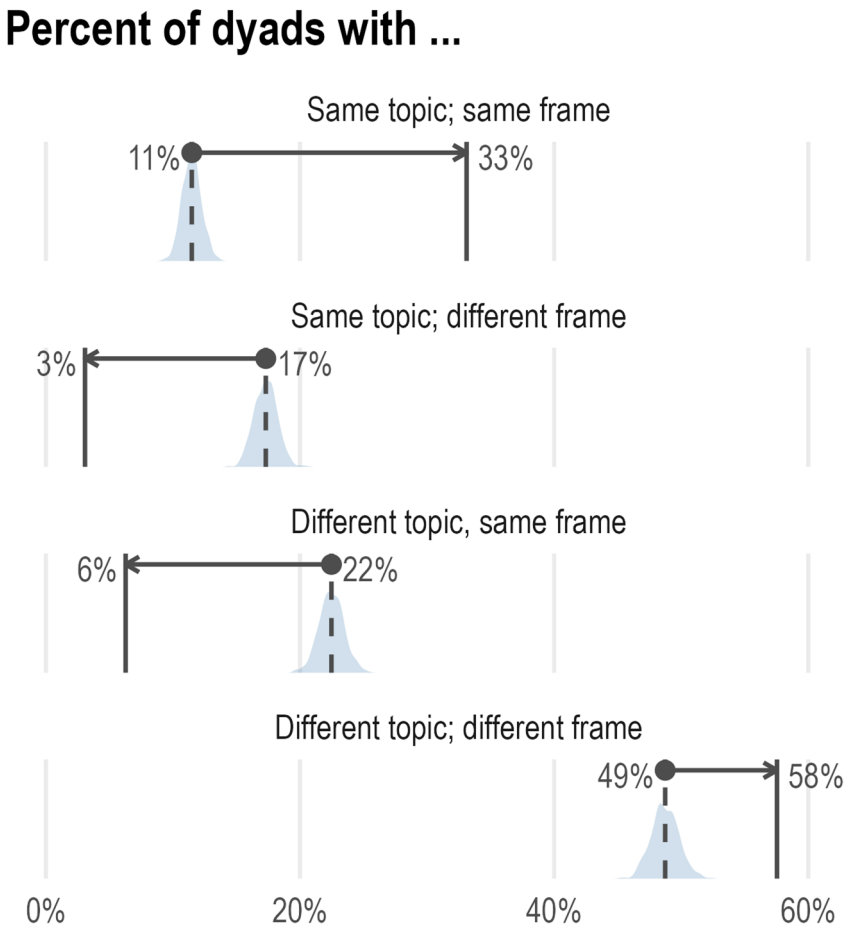


Fig. 6 Topic and frame use within dyads. The solid lines indicate the observed values in the data. The dotted lines show the means of the permutations. The density plots show the distribution of permuted values.

Robustness Checks

As detailed in the appendix, we conduct a series of additional analyses to see if the main findings discussed above hold under different assumptions. First, we repeat our analyses shown in Fig. 6, but sub-setting the data to exclude responses of only one word (see Appendix Figure 12). Second, we again repeat the Fig. 6 analyses, this time sub-setting the data to exclude responses with topics that have clear frame matches

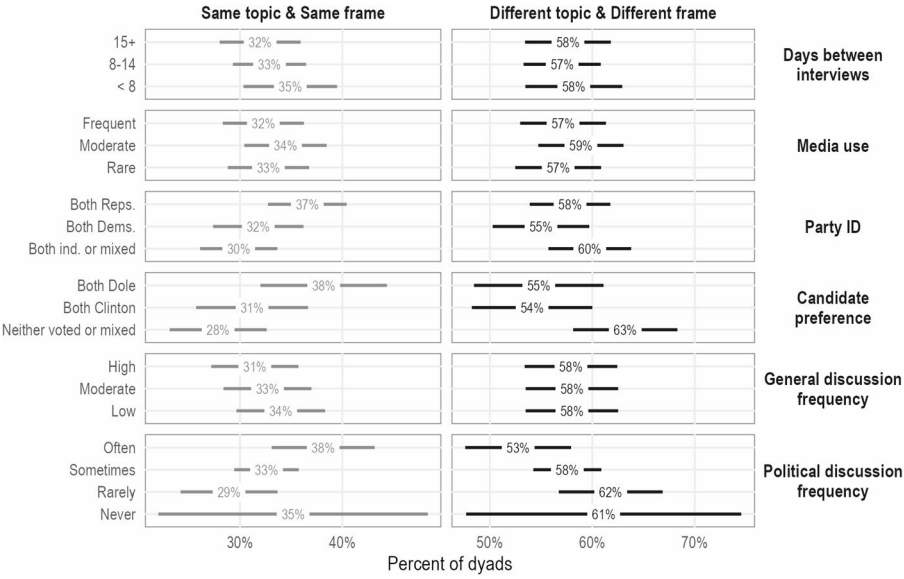


Fig. 7 Dyadic similarity as a function of context, preferences, and discussion. The left column of the plot shows the percent of dyads that identified the same topic using the same frame given the covariate value on the y axis. The right column shows the percent of dyads that identified neither the same topic nor the same frame given the covariate value. In both columns, the horizontal lines indicate 95% confidence intervals.

(see Appendix Figure 13). Third, we use simulated data to generate a null model in which the correlation between topics and frames is allowed to vary, but egos and alters are paired at random (see Appendix E). In each of these robustness tests, we find that we still see both same-topics-same-frames *and* different-topics-different-frames networks.

When Do Network Ties Share Priorities and Frames?

What distinguishes the same-topics-same-frames vs. different-topics-different-frames dyads? Though our design cannot identify the causes of dyadic similarity in issue priorities and frames, we can provide guidance for future work by examining the covariates that best distinguish these two types of dyads. In Fig. 7, we examine within-dyad alignment of topics and frames as a function of several covariates. The first column of the figure plots the percentage of all dyads that fit our same-topics-same-frames classification. The second column of the figure plots the percentage of all different-topics-different-frames dyads. Each row of the plot displays the estimated value of these outcomes (and 95% confidence intervals) given a specific value of a theoretically relevant covariate.

The first two rows of the plot focus on media use. Since media agendas often change rapidly (Boydstun 2013), we might expect greater similarity for dyads

with fewer days between ego's interview and alter's interview. But the top two panels show little evidence for this expectation. A total of 32% of dyads whose interviews were 15 or more days apart used the same topic and same frame, which is just 3 percentage points lower than the 35% of dyads whose interviews were under eight days apart (within a week of each other). Likewise, we might expect greater similarity for dyads that report a greater frequency of reading or watching the news. Yet the second row of panels suggest no evidence for greater dyadic similarity for dyads with more frequent media use.[11] Taken together, these results suggest that the dyadic similarity of topics and frames we observe is not just a function of media use.

The panels in the third and fourth rows focus on political preferences. If political preferences shape priorities, we might expect dyads that share the same partisan identity or candidate preferences to be more likely to also share the same priorities and frames. Moreover, this dyadic similarity might arise if partisan identity or candidate preference shape each dyad member's attention to campaign messages.[12] The panels in row 3 of the figure suggest that, indeed, dyads composed of two Republicans are seven percentage points more likely than mixed dyads to identify the same topic and same frame (difference = 6.7; Standard Error = 2.74; $p = 0.01$).[13] Similarly, the row 4 panels show that dyads featuring two Dole (R) voters are ten percentage points more likely than mixed dyads to identify the same topic and same frame ($d = 10.3$; $SE = 3.89$; $p < 0.01$). And mixed dyads are nine percentage points more likely than Clinton (D) supporters to identify different topics using different frames ($d = 9.1$, $SE = 3.96$, $p = 0.02$). Yet dyads composed of two Democrats are not measurably more likely to share priorities and frames than mixed dyads ($d = 1.9$, $SE = 3.00$, $p = 0.52$). These asymmetric findings regarding the network homophily of Republicans vs. Democrats in the pre-social media era may speak to other asymmetric partisan findings in online platforms (Boutyline and Willer 2017; Chang et al. 2025).

The bottom two rows of the figure examine social influence by plotting dyadic similarity as a function of discussion frequency. If dyadic similarity arises from social influence, it should be more likely within dyads that more regularly discuss politics. As a quasi-placebo, we also examine the dyad's overall frequency of interaction over

[11] We measure *media use* by summing the number of days in the previous week that ego and alter reported watching a national network news program or reading a newspaper. We then divide the dyads into terciles based on the sum of ego's and alter's media use.

[12] When measuring party ID, we treat leaners (independents who feel closer to one party) as partisans, grouping them with those who explicitly identify with the party. When measuring dyadic party ID, we define mixed dyads as those composed of people who support different parties or those in which at least one member identifies as a pure independent or supports a third party. When measuring candidate preferences, we define mixed dyads as those composed of people who support different candidates or those with at least one non-voter or someone who reported voting for a candidate other than Dole or Clinton.

[13] In this section, we report Huber-White robust standard errors and associated (two-tailed) p-values to adjust for potential heteroskedasticity.

the previous week.[14] As row 5 shows, dyads that talk more frequently are *not* measurably more similar in their policy priorities and frames. Instead, row 6 shows it is specifically the dyads that talk more frequently *about politics* that are more likely to identify the same topic and same frame. For instance, compared to dyads that report discussing politics rarely, those that report discussing politics often are about nine percentage points more likely to identify the same topic with the same frame (d = 9.2, SE = 3.51, $p < 0.01$). Likewise, dyads with more frequent political discussion are less likely to feature egos and alters that choose different topics and different frames from one another. Together, these results suggest that dyadic similarity may arise through discussions of the issues. But, as we note above, more research is needed to establish such cause-and-effect relationships.

Discussion

Do policy priorities and policy frames tend to co-occur within social networks? Yes. In this paper, we demonstrate that social network ties are more likely than chance to share the same policy priorities and to think about those priorities through the same frames. We also demonstrate that policy priorities tend to co-occur with specific frames; some policy frames are more closely connected to some policy priorities than to others. These findings hold across several robustness tests. The specific relationship we observe between political discussion and shared policy priorities and frames is strong relative to other relationships commonly studied in the political discussion literature. For instance, the observed relationship in our study is at least as large as the association found in past work between political discussion and political knowledge—one of the most commonly studied relationships in the literature.[15]

Our results are nonetheless limited because we lack the ability to cleanly isolate causal mechanisms and, like all cross-sectional research, our study is limited to a specific time—in our case, 1996. We discuss each of these limitations below.

Our theory suggests several mechanisms that may contribute to the patterns of network similarity that we observe, but our design can provide only limited leverage in evaluating their relative influence. Although we can credibly test whether the patterns we observe occurred at rates greater than chance, we cannot deter-

[14] We measure *general discussion frequency* by dividing dyads into terciles based on ego's answer to the question, "During a normal week, how many days do you talk with [alter's name]?". We measure *political discussion frequency* as ego's answer to the question, "When you talk with [alter's name], do you discuss political matters: [often; sometimes; rarely, or; never]?".

[15] For instance, in a meta-analysis of 113 independent studies, Amsalem and Nir (2021) find a correlation of 0.15 between political discussion and political knowledge, which corresponds to a Cohen's d of about 0.30 assuming equal group sizes. As we show in Fig. 6, political discussion partners are three times more likely than expected to identify the same policy priority using the same frame, which corresponds roughly to a Cohen's d of 0.55. (Using the values from the top panel of Fig. 6 and assuming equal group sizes, $d = \frac{p_1 - p_0}{\sigma_p} = \frac{.33 - .11}{\sqrt{[.33\,(.67) + .11\,(.89)]\,/2}} \approx \frac{.22}{.40} = .55$.) And thus the observed relationship in our study (d ≈ 0.55) is at least as large as the association between political discussion and political knowledge (d ≈ 0.30).

mine the extent to which such patterns are produced by social influence rather than selection into discussion networks. These patterns would arise through social influence if opinion leaders within networks influence their peers via interpersonal communication to adopt the same policy priorities and frames. But these patterns would also arise through selection if people tend to interact with others who hold similar policy priorities and frameworks for thinking about politics. Further, the dyadic similarity we observe could arise because of the logical association between specific sets of policy topics and frames. As we show here, some policies and frames seem to go together more readily than others. For example, morality frames seem to lend themselves more naturally to abortion policy than to economic policy.

Causal identification is notably challenging in social networks research (Rogowski and Sinclair 2012), and we encourage future research to tease out these possible mechanisms. Yet we argue that measuring the co-occurrence of policy priorities and frames within networks is important regardless of the mechanism and is a necessary first step to evaluating the causal mechanisms.

These findings tell us that social networks can facilitate the precursors to policy preferences by also sharing priorities and frames. Indeed, it is possible that the well-documented agreement on policy *preferences* within dyads (e.g., Alt et al. 2022; Furth-Matzkin and Sunstein 2017; Huckfeldt and Sprague 1995; Liu et al. 2022) could be connected to shared policy priorities and frames. Moreover, it adds a new dimension to our understanding of disagreement within networks. Some dyads might agree on their policy preferences, but disagree on whether that policy is important, which could alter the social dynamics and political consequences of the conversations themselves. We hope this work motivates future research examining the correlations between policy priorities and frames across dyads.

Our reliance on data from Indianapolis and St. Louis in 1996 also limits the external validity of our results. The world has changed quite a bit in the last 30 years. Today, political conversations are nested in the context of partisan cable news, heightened affective polarization, and social media that facilitates forms of virtual political discussion that did not exist in 1996. Yet our study is not unique in this manner—virtually any empirically rich study of political communication will be bound in time and space and thus limited in its generalizability (see Munger 2023 for a discussion of temporal validity). In this way, our findings offer a snapshot of what political discussion looked like in "the before times." These snapshot findings are necessary to provide context for understanding results from other eras including contemporary contexts. And, by studying real-world political discussion networks, our study provides evidence supporting results from experimental studies examining media agenda-setting effects via social networks (e.g., Aarøe and Petersen 2020; Druckman et al. 2018). We therefore offer greater external validity for patterns that have been detected in experiments with high internal validity, but lower external validity.

Conclusion

Our study makes at least three contributions. First, our descriptive analysis demonstrating topic-to-topic variation in dyadic similarity of policy priorities (Figs. 1 and 2) has important implications for work on policy diffusion and agenda setting. The tendency for some policy topics, such as moral family values, to co-occur within networks more strongly than other topics, such as labor and employment, suggests that social networks (at least those in Indianapolis and St. Louis in 1996) are simply more likely to amplify some topics than others. This, in turn, offers a means to inform elite discourse because policymaking is a cyclical process, where politicians influence the issues the public thinks are important and the public influences politicians to craft policy on issues they deem important. By examining how individual priorities and frames aggregate across discussion partners, we provide a means to identify the policies and frameworks that have the greatest potential to resonate across social networks.

Second, we contribute jointly to the political communication and political networks literatures by demonstrating a tendency for network ties to share policy priorities and frames, not just preferences. Specifically, we provide systematic quantitative evidence that supports claims from Cramer Walsh's (2004) ethnographic study. Just as previous work has documented that political discussion partners tend to share each other's policy and candidate preferences, our work shows that this dyadic similarity extends to both policy priorities and policy frames. Despite this tendency for dyads to share priorities and frames at rates greater than chance, we also find that the most common outcome was for people to hold different priorities and rely on different frames than their social ties. As the bottom panel of Fig. 6 shows, about 60 percent of dyads expressed different priorities and different frames. That the modal outcome is for dyads to hold different policy priorities and frames stands in contrast to network scholarship suggesting that homophily is the norm across a wide variety of characteristics (McPherson et al. 2001). Therefore, these results serve as a baseline against which future work can compare how changes in mass media and social sorting may have amplified or attenuated network homophily.

Third, we provide evidence that topics and frames go hand-in-hand, suggesting that it might be much harder to reframe a policy topic (and get that different frame to stick) in the context of social networks than, say, in a framing experiment. This finding has important implications for framing experiments that manipulate frames but not topics; or manipulate frames without considering whether that frame is commonly used to think about that topic.

Given these contributions, we see several fruitful avenues for research on the diffusion of policy priorities through social networks. In particular, we hope our work encourages research along two broad streams: first, to examine diffusion through individuals' broader social networks and, second, to examine these patterns in contemporary contexts where a great deal of political discussion now occurs online.

First, future research should examine the extent to which the co-occurrence of policy priorities and frames extend beyond *dyads* to individuals' broader social networks. In our study, we could not examine the extent of co-occurrence in network structures larger than dyads or along paths longer than one degree of separation because our data included only four egos with all five alters in the data (n = 4). Although much of the political discussion literature similarly focuses on dyads (e.g., Carlson et al. 2020; Huckfeldt 2001; Huckfeldt and Mendez 2008; Rossiter and Carlson 2023), it is important to consider how to best interpret our findings. It is possible that the dyads we observe could be uniquely (dis)agreeable relative to an ego's or alter's broader social network, which makes it challenging to benchmark the homophily we observe against another quantity of interest. Nonetheless, the dyads we examine are often considered an individual's "core" network (Marsden 1987). These strong, intimate ties have a long tradition of attention in the networks literature because of the outsized roles they play in socialization and social influence (Burt 1984).

Existing work suggests dyadic similarity tends to generalize to similarity within larger portions of the social network. A variety of studies demonstrate a strong, positive correlation between local transitivity and trait assortativity—the technical term for dyadic similarity on an attribute such as policy priorities (e.g., Foster et al. 2011; Pietryka et al. 2018). And thus the dyadic similarity we observe, combined with the knowledge that interpersonal networks tend to feature high levels of local transitivity (Louch 2000), suggest that these dyadic patterns are likely to permeate further into the network. Indeed, the tendency toward local transitivity may be a key explanation for the assortativity we observe here (Kossinets and Watts 2009). We hope future research extends the examination of topic and frame priorities to broader networks.

A second direction we hope future researchers take will be to consider the ways in which network discussions have changed since 1996. Specifically, the literature will benefit from work examining variation in information exchange and political discussion in online vs. offline settings—and settings in which people discuss politics both online and offline. On the one hand, we might expect the same patterns we observed in a purely offline network to be similar, or perhaps amplified, in a social media setting. Social media allows people to self-sort into their network ties even more than before (Lane et al. 2023), likely amplifying the topic and frame priorities embedded in political discussions. Online spaces may further facilitate echo chambers that could amplify homophily, echoing our finding that frame and priority homophily is more likely than chance. At the same time, social media enables people to connect with others intentionally or inadvertently who disagree, leading to potentially more exposure to cross-cutting views than we might otherwise expect in a purely offline world. Although inadvertent exposure might fuel selective exposure of like-minded political content (Weeks et al. 2017), it might also facilitate decreased homophily in frames and priorities within networks.

Future studies of political discussion should include observations of how individuals within networks describe their policy priorities with which frames via social

media posts. Ideally this work should obtain data on individuals and those they are connected to in the social network (although individual-level metadata would be limited). Future work in this area should also account for the fact that the internet has transformed news consumption to be increasingly niche, such that individuals can self-select into consuming ideologically congruent content easier than ever before (Stroud 2011). As such, an extension of our work ought to consider the ways in which the information flows prior to a political discussion unfolding might shape conversations themselves (Carlson 2024). If individuals are increasingly likely to consume like-minded, partisan content, communicating distinct policy priorities and frames, we might expect that to get filtered into political discussions in a more homogeneous way. Alternatively, there are also far more options for news available today than in 1996 (and earlier), meaning that there is a greater variety of starting points from which individuals might form their policy priorities and how they frame them, leading to less homophily in conversations and networks.

In these and other lines of research, we hope our work offers theoretical motivation, as well as a valuable benchmark of the topics and frames shared (and not shared) by network dyads in 1996. To summarize once more, using the 1996 Indianapolis-St. Louis study data, we found that although the modal outcome is for people to hold both different priorities and different frames than their discussion partners, discussion partners are also more likely to share the *same* topic priorities and to think about those priorities using the *same* frames than we would expect by chance. This co-occurrence of priorities and frames is especially likely for discussion partners who discuss politics often. We also demonstrate that policy topics tend to co-occur with specific frames in people's descriptions of their most important problem; some policy topics and frames go together more than others.

Appendix A. Descriptive Statistics

See Figs. 8, 9 and Table 1.

Table 1 Sample means and associated uncertainty for the observed values plotted in Figs. 5–6. The means represent the percentage of dyads that are similar according to a given statistic

Statistic	Displayed in	Sample mean	Std. Dev	Std. Error	95% Confidence interval	
					Lower bound	Upper bound
Same topic	Fig. 5A	36.2	48.1	1.19	33.8	38.5
Same frame	Fig. 5B	39.4	48.9	1.21	37.0	41.8
Different topic; same frame	Fig. 6	6.3	24.3	0.60	5.1	7.5
Different topic; different frame	Fig. 6	57.5	49.4	1.23	55.1	59.9
Same topic; different frame	Fig. 6	3.1	17.3	0.43	2.2	3.9
Same topic; same frame	Fig. 6	33.1	47.1	1.17	30.8	35.4

N = 1,625 dyads

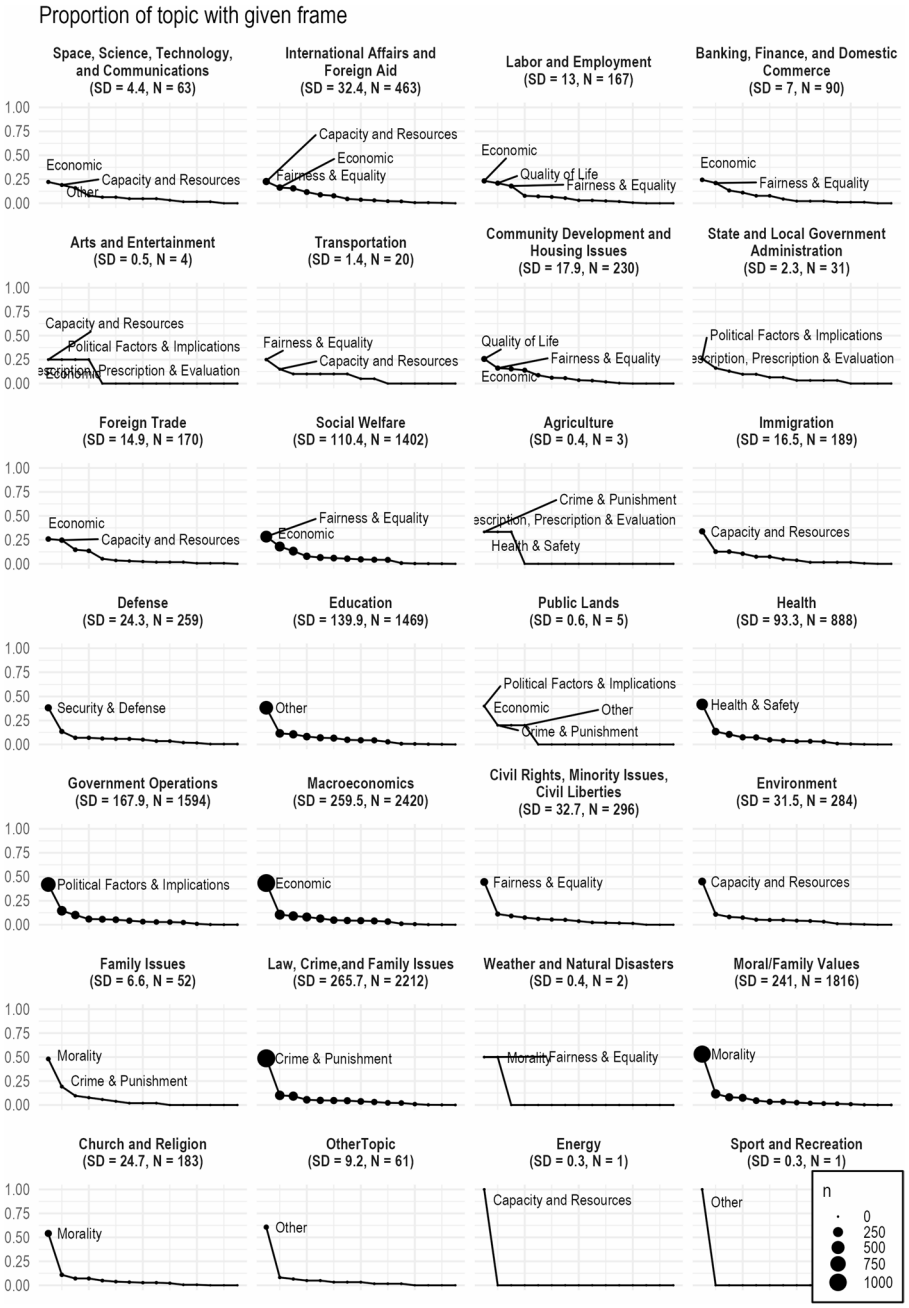


Fig. 8 The most common frames for each topic. The dots indicate the proportion of responses focusing on a topic that rely on a given frame. The panel label shows the standard deviation of frame popularity within the topic, and the number of responses identifying the topic as most important. The topics are ordered by the maximum proportion of responses relying on any single frame

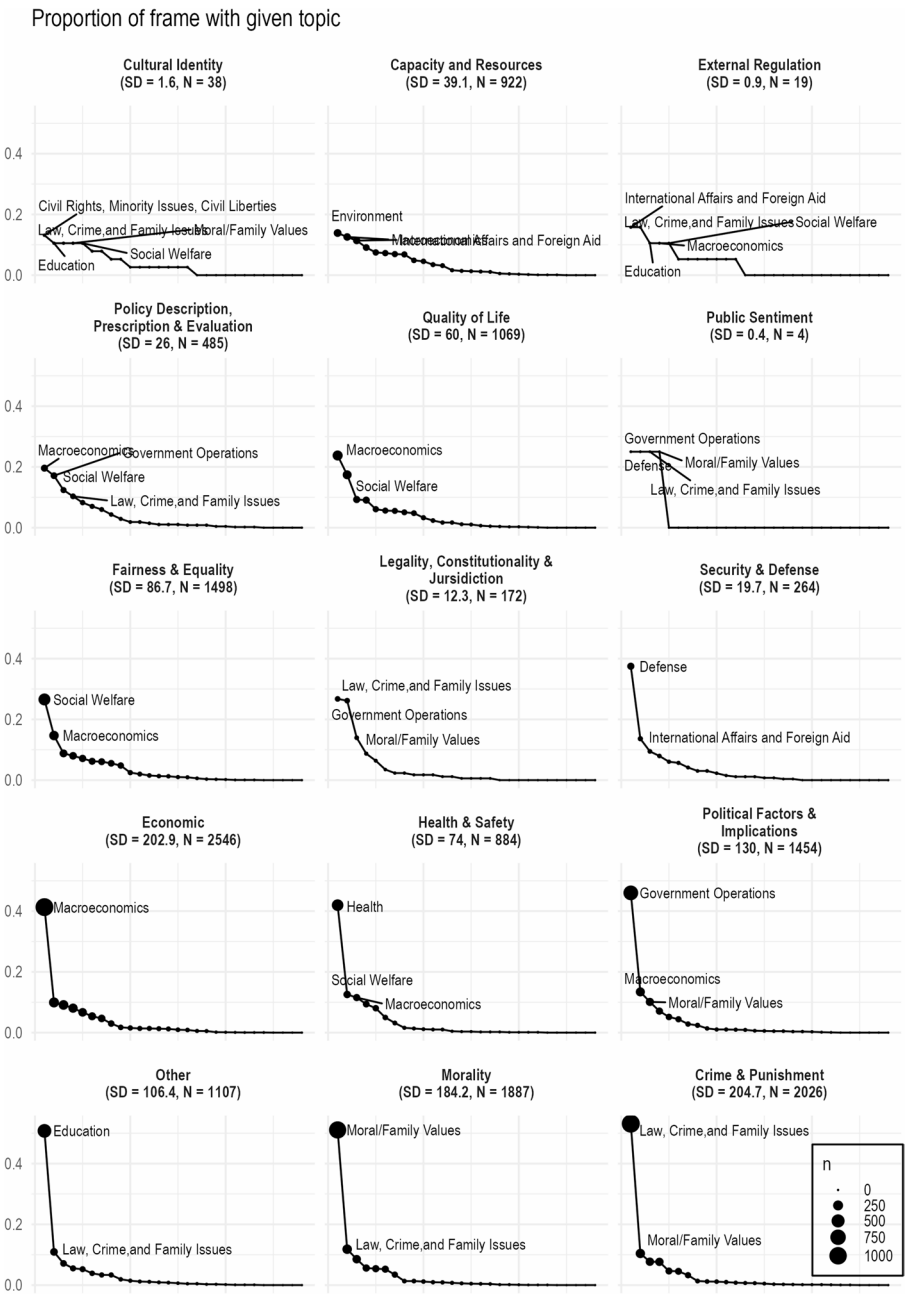


Fig. 9 The most common topics for each frame. The dots indicate the proportion of responses relying on a frame that identify a given topic as most important. The panel label shows the standard deviation of topic popularity within the frame, and the number of responses relying on the frame. The frames are ordered by the maximum proportion of responses relying on any single topic

Appendix B. Randomization Inference

See Fig. 10.

	Observed		Permuted Alters				
	Ego	Alter	#1	#2	#3	#4	#5
Dyad 1	E1	A1	A6	A4	A1	A2	A7
Dyad 2	E2	A2	A5	A6	A2	A1	A4
Dyad 3	E3	A3	A7	A1	A6	A4	A9
Dyad 4	E4	A4	A8	A9	A5	A3	A5
Dyad 5	E5	A5	A2	A7	A8	A6	A2
Dyad 6	E6	A6	A4	A8	A9	A8	A6
Dyad 7	E7	A7	A3	A2	A7	A7	A1
Dyad 8	E8	A8	A9	A5	A3	A5	A3
Dyad 9	E9	A9	A1	A3	A4	A9	A8

Fig. 10 Using randomization inference to produce a null distribution. The table on the left shows nine hypothetical dyads. The table on the right displays five random permutations of the observed vector of alters. Using randomization inference, we compare the similarity of the dyads in the observed data (on the left) to the similarity of the dyads constructed through the permutations (the original egos on the left and the alters on the right)

Our analysis uses randomization inference to test whether the observed similarity within dyads is greater than what would be expected by chance. Figure 10 provides a schematic depiction of the procedure, which occurs in the following steps:

1. Calculate the similarity statistic for observed dyads. (In Fig. 5A in the manuscript, for example, this statistic equals the percentage of dyads that were each classified as using the same topic in their MIP responses. In the figure, the value of this statistic is represented by the solid vertical line labeled “Observed.”)
2. Holding the vector of egos fixed, we randomly permute the vector of alters. (In Figure 10, this step is represented by the column labeled #1 under the "Permuted Alters" heading.)
3. Recalculate the similarity statistic for the dyads generated in step 2.
4. Repeat steps 2 and 3 another 999 times. These 1,000 similarity statistics represent the null distribution. (In Fig. 5A, the 1,000 permuted similarity statistics are represented by the density plot and the mean of those permuted similarity statistics is represented by the dashed vertical line labeled "Permutation mean.")
5. The p-value is calculated as the proportion of permuted similarity statistics that are at least as large as the observed similarity statistic. This p-value represents the probability of observing a similarity statistic as high as we did, assuming the dyadic pairings were random.

Appendix C. Robustness Checks

See Figs. 11, 12, 13.

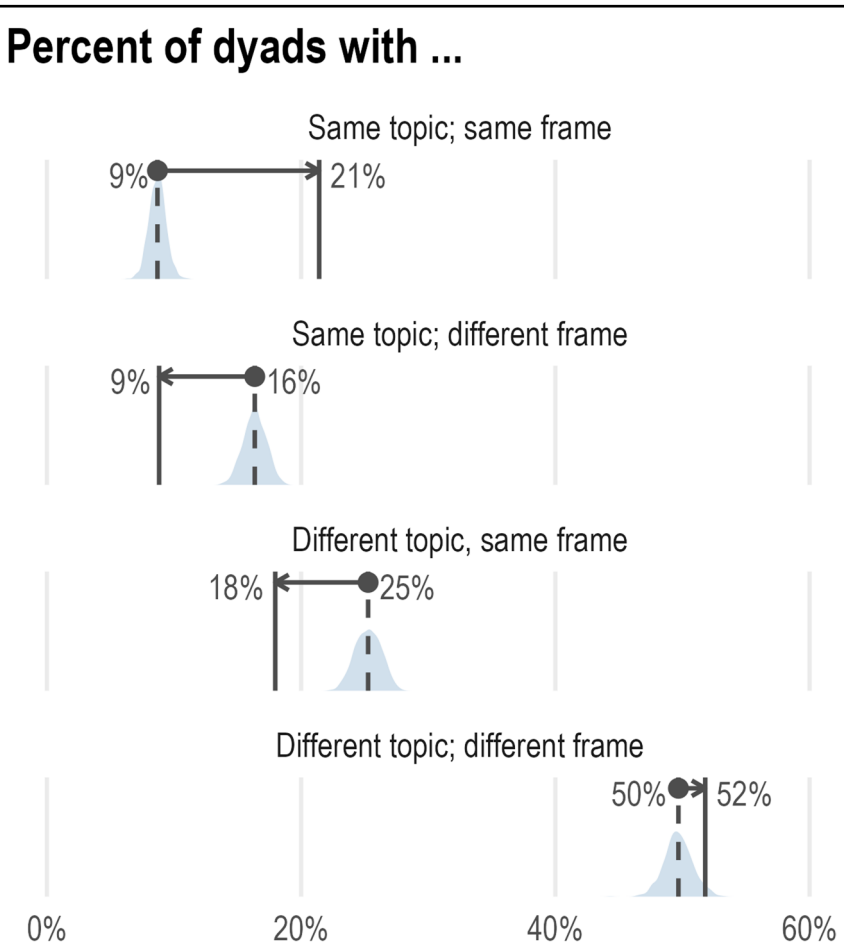


Fig. 11 Replication of Fig. 6 using Huckfeldt and Sprague's (2007) topic codes. The solid lines indicate the observed values in the data. The dotted lines show the means of the permutations. The density plots show the distribution of permuted values. For details on Huckfeldt and Sprague's topic codes, see Appendix 2 (pp. 23–30) of the codebook for the Indianapolis-St. Louis Study. This plot omits five dyads in which one of the members had an unclassifiable topic code according to Huckfeldt and Sprague's codebook. The plot shows differences that are similar in direction, though weaker in magnitude to those shown in Fig. 6. Using Huckfeldt and Sprague's topic codes, observed dyads chose the same topic and used the same frame at a rate that is 12 percentage points greater than the mean of all 1,000 permutations ($p < .01$), as shown in the top panel. The second panel shows that the observed dyads chose the same topic while using different frames at a rate seven percentage points lesser than the permutation mean ($p < .01$). The third panel shows that they chose different topics while relying on the same frame at a rate that is also seven points lower than the permutation mean ($p < .01$). Finally, the bottom panel shows that they chose different topics and used different frames at a rate two points greater than the permutation mean, and a rate that exceeds 96% of all permutations (i.e., $p = .04$)

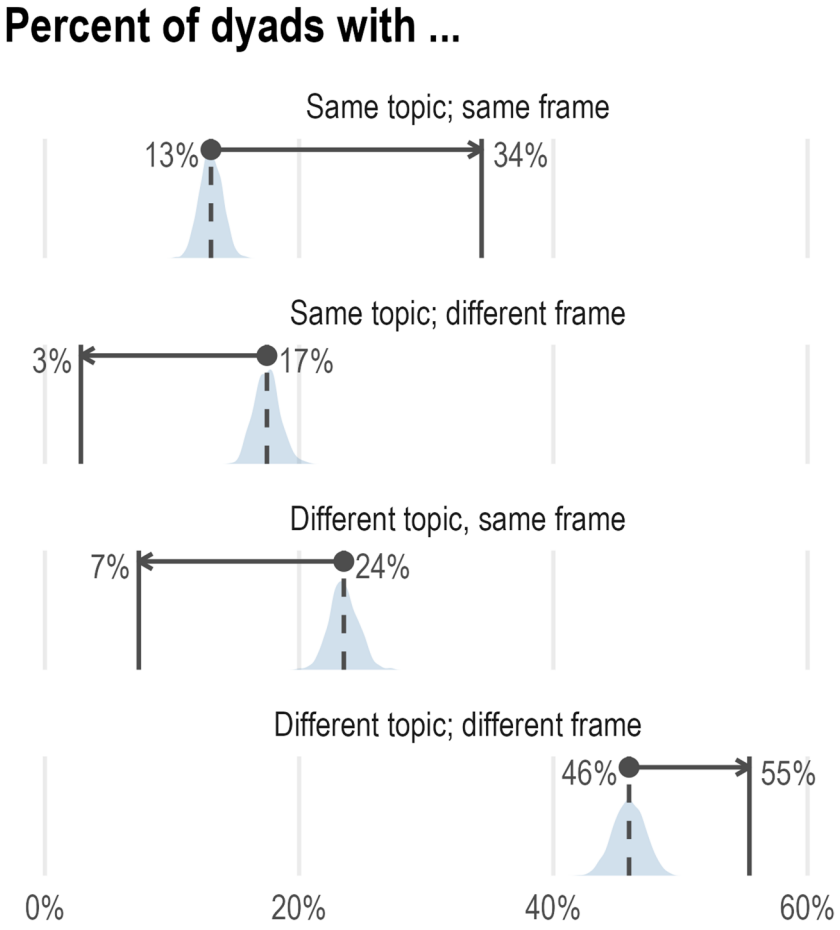


Fig. 12 Replication of Fig. 6, restricting the analysis to N = 1,272 dyads in which both members provided a response of two or more words to the Most Important Problem item. The solid lines indicate the observed values in the data. The dotted lines show the means of the permutations. The density plots show the distribution of permuted values. The plot shows differences that are similar in direction and magnitude to those shown in Fig. 6

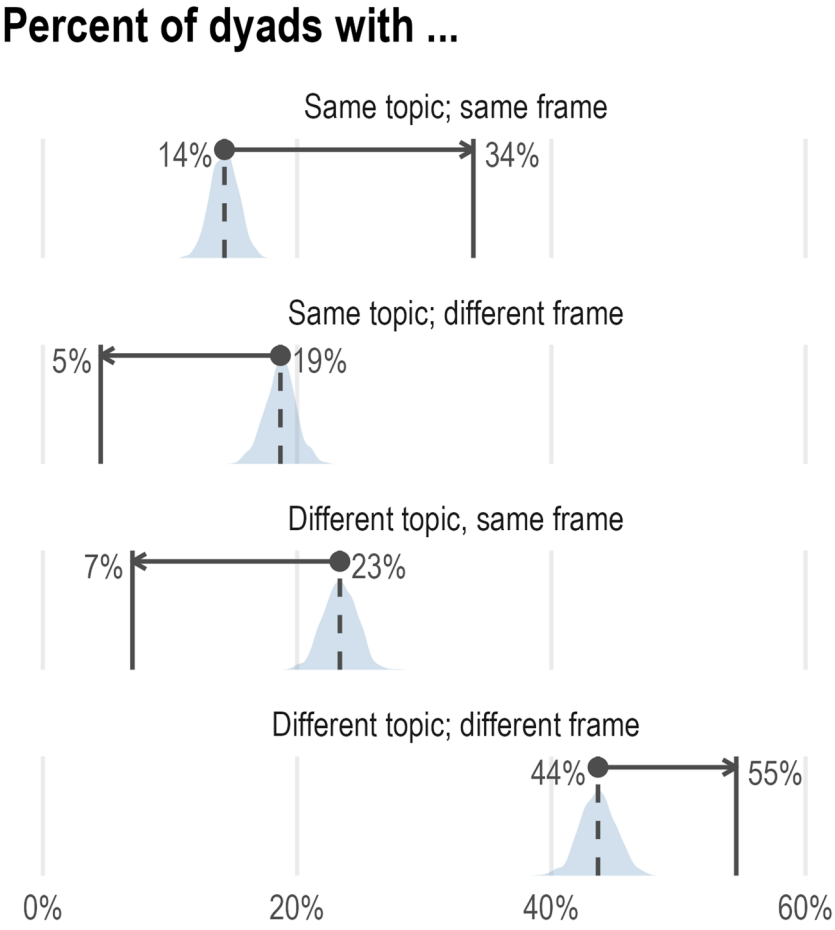


Fig. 13 Replication of Fig. 6, restricting the analysis to N = 880 dyads in which the main respondent's MIP response did not mention a topic or frame with an obvious match (see Topics and Frames with obvious matches in the table, below). The solid lines indicate the observed values in the data. The dotted lines show the means of the permutations. The density plots show the distribution of permuted values. The plot shows differences that are similar in direction and magnitude to those shown in Fig. 6

Topic	Frame
Macroeconomics	Economic
Civil Rights, Minority Issues, Civil Liberties	Fairness & Equality
Health	Health & Safety
Defense	Security & Defense
Government Operations	Political Factors & Implications
Banking, Finance, and Domestic Commerce	Economic
Foreign Trade	Economic
Church and Religion	Morality
Moral/Family Values	Morality

Topics and their matched frames. Dyads in which the main respondent's MIP responses mentioned any of these topics or relied on any of these frames were removed from the analysis depicted in Figure 13.

Appendix D. Coding Details and Examples

See Tables 2 and 3.

Table 2 List of topics and frames

Topics	Frames
Macroeconomics	Economics
Civil Rights, Minority Issues and Civil Liberties	Capacity and Resources
Health	Morality and Ethics
Agriculture	Fairness and Equality
Labor and Employment	Legality, Constitutionality, and Jurisdiction
Immigration	Crime and Punishment
Education	Security and Defense
Environment	Health and Safety
Energy	Quality of Life
Transportation	Cultural Identity
Law & Crime	Public Sentiment
Family Issues	Political Factors and Implications
Morality/Family Values	Policy Description, Prescription, and Evaluation
Social Welfare	External Regulation and Reputation
Community Development and Housing Issues	Other
Banking, Finance, and Domestic Commerce	
Defense	
Space, Science, Technology and Communications	
Foreign Trade	
International Affairs and Foreign Aid	
Government Operations	
Public Lands	
State and Local Government Administration	
Weather and Natural Disasters	
Arts and Entertainment	
Sport and Recreation	
Church and Religion	
Other	

Each respondent's "most important problem" (MIP) response was coded by topic and by frame. The topic codebook employed was the Comparative Agendas Codebook, adjusted slightly for MIP coding by differentiating Law & Crime, Family Issues, and Morality / Family Values; the full set of topics is shown in the first column above. The frame codebook employed was the Policy Frames Codebook; the full set of frames is shown in the second column above. In addition to receiving training on the codebooks, the main coder was required to meet a minimum of 90% agreement (Cohen's Kappa and Krippendorff's Alpha ≥ 0.80) on an independent coding of a gold-standard sample of responses before being allowed to conduct the coding. The random sample of 219 respondents' items used to calculate intercoder reliability was selected without the coder's knowledge from the full sample after the data were collected.

Table 3 Examples of dyads with shared/different topics and frames

Category	Ego Response	Topic Code(s)	Frame Code(s)	Alter Response	Topic Code(s)	Frame Code(s)
Same Priority / Same Frame	i'm interested in chopping off the welfare from the ppl who don't need it and giving it to the ppl who do need it	Social Welfare	Fairness and Equality	I'm strictly against the welfare system, everyone should get out and do their share, there's a lot of people on welfare who can work but they don't	Social Welfare	Fairness and Equality
Same Priority / Same Frame	decline from bibical truth and away form god no moral or valuea at all no consious of god	Church and Religion; Morality/ Family Values	Morality and Ethics	this country has gotten away from our cretor, which is god, and we've just gotten so far a away from him that we have no conceince, no morality, no absolutes.. i think we need to get back into taking responsibilty for our own actiosn & taking t	Church and Religion; Morality/ Family Values	Morality and Ethics
Same Priority / Same Frame	Crime	Law & Crime	Crime and Punishment	Crime	Law & Crime	Crime and Punishment
Same Priority / Different Frame	It's just that if your ging to have abay you need to think about how your'e support it if you're goin to do drugs you have to think where you rlife is headed	Law & Crime	Morality and Ethics	I would say drugs and crime. But if you got rid of the drugs you'd probably get rid of the crime. At least 80% of the crime. I don't think people rob to eat anymore	Law & Crime	Crime and Punishment
Same Priority / Different Frame	ritht now would be not enoughfunds for education metro politan areas are going down hil alot of schools are being closed	Education; Macroeconomics	Economics; Fairness and Equality	Education	Education	Other
Same Priority / Different Frame	I think the polorization of our society into wealthy people who don't care about anyone who is poor, and the poor who donk't have any political polwer to express their demands	Macroeconomics	Fairness and Equality; Morality; Political Factors and Implications	the most important problem…. that relates to spending too much on miliatry things and not enough creating good jobs for people	Macroeconomics; Defense	Quality of Life; Security and Defense
Different Priority / Same Frame	the fact that we have the tendency to take care of other people instead of taking care of oursel es	International Affairs and Foreign Aid	Fairness and Equality; Capacity and Resources	How to get people off welface and into the job market so that they can support themselves and develop good self esteem. I think we have caused people to become welfare dependent	Social Welfare	Fairness and Equality; Quality of Life

Table 3 (continued)

Category	Ego Response	Topic Code(s)	Frame Code(s)	Alter Response	Topic Code(s)	Frame Code(s)
Different Priority / Same Frame	the spread between the rich and the poor…	Macroeconomics	Fairness and Equality; Economics	I would say it's more along the racial tension which kind of goes along with equal opportunity	Civil Rights, Minority Issues and Civil Liberties	Fairness and Equality
Different Priority / Same Frame	Besides the lying by our officials and judges, I would say immigration–send the people back and close the borders	Immigration	Capacity and Resources	keeping the jobs over in America and helping our own people inste of foreign people	Social Welfare	Capacity and Resources
Different Priority / Different Frame	crime and violence our young people seem to lack direction. today it's a lot tougher for our young people. I'm 71, though i'm a depression person, today our young people face many bad things that they can't cope with, they're running loose with	Law & Crime	Quality of Life; Crime and Punishment	resource management; including citizens, educating them and carinf for them, and natural resources as well	Environment	Capacity and Resources
Different Priority / Different Frame	If congress and president were interested in taking care of this problem then it would be taken care of but I just don't think that their putting forth the effort	Government Operations	Political Factors and Implications	i think social security needs to be thoughoughly studied. and their are way to fix it. it should be high priority	Social Welfare	Policy Description, Prescription, and Evaluation
Different Priority / Different Frame	Morals	Morality/Family Values	Morality and Ethics	lack of education	Education	Other

The examples above showcase different ego/alter pairs whose MIP responses were coded as having either the same or different topic(s) and frame(s). These examples also highlight the variance in responses, from short and ambiguous to long and detailed.

Appendix E. Robustness Check Simulating the Asocial Process

A challenge in social network research is that we are observing networks that already exist, making it difficult to discern whether patterns we observe in the network are due to the *social* connections in some capacity or are purely coincidental. To examine the extent to which the patterns we observe in social networks are more likely to be due to social, rather than coincidental, processes, we need to simulate an *asocial* process.

Further complicating this task is the possibility that our results are driven by inherent correlations between topics and frames. If some topics and frames are co-occurring at very high rates, the results in Figs. 2, 4, and 6 could be artifacts of these correlations. To address this, we simulate worlds in which the topics and frames are highly correlated or not highly correlated and evaluate the results again from these simulated distributions.

We simulate an asocial process by repeatedly generating new datasets. In each dataset, 1,000 egos and 1,000 alters are each assigned a topic and a frame from a set of topics $T = \{t_1, t_2, \ldots, t_{10}\}$ and a corresponding set of frames $F = \{f_1, f_2, \ldots, f_{10}\}$.

For each individual, a topic t_i is first drawn from T at random with equal probability. A frame f_i is then drawn from F as a function of the parameter P(Match), which represents the probability that the individual is assigned a frame that matches its assigned topic. That is, P(Match) denotes the probability that $t_i = f_i$. For instance, if $t_i = 3$, then P(Match) is the probability that $f_i = 3$. Likewise, if $t_i = 7$, then P(Match) is the probability that $f_i = 7$. Conversely, the probability that an individual is assigned a non-matching frame ($t_i \neq f_i$) is $1 - \text{P(Match)}$. The probability the individual draws any one of the remaining nine non-matching frames is therefore $\frac{1 - \text{P(Match)}}{9}$.

After topics and frames are assigned, egos are paired with an alter in the dataset, selected at random without replacement. And thus there is no expected correlation between ego's topic and alter's topic, or ego's frame and alter's frame.

Following these steps, we simulate 1,000 datasets for each value of P(Match) in the set $\{0.0, 0.1, 0.2, \ldots, 0.9\}$, allowing us to examine how the correspondence between an individual's topic and frame shapes the probabilities of dyadic correspondence between the topics and frames of ego and alter. That is, we can examine how the topic and frame agreement between ego and alter varies as a function of how likely a topic and frame are to go together.

The table below shows the results of the simulations. For reference, the final row of the table reports the true values from the observed data, previously plotted in Fig. 6. Across the range of P(Match), the mean proportion of simulated dyads with the same topic and same frame never exceeds 0.08 or 8%, far below the 33% in our observed data. Likewise, the mean proportion of simulated dyads with different topics and different frames ranges from 81 to 88%. These values far exceed the 58% rate in our observed data. Only as P(Match) approaches its highest values do we see proportions of dyads with the same topic and different frames comparable to the 3% we observed in our data. The same goes for dyads with different topics and the same frame.

To put these values of P (Match) in perspective, consider the likelihood of topic and frame matches in our observed data, as depicted in Figures 8 and 9. Figure 8 shows that the most common frame for most topics occurs around 30% of the time, though some topics such as the Economy or Crime & Punishment have a frame that matches roughly 50% of the time. And thus the values of P (Match) that seem most comparable to our observed data are in the range of 0.3 to 0.5.

P(Match)	Same topic; same frame		Same topic; different frame		Different topic; same frame		Different topic; different frame	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
0	0.01	0.003	0.09	0.009	0.09	0.009	0.81	0.013
0.1	0.01	0.003	0.09	0.009	0.09	0.009	0.81	0.012
0.2	0.01	0.003	0.09	0.009	0.09	0.009	0.81	0.012
0.3	0.01	0.004	0.09	0.009	0.09	0.009	0.81	0.012
0.4	0.02	0.004	0.08	0.009	0.08	0.008	0.82	0.012
0.5	0.03	0.005	0.07	0.008	0.07	0.008	0.83	0.012
0.6	0.04	0.006	0.06	0.008	0.06	0.007	0.84	0.012
0.7	0.05	0.007	0.05	0.007	0.05	0.007	0.85	0.011
0.8	0.06	0.008	0.04	0.006	0.04	0.006	0.86	0.011
0.9	0.08	0.009	0.02	0.004	0.02	0.004	0.88	0.010
Observed	0.33		0.03		0.06		0.58	

The table displays the proportion of dyads with each combination of topics and frames across the range of P(Match). The Mean and Std. Error columns represent the mean and standard deviation of the proportion across the 1,000 simulated datasets for a given value of P(Match). The final row, labeled *Observed*, shows the true values in our observed data (those plotted in Fig. 6)

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11109-026-10188-x.

Acknowledgements We are grateful to Scott McClurg for thoughtful suggestions on an earlier draft and to Veronica Serrato and, especially, Hannah Dillman Murnane for expert data collection. We thank the reviewers for providing excellent feedback that has greatly improved this manuscript.

Data availability The data that support the findings of this study are openly available from the Inter-university Consortium for Political and Social Research at https://doi.org/10.3886/ICPSR02962.v2. All other replication files can be found at https://doi.org/10.7910/DVN/GSJS0A.

Declarations

Conflict of interest The authors did not receive support from any organization for the submitted work and they have no competing interests to declare that are relevant to the content of this article.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

Aarøe, Lene, and Michael Bang Petersen. 2020. Cognitive biases and communication strength in social networks: The case of episodic frames. *British Journal of Political Science* 50 (4): 1561–1581. https://doi.org/10.1017/S0007123418000273.

Alt, James E., Amalie Jensen, Horacio Larreguy, David D. Lassen, and John Marshall. 2022. Diffusing political concerns: How unemployment information passed between social ties influences Danish voters. *Journal of Politics* 84 (1): 383–404. https://doi.org/10.1086/714925.

Amsalem, Eran, and Lilach Nir. 2021. Does interpersonal discussion increase political knowledge? A meta-analysis. *Communication Research* 48 (5): 619–641. https://doi.org/10.1177/0093650219866357.

Arbour, Brian. 2014. Issue frame ownership: The partisan roots of campaign rhetoric. *Political Communication* 31 (4): 604–627. https://doi.org/10.1080/10584609.2013.852639.

Barberá, Pablo, Andreu Casas, Jonathan Nagler, Patrick J. Egan, Richard Bonneau, John T. Jost, and Joshua A. Tucker. 2019. Who leads? Who follows? Measuring issue attention and agenda setting by legislators and the mass public using social media data. *American Political Science Review* 113 (4): 883–901. https://doi.org/10.1017/S0003055419000352.

Baumgartner, Frank R., and Bryan D. Jones. 2009. *Agendas and instability in American politics*. 2nd ed. Chicago, IL: University of Chicago Press.

Bearman, Peter, and Paolo Parigi. 2004. Cloning headless frogs and other important matters: Conversation topics and network structure*. *Social Forces* 83 (2): 535–557. https://doi.org/10.1353/sof.2005.0001.

Berinsky, Adam J., and Donald R. Kinder. 2006. Making sense of issues through media frames: Understanding the Kosovo crisis. *The Journal of Politics* 68 (3): 640–656.

Bevan, Shaun, and Mona Krewel. 2015. Responsive elections: The effect of public opinion on political campaigns. *Electoral Studies* 40:548–555. https://doi.org/10.1016/j.electstud.2015.07.006.

Bond, Robert M., Christopher J. Fariss, Jason J. Jones, Adam D. I. Kramer, Cameron Marlow, Jaime E. Settle, and James H. Fowler. 2012. A 61-million-person experiment in social influence and political mobilization. *Nature* 489 (7415): 295–298. https://doi.org/10.1038/nature11421.

Boutyline, Andrei, and Robb Willer. 2017. The social structure of political echo chambers: Variation in ideological homophily in online networks. *Political Psychology* 38 (3): 551–569. https://doi.org/10.1111/pops.12337.

Boydstun, Amber E. 2013. *Making the news: Politics, the media and agenda setting*. Chicago, IL: University of Chicago Press.

Boydstun, Amber E., Dallas Card, Justin H. Gross, Philip Resnik, and Noah A. Smith. 2020. The Policy Frames Codebook. https://minio.la.utexas.edu/compagendas/codebookfiles/Policy_Frames_Codebook.pdf.

Burt, Ronald S. 1984. Network items and the General Social Survey. *Social Networks* 6 (4): 293–339. https://doi.org/10.1016/0378-8733(84)90007-8.

Butters, Ross, and Christopher Hare. 2022. Polarized networks? New evidence on American voters' political discussion networks. *Political Behavior* 44 (3): 1079–1103. https://doi.org/10.1007/s11109-020-09647-w.

Carlson, Taylor N. 2018. Modeling political information transmission as a game of telephone. *Journal of Politics* 80 (1): 348–352. https://doi.org/10.1086/694767.

Carlson, Taylor N. 2019. Through the grapevine: Informational consequences of interpersonal political communication. *American Political Science Review* 113 (2): 325–339. https://doi.org/10.1017/S0003055419000008X.

Carlson, Taylor N. 2024. *Through the grapevine: Socially transmitted information and distorted democracy*. Chicago, IL: University of Chicago Press.

Carlson, Taylor N., Charles T. McClean, and Jaime E. Settle. 2020. Follow your heart: Could psychophysiology be associated with political discussion network homogeneity? *Political Psychology* 41 (1): 165–187. https://doi.org/10.1111/pops.12594.

Chang, Ho-Chun Herbert., James N. Druckman, Emilio Ferrara, and Robb Willer. 2025. Liberals and conservatives share information differently on social media. *PNAS Nexus* 4 (7) : pgaf206. https://doi.org/10.1093/pnasnexus/pgaf206.

Chong, D., and J. Druckman. 2007. Framing theory. *Annual Review of Political Science* 10 (1): 103–126. https://doi.org/10.1146/annurev.polisci.10.072805.103054.

Claibourn, Michele P. 2008. Making a connection: Repetition and priming in presidential campaigns. *Journal of Politics* 70 (4): 1142–1159. https://doi.org/10.1017/S0022381608081115.

Cramer Walsh, Katherine. 2004. *Talking about politics: Informal groups and social identity in American life*. Chicago, IL: University of Chicago Press.
Djupe, Paul, Scott McClurg, and Anand Edward Sokhey. 2018. The political consequences of gender in social networks. *British Journal of Political Science* 48 (3): 637–658. https://doi.org/10.1017/S0007123416000156.
Druckman, James N. 2001. The implications of framing effects for citizen competence. *Political Behavior* 23 (3): 225–256.
Druckman, James N., Matthew S. Levendusky, and Audrey McLain. 2018. No need to watch: How the effects of partisan media can spread via interpersonal discussions. *American Journal of Political Science* 62 (1): 99–112. https://doi.org/10.1111/ajps.12325.
Dunaway, Johanna, Regina P. Branton, and Marisa A. Abrajano. 2010. Agenda setting, public opinion, and the issue of immigration reform. *Social Science Quarterly* 91 (2): 359–378.
Eissler, Rebecca, and Bryan D. Jones. 2019. The US Policy Agendas Project. In *Comparative Policy Agendas: Theory, Tools, Data,* Oxford 184–90.
Erikson, Robert S., Pablo M. Pinto, and Kelly T. Rader. 2017. Dyadic analysis in international relations: A cautionary tale. *Political Analysis* 22 (4): 457–463. https://doi.org/10.1093/pan/mpt051.
Feezell, Jessica T., Rebecca A. Glazier, and Amber E. Boydstun. 2019. Framing, identity, and responsibility: Do episodic vs. thematic framing effects vary by target population? *Politics, Groups, and Identities* 9 (2): 347–368. https://doi.org/10.1080/21565503.2019.1584751.
Foster, David V., Jacob G. Foster, Peter Grassberger, and Maya Paczuski. 2011. Clustering drives assortativity and community structure in ensembles of networks. *Physical Review E* 84 (6) : 066117. https://doi.org/10.1103/PhysRevE.84.066117.
Furth-Matzkin, Meirav, and Cass R. Sunstein. 2017. Social influences on policy preferences: Conformity and reactance. *Minnesota Law Review* 102 (3): 1339–1380.
Glazier, Rebecca A., and Amber E. Boydstun. 2012. The president, the press, and the war: A tale of two framing agendas. *Political Communication* 29 (4): 428–446.
Goel, Sharad, Winter Mason, and Duncan J. Watts. 2010. Real and perceived attitude agreement in social networks. *Journal of Personality and Social Psychology* 99 (4): 611–621. https://doi.org/10.1037/a0020697.
Heffington, Colton, Brandon Beomseob Park, and Laron K. Williams. 2019. The 'most important problem' dataset (MIPD): A new dataset on American issue importance. *Conflict Management and Peace Science* 36 (3): 312–335. https://doi.org/10.1177/0738894217691463.
Hemphill, Libby, Annelise Russell, and Angela M. Schöpke-Gonzalez. 2021. What drives U.S. congressional members' policy attention on Twitter? *Policy & Internet* 13 (2): 233–256. https://doi.org/10.1002/poi3.245.
Hemphill, Libby, and Andrew J. Roback. 2014. Tweet acts: How constituents lobby congress via Twitter. In Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing: 1200-1210.
Herbst, Susan. 1998. *Reading public opinion: How political actors view the democratic process*. University of Chicago Press.
Hopkins, Daniel J., and Jonathan Mummolo. 2016. Assessing the Breadth of Framing Effects. https://doi.org/10.2139/ssrn.2863930.
Huckfeldt, Robert. 2001. The social communication of political expertise. *American Journal of Political Science* 45 (2): 425–438. https://doi.org/10.2307/2669350.
Huckfeldt, Robert, and Jeanette Morehouse Mendez. 2008. Moths, flames, and political engagement: Managing disagreement within communication networks. *The Journal of Politics* 70 (1): 83–96. https://doi.org/10.1017/S0022381607080073.
Huckfeldt, Robert, Paul E. Johnson, and John Sprague. 2004. *Political disagreement: The survival of diverse opinions within communication networks*. New York, NY: Cambridge University Press.
Huckfeldt, Robert, and John Sprague. 1995. Citizens, Politics, and Social Communication: Information and Influence in an Election Campaign. Cambridge University Press. 1995. *New York*. NY: Cambridge University Press.
Iyengar, Shanto. 1991. *Is anyone responsible? How television frames political issues*. Chicago, IL: University of Chicago Press.
Iyengar, Shanto, and Adam Simon. 1993. News coverage of the Gulf crisis and public opinion. *Communication Research* 20 (3): 365–383.
Jennings, Will, and Christopher Wlezien. 2015. Preferences, problems and representation. *Political Science Research and Methods* 3 (3): 659–681. https://doi.org/10.1017/psrm.2015.3.

Jones, Bryan D., Frank R. Baumgartner, Sean M. Theriault, Derek A. Epp, Cheyenne Lee, and Miranda E. Sullivan. 2023. Policy Agendas Project: Codebook.

Kaid, Lynda Lee, and Anne Johnston Wadsworth. 1989. ContentAnalysis. In *Measurement of Communication Behavior, Ed. Philip Emmert and Larry L. Barker*, Longman, 208.

Katz, Elihu. 1957. The Two-Step Flow of Communication: An Up-To-Date Report on an Hypothesis. *The Public Opinion Quarterly* 21 (1): 61–78. https://doi.org/10.2307/2746790.

Kinder, Donald R., and Don Herzog. 1993. Democratic discussion. In *Reconsidering the democratic public*, ed. George E. Marcus and Russell L. Hanson, 347–377. University Park, PA: Pennsylvania State University Press.

Kinder, Donald R., and Lynn M. Sanders. 1996. *Divided by color: Racial politics and democratic ideals*. Chicago: University of Chicago Press.

Klofstad, Casey A., Scott D. McClurg, and Meredith Rolfe. 2009. Measurement of political discussion networks a comparison of two ``name generator'' procedures. *Public Opinion Quarterly* 73 (3): 462–483.https://doi.org/10.1093/poq/nfp032.

Kossinets, Gueorgi, and Duncan J. Watts. 2009. Origins of homophily in an evolving social network. *American Journal of Sociology* 115 (2): 405–450. https://doi.org/10.1086/599247.

Krippendorff, Klaus. 2019. The changing landscape of content analysis: Reflections on social construction of reality and beyond. *Communication & Society* 47 (1): 1–27.

Krosnick, Jon A. 1988. The role of attitude importance in social evaluation: A study of policy preferences, presidential candidate evaluations, and voting behavior. *Journal of Personality and Social Psychology* 55 (2): 196–210.

Lacy, Stephen, and Daniel Riffe. 1996. Sampling error and selecting intercoder reliability samples for nominal content categories. *Journalism & Mass Communication Quarterly* 73 (4): 963–973. https://doi.org/10.1177/107769909607300414.

Lane, Daniel S., Cassandra M. Moxley, and Cynthia McLeod. 2023. The group roots of social media politics: Social sorting predicts perceptions of and engagement in politics on social media. *Communication Research* 50 (7): 904–932. https://doi.org/10.1177/00936502231161400.

Lazer, David, Brian Rubineau, Carol Chetkovich, Nancy Katz, and Michael Neblo. 2010. The coevolution of networks and political attitudes. *Political Communication* 27 (3): 248–274. https://doi.org/10.1080/10584609.2010.500187.

Ledgerwood, Alison, and Amber E. Boydstun. 2014. Sticky prospects: Loss frames are cognitively stickier than gain frames. *Journal of Experimental Psychology: General* 143:376–385.

Lefevere, Jonas, Julie Sevenans, Stefaan Walgrave, and Christophe Lesschaeve. 2019. Issue reframing by parties: The effect of issue salience and ownership. *Party Politics* 25 (4): 507–519. https://doi.org/10.1177/1354068817736755.

Liu, Lisha, Alexander Kuo, and Jose Fernandez-Albertos. 2022. Economic crisis, social networks, and political preferences. *Socio-Economic Review* 20 (1): 199–231. https://doi.org/10.1093/ser/mwaa024.

Lopez-Escobar, Esteban, Juan Pablo Llamas, Maxwell McCombs, and Federico Rey Lenon. 1998. Two levels of agenda setting among advertising and news in the 1995 Spanish elections. *Political Communication* 15:225–238.

Louch, Hugh. 2000. Personal network integration: Transitivity and homophily in strong-tie relations. *Social Networks* 22 (1): 45–64. https://doi.org/10.1016/S0378-8733(00)00015-0.

Marsden, Peter V. 1987. Core discussion networks of Americans. *American Sociological Review* 52 (1): 122–131. https://doi.org/10.2307/2095397.

Marsden, Peter V. 2002. Egocentric and sociocentric measures of network centrality. *Social Networks* 24 (4): 407–422.

McClurg, Scott D. 2006. The electoral relevance of political talk: Examining disagreement and expertise effects in social networks on political participation. *American Journal of Political Science* 50 (3): 737–754.

McCombs, Maxwell. 2004. *Setting the agenda: The mass media and public opinion*. Cambridge, UK: Polity Press.

McCombs, Maxwell, and D. L. Shaw. 2005. *The agenda-setting function of the press*. Oxford: Oxford University Press.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook. 2001. Birds of a feather: Homophily in social networks. *Annual Review of Sociology* 27:415–444. https://doi.org/10.1146/annurev.soc.27.1.415.

Morehouse Mendez, Jeanette. 2008. Where's the Party? A Cross-County Comparison of Agenda-Setting Effects and the Role of Party Identification. *Midsouth Political Science Review* 9: 75–93.

Minozzi, William, Hyunjin Song, David M. J. Lazer, Michael A. Neblo, and Katherine Ognyanova. 2020. The incidental pundit: Who talks politics with whom, and why? *American Journal of Political Science* 64 (1): 135–151. https://doi.org/10.1111/ajps.12469.

Munger, Kevin. 2023. Temporal validity as meta-science. *Research & Politics* 10 (3): 1-10.

Nelson, Thomas E., and Donald R. Kinder. 1996. Issue Frames and Group-Centrism in American Public Opinion. *Journal of Politics* 58 (4): 1055–1078.

Nelson, Thomas E., Rosalee A. Clawson, and Zoe Oxley. 1997. Media Framing of a Civil Liberties Controvery and Its Effect on Tolerance. *American Political Science Review* 91 (3): 567–584.

Nelson, Thomas E. 2019. Emphasis Framing and Political Decision Making. In Oxford Research Encyclopedia of Politics, ed. Erin Hannah, New York, NY: Oxford Academic. https://doi.org/10.1093/acrefore/9780190228637.013.965

O'Connor, Brendan, Ramnath Balasubramanyan, Bryan Routledge, and Noah Smith. 2010. From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. *Proceedings of the International AAAI Conference on Web and Social Media* 4 (1): 122–129. https://doi.org/10.1609/icwsm.v4i1.14031.

Osborn, Tracy, and Jeanette Morehouse Mendez. 2011. Two become one? spouses and agreement in political opinions. *American Politics Research* 39 (5): 783–803. https://doi.org/10.1177/1532673X11404133.

Pietryka, Matthew T., Jack Lyons Reilly, Daniel M. Maliniak, Patrick R. Miller, Robert Huckfeldt, and Ronald B. Rapoport. 2018. From respondents to networks: bridging between individuals, discussants, and the network in the study of political discussion. *Political Behavior* 40 (3): 711–735. https://doi.org/10.1007/s11109-017-9419-3.

Roberts, Margaret E., Brandon M. Stewart, Dustin Tingley, Christopher Lucas, Jetson Leder-Luis, Shana Kushner Gadarian, Bethany Albertson, and David G. Rand. 2014. Structural topic models for open-ended survey responses. *American Journal of Political Science* 58 (4): 1064–1082. https://doi.org/10.1111/ajps.12103.

Rogowski, Jon C., and Betsy Sinclair. 2012. Estimating the causal effects of social interaction with endogenous networks. *Political Analysis* 20 (3): 316–328. https://doi.org/10.1093/pan/mps016.

Rossiter, Erin, and Taylor N. Carlson. 2023. The Similar and Distinct Effects of Political and Non-Political Conversation on Affective Polarization. Preprint at https://erossiter.com/files/conversations.pdf (November 17, 2025).

Ryan, John Barry. 2011. Accuracy and bias in perceptions of political knowledge. *Political Behavior* 33 (2): 335–356. https://doi.org/10.1007/s11109-010-9130-0.

Settle, Jaime E., and Taylor N. Carlson. 2019. Opting out of political discussions. *Political Communication* 36 (3): 476–496. https://doi.org/10.1080/10584609.2018.1561563.

Sinclair, Betsy. 2012. *The social citizen: Peer networks and political behavior*. Chicago, IL: University of Chicago Press.

Sniderman, Paul M., and Sean M. Theriault. 2004. The structure of political argument and the logic of issue framing. In *Studies in public opinion*, ed. Willem E. Saris and Paul M. Sniderman, 133–165. Princeton, NJ: Princeton University Press.

Stier, Sebastian, Wolf J. Schünemann, and Stefan Steiger. 2018. Of activists and gatekeepers: Temporal and structural properties of policy networks on Twitter. *New Media & Society* 20 (5): 1910–1930. https://doi.org/10.1177/1461444817709282.

Stroud, Natalie Jomini. 2011. *Niche news: The politics of news choice*. Oxford: Oxford University Press.

Tan, Yue, and David H. Weaver. 2007. Agenda-setting effects among the media, the public, and Congress, 1946–2004. *Journalism & Mass Communication Quarterly* 84 (4): 729–744. https://doi.org/10.1177/107769900708400405.

Tesler, Michael. 2015. Priming predispositions and changing policy positions: An account of when mass opinion is primed or changed. *American Journal of Political Science* 59 (4): 806–824. https://doi.org/10.1111/ajps.12157.

Tversky, Amos, and Daniel Kahneman. 1981. The framing of decision and the psychology of choice. *Science* 211 (4481): 453–458.

Vidigal, Robert, and Jennifer Jerit. 2022. Issue importance and the correction of misinformation. *Political Communication* 39 (6): 715–736. https://doi.org/10.1080/10584609.2022.2123580.

Walgrave, Stefaan, and Peter Van Aelst. 2006. The contingency of the mass media's political agenda setting power. Towards a preliminary theory. *Journal of Communication* 56 (1): 88–109.

Weeks, Brian E., Daniel S. Lane, Dam Hee Kim, Slgi S. Lee, and Nojin Kwak. 2017. Incidental exposure, selective exposure, and political information sharing: Integrating online exposure patterns and expression on social media. *Journal of Computer-Mediated Communication* 22 (6): 363–379. https://doi.org/10.1111/jcc4.12199.

Wlezien, Christopher. 2005. On the salience of political issues: The problem with 'most important problem.' *Electoral Studies* 24 (4): 555–579.

Zelizer, Adam. 2019. Is position-taking contagious? Evidence of cue-taking from two field experiments in a state legislature. *American Political Science Review* 113 (2): 340–352. https://doi.org/10.1017/S0003055419000078.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Authors and Affiliations

Matthew T. Pietryka[1] · Amber E. Boydstun[2] · Taylor N. Carlson[3]

✉ Matthew T. Pietryka
mpietryka@wisc.edu

Amber E. Boydstun
aboydstun@ucdavis.edu

Taylor N. Carlson
tncarlson@wustl.edu

[1] University of WI–Madison, 110 North Hall, 1050 Bascom Mall, Madison, WI 53706, USA

[2] University of California, Davis, 469 Kerr Hall, One Shields Avenue, Davis, CA 95616, USA

[3] Washington University in St. Louis, One Brookings Drive, St. Louis, MO 63130-4899, USA