

The Cross-Partisan Voices of Podcasts and Their Social Media Ties

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Abstract

Heightened polarization in the United States has raised public and scholarly concern about podcasts and their role in political division. Podcasts that repeatedly host cross-partisan discussions, however, remain understudied. In this work, we examine whether individuals who engage with politically heterogeneous voices on podcasts also display bridging behavior on social media and in their cross-cutting conversations. Specifically, we investigate whether bridging actors pay attention to a politically diverse set of accounts on social media and whether they discuss topics that differ from those of their non-bridging counterparts. To do so, we collect data on roughly 5,000 individuals who appeared on popular political podcasts over a 13-month period, including their podcast appearances and discussion content. We also identify their X accounts and extract the follower relationships among them. We find that podcasters and their guests interact with a smaller but more politically diverse set of individuals on podcasts than on X, except for liberal podcasts, which maintain similar cross-cutting ties across both media. To study cross-ideological conversation, we transcribed and diarized over 10,000 podcast episodes. We find that bridging guests tend to discuss a narrower set of topics during cross-cutting podcast interviews compared to non-bridging guests. These findings indicate that bridging actors in the podcasting space exhibit distinguishable conversational and attentional behaviors, laying the groundwork for further research examining these actors and their conversations across various media.

Introduction

Political division pervades the American media ecosystem (Liedke and Shearer 2025; Shearer et al. 2025). While some level of polarization is healthy in a democracy—voters need meaningful political choices—the maintenance of democratic states requires the good-faith cross-partisan discussion of political ideas, philosophies, and policies (Tucker et al. 2018). The partisan siloing of venues for news and political information simultaneously reflects and can engender high levels of political homophily in the US (Torcal and Hartevelde 2025; Sunstein 2018). This reduction in public cross-party engagement can undermine democratic functioning: Beyond the loss of coherent discourse about policy

preferences, which are not strongly correlated to party affiliation, it reduces the number of times individuals can express their ideas at length directly to audiences, minimizing opportunities for persuasion and debate (Iyengar et al. 2019).

Within this fracturing information environment, public and academic interest in the role that prominent individuals play in increasing political tension has risen, particularly with the rise of digital platforms where individuals command the attention of large audiences (Torcal and Hartevelde 2025). Some note the divisive potential of these influential actors in digital spaces: Prominent individuals are positioned to quickly spread claims that align with their followers' existing viewpoints (Centola 2021) and model adversarial political discourse (Ruggiero 2000), making the rapid diffusion of divisive content possible.

The swift ascent of podcasts, popular sources of political information and discourse in the US, has placed podcast hosts and their featured guests in such positions of influence over their loyal audiences. 55% of Americans ages 12 and up listen to podcasts at least monthly, and 89% of listeners believe most content they hear to be accurate (Edison Research 2025; Shearer et al. 2023). This popularity and persuasive potential created interest in partisan divisions in the podcasting space. Prior work has found that the most popular political podcasters in the US largely attend to and share guests with podcasts of the same partisan lean, indicating that efforts to even *observe* outgroup ideas, which underpin effective debate and intergroup understanding, are thin (DeMets and Spiro 2025). Additionally, investigation of the content of these podcasts found divisive material, including false narratives and toxic speech targeting political outgroups, to be common (Wirschafter 2023; Rizwan et al. 2025). Simply, high levels of political homophily and partisan animus signal that the political podcasting space is polarized.

While the partisan tendencies of actors in this system are better documented, investigations of *bridging actors*, i.e., those who engage with a diverse set of voices, are limited. Bridging actors play the vital and uncommon role of modeling the democratic norm of cross-cutting engagement, but it is unknown if their efforts to comprehend and converse with members of outgroups differ from their more insulated peers. To date, we lack a systematic identification of bridging actors in the podcasting space. DeMets and Spiro (2025) identify the podcasts which facilitate the movement

of guests across partisan lines, but do not find the bridging actors of interest here. Similarly, they infer which podcasts attend to *and hold* the attention of a cross-partisan set of podcasts using guest adoption data, yet do not find the guests and podcasts that pay attention to a heterogeneous set of peers. Such attentional ties, observable on social media platforms like X, would allow us to assess whether bridging actors also invest in observing and grasping ideologically diverse ideas and views (Almquist, Spiro, and Butts 2017). Moreover, little is known about the conversational practices of these actors. Experimental work has shown that cross-partisan discussions on topics of known agreement reduce affective polarization (Santoro and Broockman 2022), yet it is uncertain if public figures who organically sustain inter-group contact show similar patterns.

In this work, we examine the attentional and conversational patterns of bridging actors. First, we build a network of popular political podcasts and their guests and identify the actors who follow each other on X in this network. We then evaluate whether actors in this network pay attention to a more politically heterogeneous set of actors on X compared to those they interact with on podcasts or *vice versa* (RQ1). Next, we identify the particularly bridging actors in the podcasting network, and examine whether these actors also demonstrate a tendency to form cross-cutting ties at relatively high rates on X (RQ2). Last, using diarized transcript data from these podcasts, we investigate if bridging actors on podcasts discuss topics that are distinct relative to their peers (RQ3). We find that actors tend to engage with a more politically diverse set of individuals on podcasts than among those they follow on X. Moreover, actors who display bridging behaviors on podcasts attend to a more politically diverse set of alters on X, yet engage in a topically narrower set of discussions compared to their non-bridging counterparts.

Related Work

This study brings together two lines of work: research on podcasts and work on bridging positions. Prior work shows that the podcasting space is heavily structured by partisan lean, underlining the importance of bridges in this system. However, research on the key actors holding cross-cutting conversations—and whether their attempts to comprehend and converse with outgroups are distinct—is missing. We start by reviewing existing work on podcasts, then position our contribution within the body of research on bridges.

Podcasts. Given the nascent state of research on podcasts, most studies focus on mapping the actors and topics in the podcasting space. An emerging line of work maps relations between podcasts and their featured guests, and identifies the attributes which structure these networks (Stocking and Odabas 2024; Litterer, Jurgens, and Card 2025; DeMets and Spiro 2025). Across the larger podcasting ecosystem, genre, almost by definition, largely organizes the social network: Hosting norms vary greatly per genre, leading to distinct communities in this network (Stocking and Odabas 2024; Litterer, Jurgens, and Card 2025). More pertinent to the work here is research on the networked structure of the most popular political podcasts in the US, which found strong as-

sortative mixing by partisan lean (DeMets and Spiro 2025). Conservative and liberal podcasts were linked by common guests at a significantly lower rate than expected, whereas within-group mixing was significantly higher than anticipated.

Another line of work explores the conversational content of podcasts (Wirschafter 2023; Stocking and Odabas 2024; Litterer, Jurgens, and Card 2025; Kurek et al. 2025; Rizwan et al. 2025). While genre heavily influences discussed topics, these topical boundaries can dissolve: Highly-salient current events can spark discussion across multiple genres (Litterer, Jurgens, and Card 2025). Cross-genre discussion of widely visible political events coincides with findings that two-thirds of podcast listeners reported hearing the news discussed on *any* popular podcast in a one-year time frame, despite the fact that 85% of popular podcasts are not news-related (Shearer et al. 2023).

Some research explores the content specific to political podcasts, which are typically oriented towards covering current events, providing corresponding analysis, or doing “deep dives” into a topic (Stocking 2023). One report on popular political podcasts in the US revealed that conservative-leaning shows typically produce more episodes and, correspondingly, feature more guests than liberal-leaning podcasts, resulting in overall higher content production from conservative podcasts (Wirschafter 2023). Rizwan et al. (2025) examined the emotional valence and speech of 31 of these popular political podcasts, and found that every show in this study contained toxic language. Nine of these podcasts contained toxic speech in over half of their episodes, and 29 contained toxic language in over 10% of their episodes. Other work examines podcasts affiliated with specific media groups. Early topic modeling of political podcast-videos from Tenet Media, a right-leaning information operation from Russia, found that, after high-level national and election politics, podcasters tended to focus on identity politics related to sexuality, gender, and race (Kurek et al. 2025). While much research explores the content coming from actors who divide this space, we examine the topics that guests who sustain cross-cutting rapport engage in, establishing which subjects bridging individuals focus on.

Bridging Positions. Actors occupying different social roles have long been studied in order to understand the unique impacts these positions have on different social processes, and to understand whether certain behaviors and individual attributes are characteristic of those who occupy these positions. *Bridges* and *brokers* have been of particular interest to social scientists, as such positions can prevent systems from balkanizing, and can also afford their occupants power over the diffusion processes within a social network (Simmel 1950; Gould and Fernandez 1989; Burt 1992; Jasny and Lubell 2015).

To date, one study has investigated the podcasts that bridge partisan communities in the podcasting space. DeMets and Spiro (2025) examine podcasts that mediate the movement of guests between shows of different partisan tilts by conferring the attention of cross-boundary podcasts onto these guests. They find that only a small number

of shows occupied these brokerage positions, and suggesting politically homophilous attention between podcasters in this network. Interestingly, the authors note that the shows that self-describe as seeking to spark cross-partisan conversations played an outside role in facilitating guest movement between podcasts of different partisan leans, indicating that these actors that (ostensibly) engage in cross-cutting conversations have unique attentional networks. However, this study lacked information on the partisan leaning of guests, limiting their ability to pointedly identify the shows directly featuring cross-cutting conversations.

While DeMets and Spiro (2025) study brokers, we focus on bridging actors. Bridging actors are of interest here because such roles are uncommon and important; in polarized contexts, people avoid and try to cut engagements with outgroup members short (e.g., see Santoro and Broockman (2022) for a more comprehensive overview of reduced intergroup contact). This makes bridging actors unique. Because these individuals willingly and more consistently interface with a heterogeneous group of actors, it is important to understand whether these individuals make a concerted effort to better comprehend outgroup viewpoints, and whether they have peculiar conversational habits that might help them perpetuate intergroup contact.

The first behavior we examine concerns bridging actors' allocation of attention. Having access to the X follower networks of podcast hosts and guests allows us to quantify whether they choose to pay attention to more diverse voices by following accounts with different partisan leanings. Theoretically, whether bridging actors exhibit comparatively high attentional diversity is not clear *ex ante*. On the one hand, intergroup contact theory suggests that direct exposure to outgroup members would reduce partisan animus (Paluck, Green, and Green 2019). Thus, it is possible that bridging actors are more willing to engage with and attend to outgroup members *because* they have engaged previously with them. By contrast, more insulated actors might not experience the benefits of reduced partisan animus from intergroup contact, reducing opportunities for cross-partisan engagement. Accordingly, the contact hypothesis suggests that bridgingness should be correlated across platforms. On the other hand, the actors examined here are largely prominent individuals, many of whom share a vocation and serve as leaders in their respective domains. Katz and Lazarsfeld's two-step model (1955) suggests that such figures attend to a diverse array of informational sources regardless of their own partisanship. It is therefore possible that while bridging actors are distinctive in their decision to cross partisan boundaries on podcasts, their attentional heterogeneity (i.e., their decision to follow diverse accounts on X) may not be exceptional given the population under study.

The second behavior we examine concerns bridging actor's conversational tendencies. Because bridging actors are able to get invited back for conversations with outgroup members, we are interested in seeing if these individuals stick to a handful of topics, or if they are engaging in a wide array of discussions. Previous work in experimental settings demonstrates that engaging in cross-cutting discussions on topics of known agreement can reduce partisan animus (San-

toro and Broockman 2022). Empirical work on relationships between podcasts has also shown that Trump-opposed conservative podcasts also tend to share more guests with liberal podcasts (DeMets and Spiro 2025). It is possible that the guests and hosts shared between these shows may find common ground on their dislike for President Trump. Here, we examine if those who uphold cross-cutting conversations also attend to a narrow number of discussions, a move which might explain why these individuals operate as bridging actors in this system.

In short, as research on podcasts is still comparatively new, research on the actors who operate as critical links in this system is still needed. DeMets and Spiro (2025) identify shows that share common guests, but, again, missing data around the partisan leaning of guests prevents the identification of shows featuring a politically diverse set of guests. Another gap in this work is that it is unclear if guests occupying bridging positions engage in a range of topics or if they typically focus on one topic where they know they may find common ground. In this work, we take a bridging-centered approach to understanding discussed content. We try to identify whether those who engage in cross-cutting conversations discuss the same topics or whether those who engage in cross-cutting conversations discuss the same topics as their non-bridging alters.

Data & Network Descriptions

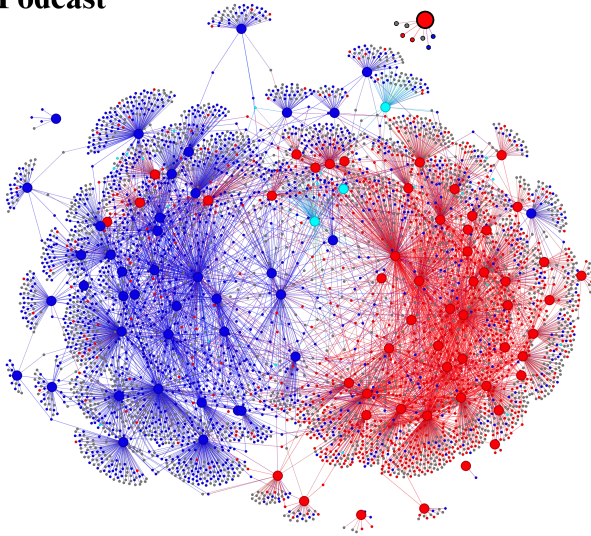
To answer RQ1 and RQ2, we first construct a social network of popular political podcasts and their guests, then identify which of these actors follow each other on X. To start this process, we first identify which guests were featured on which popular political podcasts. Then, for each actor identified in this network, we find their X account(s) and establish following relations among these actors. We use their X account data to estimate the partisan alignment of guests. Finally, we generate diarized podcast episode transcripts to answer RQ3.

Data

We derive a network of podcasts and featured guests from the Popular Political Podcasts Data from the Brookings Institute (Wirschafter and Meserole 2021). This dataset consists of talk show-style, policy, news, and current event-focused podcasts. Every included show appeared in Apple's Top 100 most-downloaded lists or was algorithmically suggested as a "Show You May Like" based on these podcasts. We include episodes from October 31st, 2021 to December 1st, 2022 in order to capture campaigns for the US midterm elections, which occurred in November 2022. The original Brookings data include the podcast title, episode titles and descriptions, episode release dates, links to the audio files for each episode, and the estimated political leaning of each show.

Identifying Actors. Using these data, we build a network in which the nodes are the podcasts and featured guests, and the edges indicate guest appearances on podcasts. We identify which guests were featured on which podcasts using episode titles and descriptions. Podcasts have a known

Podcast



X

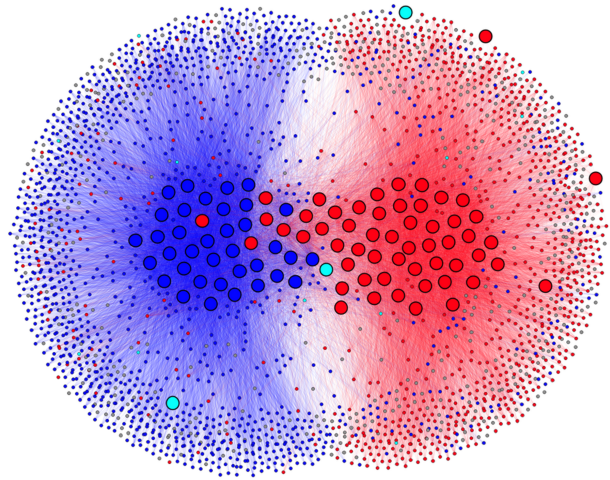


Figure 1: Podcast-guest network (left) and their corresponding ties on X (right). Larger nodes denote podcasts, smaller nodes represent guests. The edges represent guests' appearances on the podcast in the podcast-guest network, and follow relationships in the X social network. Blue, red, cyan, and grey nodes represent more liberal, more conservative, moderate, and unknown political leanings, respectively. Edges are colored by the leaning of the nodes they connect. Ties to guests with unknown leanings were excluded in the X visualization for clarity.

host(s), but guest names are not always available in a consistent format. We start by using natural language processing (NLP) methods where possible to identify guest names in episode titles and descriptions, and used manual investigations of the data when needed. First, we assess each show (98 shows were represented in the data) to see if its episode title names were formatted consistently enough so that we can extract the names of featured guests using a show-specific regular expression. Next, we used GPT-4 to identify guest names in episode titles and descriptions with inconsistent naming conventions (see Appendix for the specific prompts and procedure). Last, we manually identified the names and nicknames of hosts for each podcast, then struck them from the set of detected guest names for their show. During validity checks, the lead author reviewed data and removed any false positive and negative names to the best of their ability. Importantly, we ultimately excluded “The Clay Travis and Buck Sexton Show” and its sister show, “The Buck Sexton Show”, from the main analysis due to their inconsistent episode naming and episode description practices and prolific production (the podcast is a rebroadcast of their radio show): It was difficult to ascertain, even with manual review, who was being featured as a guest or which people were being discussed as topics. Two researchers then selected and hand-labeled 100 random observations; F1 scores were calculated to establish the accuracy after manually editing GPT’s initial results (F1 on initial results = 0.77; after manual editing, F1 = 0.969. No true or false negatives appeared in the random sample of manually edited data; precision = 0.94 and recall = 1.0).

Node Attributes. To find bridging actors, i.e., those connected to a politically diverse set of alters, we added partisan alignment to the original data. The partisan alignment of each podcast was present in the original Brookings’ data; however, we manually added this variable for shows that were listed as “unknown” or those where the estimated leaning diverged from the podcast’s cross-validated, ground-truth leaning, updating 17 of 98 shows this way.

Next, we inferred partisan alignment for guests. To begin, we used Ballotpedia to identify any individuals who served in Congress, were elected governor or lieutenant governor of a state, served in a US presidential cabinet, or worked in an advisory capacity between 2012 and 2023. We used the political party listed on Ballotpedia as their partisan alignment: Of the 1,235 individuals in this set, 258 appeared in the podcasting network. We also possessed the partisan alignment and X account for the 195 podcast hosts represented in our data. Next, we ran correspondence analysis on guests whose partisan alignment we did not know (2,327 guests) (Barberá et al. 2015). First, we identified the X accounts of all 4,645 guests in the podcasting network using the SerpAPI (we manually collected the X accounts for podcast hosts). Specifically, we searched on Google for each guest’s name plus “twitter account,” then selected the top result with a direct link to the X website. Of the 4,645 guests in the podcasting data, we were able to find 3,911 affiliated accounts for 2,550 total guests on X, after guests with multiple accounts were accounted for, and false positive accounts were removed. We next ran correspondence analysis on identified accounts using an X follow graph generated from data collected in 2023, and used a random forest to classify guests based on their ideal points as more conservative, more lib-

eral, or moderate. The random forest was trained and tested on an 80/20 split of individuals for whom we had both partisan alignment and ideal point measures (264). The out-of-bag error for the random forest was 0.4%. After this labeling was done, we added or relabeled the partisan alignment for 16 prominent individuals who had appeared on more than 3 podcasts by hand. In total, we possess the partisan alignment for 2,752 guests (59.3%) in the podcasting network and are missing the partisan alignment for 1,893 individuals (40.7%). Of the 10,330 guest appearances represented in this network (guests may appear on multiple podcasts), we have the partisan alignment for 7,653 (74.1%) of these events.

Attentional Network. In order to compare the partisan diversity of every actor’s alters in the podcasting network to those who they pay attention to on X, we identify which podcasts and guests follow each other on X using data from the X API. In the event that a guest had multiple accounts, we merged these nodes together and dropped duplicated edges, creating a one-to-one mapping of guests between the podcasting network and the corresponding X network. A similar process was used to create nodes which represented podcasts: if a podcast had more than one host, we conglomerated these nodes and dropped duplicated edges. In the event that a podcast host from a show with multiple guests was featured as a guest on a different podcast, we included their individual account in the network as well. Critically, for the attentional network, we allow podcast-podcast and guest-guest ties to more comprehensively identify attentional diversity.

Entropy. To measure how bridging each podcast and guest is in both the podcast and attentional network, we compute their Shannon Entropy using the political alignment (more liberal, moderate, or more conservative) of their alters in the podcast network and those they follow on X. Entropy is commonly used to evaluate diversity (it is often referred to as the Diversity Index) and has been used before to examine the audience diversity of social media posts (Saveski et al. 2022). Here, higher entropy scores indicate that an ego is tied to a politically diverse set of alters, and lower entropy indicates a more politically homogeneous set of alters. Note that alters whose political alignments were unknown were excluded from the calculation of this metric.

Podcast Transcript Data. To examine the topics discussed, we generated transcripts for the 10,330 podcast episodes represented in the podcasting network, covering over 600,000 minutes of audio data. The original Brookings data included links to audio files for included podcast episodes. We downloaded the audio files for each episode in the podcast network and we used OpenAI’s WhisperX (Bain et al. 2023) model to generate a transcript for each episode. We then diarized, i.e., assigned speakers to these transcripts, using the Nvidia NeMo Multi-scale Diarization Decoder (NMDD; Park et al. 2022), which assigns speakers based on signals in the audio data. We used a Microsoft Azure virtual machine with 4vCPUS, 28GiB of RAM, and an NVIDIA T4 GPU for approximately 57 days to complete this task.

Network Descriptions

There were 4,645 guests, 98 podcasts, 10,330 total edges, and 6,988 unique edges in the podcast network (Figure 1, left). Of these, there were 1,683, 1,048, and 21 liberal, conservative, and moderate guests, respectively. 1,893 guests had an unknown affiliation. There were 41, 54, and 3 more liberal, conservative, and moderate leaning shows in this network. The mean (unweighted) degree centrality of podcast guests was 1.5, and the maximum number of unique shows a guest appeared on was 15. The mean (unweighted) degree centrality of podcasts was 71.3, and the maximum number of featured guests in this time frame was 297.

There were 2,550 guests, 94 podcasts, and 450,171 edges in the corresponding X network (Figure 1, right). Of the guests, there were 1282, 810, and 11 more liberal, conservative, and moderate leaning individuals. There were 37, 54, and 3 liberal, conservative, and moderate shows, respectively. The mean (unweighted) outdegree and indegree centrality of podcast guests were 127.6 and 124, respectively. The average unweighted outdegree and indegree centralities of podcasts were 441.2 and 302.0, respectively.

Overall, ties within the podcasting network and X network were not strongly correlated, although tie presence in the podcasting network is slightly more predictive of a tie in the X network than vice versa. The probability that a show s interviewed a guest g in the podcast network given that s followed g on X is 3.6% (note that show-show and guest-guest ties were removed for this computation). Likewise, the probability that a show follows a guest on X given an interview is 12.0%.

Methods & Results

RQ 1: Entropy on Podcasts versus on X

We start by examining whether actors display more political homophily in the podcasting network or the corresponding X network, establishing the extent to which different media impact tendencies to form cross-cutting ties, while controlling for potential impacts of partisan affiliation.

Methods. To examine if egos follow a more politically varied set of alters on X compared to those that they interact with on podcasts or *vice versa*, we compare every actor’s Shannon Entropy in the podcasting network and the X network. Since podcasts may have more than one host with active X accounts, we compiled the set of individuals who each host follows, removed duplicates, then computed the entropy of this set of accounts.

To estimate the difference between every podcast’s entropy in the podcasting network and the X network, we ran the following linear mixed-effects model first on podcasts, then on guests:

$$Y_i = \beta_0 + \beta_1 \text{medium} + \beta_2 \text{alignment} + \beta_3 (\text{medium} \cdot \text{alignment}) + i_{0i}$$

where Y_i is the entropy for actor i , β_0 is the baseline entropy, β_1 is the main effect of medium, β_2 controls for the impact of partisan alignment, β_3 controls for any interaction between alignment and media (e.g., if those who lean

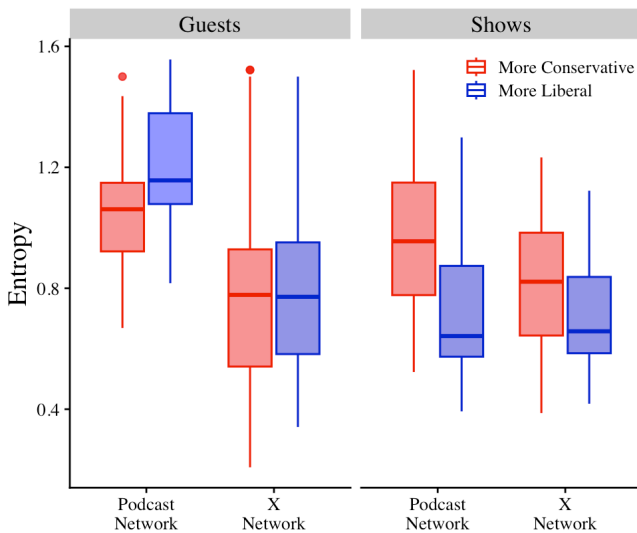


Figure 2: Guest entropy in the podcasting network and their corresponding entropy in the X network (left panel). Show entropy in the podcasting network and their corresponding entropy in the X network (right panel). Differences in partisan groups are also depicted. See Appendix Table 5 for corresponding summary statistics.

more liberal show no difference in entropy between media but conservatives do), and i_{0i} indicates the by-actor random effects. We used a linear mixed-effects model (Bates et al. 2015) to account for the fact that there are two observations for each actor (one in the podcasting and one in the X network) and to model both the between-group (partisan alignment) and within-group (actor-level) variability in outcomes. Since there were only three moderate shows, we excluded them from the model and results presented here (this exclusion did not impact our findings). Additionally, to account for the fact that certain differences in entropy could be driven by guests who have been invited to a small number of podcasts, we only included those who appeared on three or more podcasts in this analysis.

Results. Guests and podcasts both interacted with a more varied set of individuals in the podcasting network compared to those they followed in the corresponding X network. Podcasts tend to feature a more politically heterogeneous set of individuals compared to the accounts that the hosts collectively follow in this community on X. Overall, these actors show entropy that is 0.126 greater on the podcasting medium compared to their entropy in the X network (SE = 0.035, $p < 0.001$). As changes in entropy are not straightforward, we provide context for their interpretation: A 0.126 difference in entropy for a podcast whose entropy is 1.086 in the podcasting network and 0.959 on X corresponds to a 1.3% increase in ties to liberals on X, a 4.7% drop in ties to moderates, and a 6.0% decrease in ties to conservatives. We observe that, within individuals, this effect is small, and is largely driven by the increased probability of featuring a moderate individual on podcasts. It is also of

note that (a) there is no significant difference between the entropy of liberals' ties on X and their engagements in the podcasting network, and (b) that conservative podcasts also are more likely to feature and attend to a more diverse set of alters compared to liberal podcasts on both platforms (Podcasts: Effect Size = 0.215, SE = 0.049, $p < 0.001$, X: Effect Size = 0.137, SE = 0.049, $p = 0.03$; Figure 2). This difference in effect size is pronounced for podcasts: A podcast with the mean entropy of 0.878 may allocate its 41 ties to 33 liberal, 2 moderate, and 6 conservative shows, whereas a podcast with 0.215 greater entropy may allocate its 41 ties to 11 liberal, 2 moderate, and 28 conservative shows.

Guests also show entropy that is 0.342 higher on the podcasting medium compared to their community-specific entropy on X (Figure 2); to contextualize this finding, a difference in entropy for a guest whose entropy in the podcasting network was 1.299 and 0.957 on X (0.342) amounted to a 7.46% decrease in the probability of being tied to a liberal in the X network, a 4.25% decrease in the probability of being tied to a conservative in the X network, an 11.7% increase in probability of being tied to a moderate show in the podcasting network. We note that this effect was also largely driven by the increased impact of ties to moderate actors in the podcasting network. Compared to our findings for podcasts—as liberal podcasts displayed no difference in entropy between media—this effect is significant for all guests, regardless of partisan leaning.

There was also a significant interaction between medium and partisan affiliation: Liberal guests are significantly more likely to appear on a podcast with a different affiliation compared to conservative guests, whereas liberal and conservative leaning guests showed similar entropies on X, although it is unclear if liberal guests are appearing on conservative podcasts who are strongly opposed to Trump, or if they are appearing on a mixture of pro-Trump and anti-Trump conservative podcasts (More Conservative Podcasts vs. More Liberal Podcasts; Effect Size = -0.152, SE = 0.03, $p < 0.001$, More Conservative X vs More Liberal X; Effect Size = 0.437, $p = 0.032$).

We conducted a sensitivity analysis of these results by assigning partisan leans to unlabeled guests based on the community-specific distribution of labeled guests, and found substantively similar results (see Appendix for more details).

RQ 2: Bridging Podcasts & Guests

The goal of the second objective is to examine whether the podcasts and guests who demonstrate bridging behavior in the podcasting network attend to a comparatively high-entropy set of actors in this community-specific X network.

Methods. As a starting point, we run three vector permutation tests to identify whether there is a correlation between the entropy of guests a podcast features and the entropy of those the podcast host(s) follow in this community-specific X network. The first permutation test was run on all podcasts with a major partisan affiliation that featured more than 10 guests to control for the impacts of lower degrees on entropy. We ran two more on the major political subgroups in this network to ascertain whether this pattern varies based on

	Obs. Correlation	Pr($p \geq \text{obs}$)	n
Overall	0.448	0.001*	87
More Liberal	0.372	0.017·	35
More Conserv.	0.365	0.004*	52

Table 1: Correlation of a podcast’s entropy in the podcasting network and the corresponding community on X. “*” denotes statistical significance at the 0.01 level, “·” indicates significance at the 0.05 level, measured using permutation tests with 5,000 iterations.

political affiliation. We also repeated this process for guests who appeared on more than one podcast as well as for guests featured on four or more podcasts to evaluate if any potential correlations differ for more prolific guests.

Next, we identified the set of podcasts featuring the most politically diverse array of guests. To ensure bridging podcasts with similar programmatic formatting were compared to one another (i.e., to avoid comparing podcasts which are interview-centric to podcasts where guests are not a key component of the show), we computed the square-root normalized guest frequency (ratio between the number of guests and the number of episodes) for every podcast. We then sorted the podcasts into quintiles based on the transformed guest frequency. From each bin, we selected the two podcasts with the highest entropy scores, forming the set of podcasts who were most bridging for their group. We selected the top two podcasts per quintile as the differences in entropy between the top two shows were minor in several cases, and to make sure each group was equally represented. Next, using the same quintiles, we compare the entropy of out-ties for each podcast node in the X network.

In order to find our set of bridging guests in the podcasting network, we selected individuals who were featured on at least two more liberal and two more conservative podcasts. While we intended to then select individuals with the highest entropy from this set, only 24 individuals met these criteria. We used these individuals as our final set of bridging guests. We compared this list to the guests with the highest out-degree entropy scores in the X following network and found the intersection of these sets.

Results for Bridging Podcasts. We find that the entropy of the guests that podcasts featured was correlated to the entropy of the individuals that a podcast’s host(s) followed on X (Table 1). We observe a 0.076 lower correlation for liberal shows than seen overall and only marginally significant at the 0.01 level for this group. Conservative-leaning shows had a correlation that was 0.083 lower compared to the overall group.

Of the ten podcasts with the highest entropy in the podcasting network, eight leaned more conservative, one is considered moderate, and one leans more liberal, although it is worth noting that this show, “The Chris Cuomo Project”, self-describes as independent (Cuomo 2022). “RFK Jr., The Defender Podcast” also appears as one of the shows with the highest entropy: RFK Jr self-identified as liberal with vaccine-opposed positions, and he is now an appointed

Podcast and Group	%ile Entropy on X
■ 5. Honestly w. Bari Weiss	84
■ 5. The Megyn Kelly Show	76
■ 4. RFK Jr The Defender Podcast	79
■ 4. The Jimmy Dore Show	74
■ 3. The Jordan B. Peterson Podcast	81
■ 3. The Chris Cuomo Project	90
■ 2. The Michael Savage Show	94
■ 2. Breaking Points w. Krystal & Saagar	75
■ 1. PragerU: Five-Minute Videos	31
■ 1. Uncle Joey’s Joint	85

Table 2: Two podcasts with the highest entropy from each quintile of podcasts grouped by guest frequency, which are sorted highest to lowest. X rank enumerates the percentile for each podcast’s entropy score on X.

Group	Obs. Correlation	Pr($p \geq \text{obs}$)	n
2+ Shows:			
Overall	0.088	0.006*	863
More Liberal	0.144	0.001*	446
More Conserv.	0.110	0.013·	411
4+ Shows:			
Overall	0.160	0.006*	255
More Liberal	0.361	0.001*	96
More Conserv.	0.016	0.426	156

Table 3: Correlation of guest entropy between podcasts and X for guests featured on more than one podcast and more than three podcasts. “*” denotes statistical significance at the 0.01 level, “·” indicates significance at the 0.05 level, measured using permutation tests with 5,000 iterations.

member of Donald Trump’s cabinet (Fowler 2024). We conducted a sensitivity analysis of these findings and obtained substantively similar results (see Appendix for more details).

Results for Bridging Guests. There is a small correlation between the entropy of guest’s alters in the podcast network and the corresponding X network (observed correlation = 0.088, $p < 0.01$; see Table 3), suggesting that one’s tendency to engage with a politically heterogeneous set of voices is not strongly correlated to their tendency to follow a more varied set of voices on X. We observe that this correlation is 1.6 times stronger for liberal-leaning guests (0.144, $p < 0.01$) than the overall group and is 0.022 higher for conservative guests (0.11), although only marginally significant ($p = 0.013$) for the latter group. Moreover, this correlation is stronger for more prolific liberal guests (0.361) but is not significant (and weaker) for more prolific conservative guests (0.016); indicating that the bridging tendencies of more prolific liberal guests are consistent across media, whereas attention and behavior are not correlated for prolific conservative guests.

24 guests in the podcasting network had visited at least two liberal and two conservative shows. 15 of these indi-

viduals were liberal leaning, five were more conservative, two were moderate, and two had unknown leanings. Although having a higher entropy in the podcasting network was slightly correlated with having a relatively higher entropy in the corresponding X network, only one individual, Ruy Teixeira, also had one of the highest entropy scores on X. The small intersection of these sets indicates that those paying attention to the most heterogeneous set of voices in this network are not necessarily those repeatedly engaging in cross-cutting conversations, and those who do repeatedly engage in such discussion are not those with the most-diverse attention. Thus, any assumptions that bridging actors are also those most willing to consume diverging viewpoints in this network are not necessarily true.

RQ 3: Bridging Guests Discussions and Topics

Finally, we investigate whether bridging individuals collectively focus on a narrower set of topics where they suspect they may find common ground with their political counterparts (e.g., shared dislike for vaccine mandates), or cover a set of topics indistinguishable from those of their non-bridging counterparts.

Methods. To ascertain whether bridging guests largely anchor on a distinct and narrower set of topics compared to their non-bridging counterparts, we leverage the BERT topic model. We first map the topics discussed by bridging guests and non-bridging guests, then use a χ^2 test of independence to assess whether bridging guests tend to discuss a distinct set of topics compared to non-bridging guests in this network. Finally, we compare the Shannon entropy of topics discussed by bridging guests and non-bridging guests using a permutation test to examine whether bridging guests anchor on a narrower set of topics.

In order to see if bridging guests discuss different topics compared to non-bridging guests, we find all bridging events, i.e., instances where the bridging guests identified in RQ2 appear on a podcast with a different partisan leaning than their own. Next, to control for any potential impact of political leaning on results, we split this into two subsets: the liberal subset, composed of episodes from liberal-leaning podcasts featuring non-liberal bridging individuals, and the conservative subset, episodes from conservative-leaning podcasts featuring non-conservative bridging individuals. We then augmented each subset with ≈ 10 randomly selected non-bridging episodes for each bridging episode (also separated by political leaning) to capture the overall landscape of topics discussed in the podcasts we analyze. The final liberal subset was composed of 23 episodes which featured bridging guests identified for the prior research question, 159 episodes featuring non-bridging liberal guests¹, 86 episodes featuring non-bridging conservative guests, and eight episodes featuring non-bridging moderate guests. The conservative subset consisted of 71 episodes featuring bridging actors, 488 episodes featuring conservative individuals, 191 liberal non-bridging liberal guests, and 20 non-bridging moderate guests.

¹As a reminder, non-bridging individuals are any individuals who were *not* identified as a bridging guest for RQ2.

As podcast episodes may feature multiple guests, we used the Gemini-2.0 Flash Model to obtain a 200-word summary of the topics that the specified guest discussed in a given podcast episode. To account for any potential false positives in the original NER, we instructed the LLM to indicate if an individual was not featured. In brief, we asked the model to summarize what the specified individual discussed in the podcast (see Appendix for full prompt). Gemini-produced summaries also minimized differences in speaking style and in the amount of time they were given to speak, while maintaining critical information about what each guest discussed in the episode. Then, we used the Gemini text-embedding-004 model to extract one embedding for each summary.

Next, we used the BERTopic Model (Grootendorst 2022) to identify topics in our data. We used the UMAP algorithm for dimensionality reduction: we set nearest neighbors to fifteen, minimum distance between points to zero, the number of components to 300, and cosine distance for distance computations. We clustered the data points with HDBSCAN. We set minimum cluster size to five, as we considered that five distinct discussions are enough to comprise one topic. We set the minimum sample size and ϵ to three and four, respectively, and used Manhattan distance as a distance metric. We also excluded English stop words from our data (and added several data-specific terms to this list, please see Appendix for the full list). Last, we used Maximal Marginal Relevance, with diversity set to 0.3, and the Gemini-Flash 2.0 Model to assign topic labels to clusters, with 10 keywords and 4 sample documents per cluster.

To ascertain if bridging guests tend to focus on a different set of topics when featured on politically opposed podcasts compared to non-bridging liberal, moderate, and conservative guests, we ran four χ^2 tests of independence on both the liberal and conservative subsets of data. In the first test, we compare the topic distribution of bridges to all non-bridges. We then test if bridging guests discuss topics at different frequencies compared to non-bridging liberal, conservative, and moderate guests. Last, to assess if bridging guests discuss fewer topics than non-bridging guests, we use a permutation test to compare the Shannon entropy of topics discussed by bridging guests to a background distribution of Shannon entropy values generated with 5000 draws of an equal number of non-bridging guests. We also evaluate whether bridging guests discuss fewer topics than non-bridging liberal, conservative, and moderate guests using a permutation test.

Results. The BERT topic model identified 32 topics in our data. Of these, bridging actors discussed 14. In addition to focusing on the most popular topic (US politics and Trump), bridging actors mostly discuss other salient political and cultural issues, including the Russian invasion of Ukraine, content moderation on social media platforms, and legal investigations into President Trump.

Bridging guests discussed a smaller number of topics compared to their non-bridging peers (Obs. entropy = 2.90, $\Pr(p \leq obs) = 0.00$, $n = 24$) and largely stuck to topics discussed most frequently by all actors (Figure 3, Table 4): Of the 94 bridging events captured in this data, 35 centered

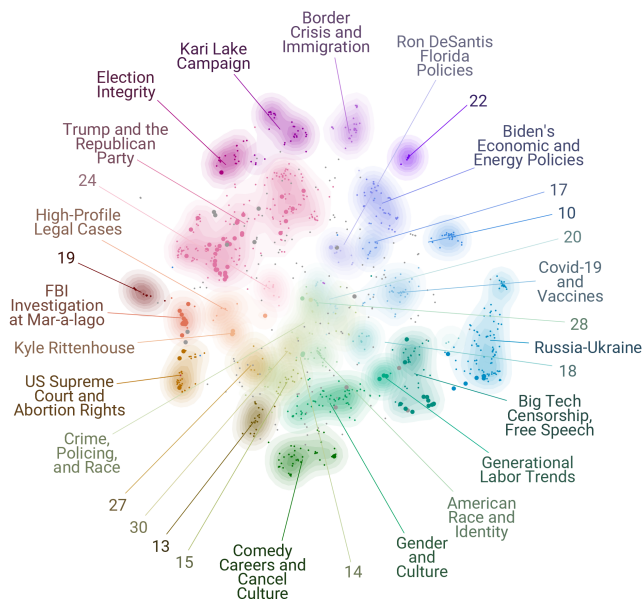


Figure 3: Embeddings map of bridging and non-bridging podcast episodes. Larger points denote conversations from bridging actors identified in the prior section; topics discussed by bridging actors are labeled here. See Appendix Table 9 for the topics key.

on the most popular topic (the state of US Politics, Trump, and the Republican Party) and 71 were distributed between the four most popular categories for guests. Bridging conservative guests appearing on liberal shows overwhelmingly tended to discuss Trump and the Republican Party, the second most popular topic in the entire dataset. This topic also comprised one quarter of liberal bridging guests’ discussions with conservative podcasters.² It is possible that bridging actors are able to sustain a politically diverse set of relationships because they stick to topics where they know they can find common ground with their partisan counterparts, and avoid issues that they know are more contentious.

While bridging guests tended to center on different topics compared to their non-bridging counterparts, this pattern was not consistent by political leaning: Episodes from liberal podcasts featuring conservative, bridging guests discuss topics at frequencies that are not statistically different from liberal podcast episodes featuring non-bridging conservative guests (Table 4). These groups, both composed of conservative individuals, largely discussed Trump and the state of the Republican Party, indicating that conservatives who appear on liberal podcasts may try to focus on discussion about Trump’s politics, policies, and conduct. By contrast, bridging liberal guests and non-bridging liberal guests who appeared on conservative podcasts discussed topics at statistically different frequencies. Liberal, bridging actors on con-

²One topic, “Debates on justice, freedom of speech, and Trump investigations,” was entirely composed of interviews with Alan Dershowitz, one of Trump’s prominent lawyers, underlining the impact one individual can have on a sole topic.

Group	χ^2	p	DoF
Liberal Podcasts:			
More Conservative	18.355	0.4988	19
More Liberal	59.155	0.0001*	25
Moderate	27.518	0.0022*	10
All	43.686	0.0223·	27
Conservative Podcasts:			
More Conservative	173.741	0.0001*	30
More Liberal	77.796	0.0001*	27
Moderate	26.751	0.0135·	13
All	184.529	0.0001*	31

Table 4: Topic distribution of bridging guests compared to non-bridges. The analyses were run on two groups: episodes from liberal podcasts and episodes from conservative shows. “*” denotes statistical significance at the 0.01 level, “·” indicates significance at the 0.05 level, measured using permutation tests with 5,000 iterations.

servative shows tended to discuss “Big tech censorship, free speech, and social media regulation,” revealing shared interest in developing stronger regulation of tech companies in the US and preservation of user privacy. Non-bridging liberal individuals, however, focused more on contemporary issues about gender, Covid-19 and vaccination, and current events in the Middle East. We observe that these non-bridging guests were still finding some commonality on these issues with their conservative counterparts, despite their non-bridging status.

Discussion and Conclusion

In this paper, we identify and investigate the actors who engage with a politically diverse set of voices on popular political podcasts. We construct one network of 98 popular political podcasts and 4,654 of the guests they featured over a 13-month period. We then identify the attentional relations, or who follows whom, between these actors on X, and generate over 10,000 hours of podcast transcripts which correspond to the podcast episodes these guests were featured on. To measure each podcast’s and guest’s bridgingness—their tendency to form ties with a politically heterogeneous set of voices—we estimate the partisan alignment of each actor, then compute their entropy in both the podcasting network and the X network, using the partisan alignment of those they are connected to as our focal variables. Using these data, we compare every actor’s entropy in the podcasting network and the X network to evaluate if one’s bridging tendencies carry across media. Finally, we identify the most bridging podcasts and guests and examine whether they focus on a different set of topics compared to their non-bridging counterparts.

We find that tendencies to interact with a politically diverse set of alters on podcasts correlate to tendencies to follow a more diverse set of alters on X. This pattern is stronger for both liberal podcasts and guests compared to conservative podcasts and guests, and is 1.3 times greater for liberal

guests compared to conservative guests (and 22.56 times greater for prolific liberal guests compared to conservative guests). These differences may be due to asymmetries in guest selection and participation. Liberal shows may invite more central and more extreme conservatives, and all conservatives guests may accept these invitations. By contrast, conservative shows may either avoid inviting more insulated liberals, favoring their more heterodox peers, or, assuming no differences in invitation rates, more polarized liberals may be less likely to accept such invitations. We also find that bridging guests tend to focus on a different and more narrow set of topics compared to non-bridging guests. While we did not analyze the emotional valence and tenor of these conversations, it is of note that research indicates that cross-partisan discussions which center around topics of known agreement tend to reduce affective polarization (Santoro and Broockman 2022). It is possible that bridging individuals are able to sustain rapport with those of different ideological bents and possibly decrease affective polarization because they *avoid* discussing contentious issues. In short, our results illustrate that bridging individuals display distinguishable behaviors on social media and in the topics they choose to discuss—and those they choose not to—in their cross-cutting conversations.

Research on political polarization has largely focused on social media, and those that do focus on podcasts often focus on polarizing actors, political homophily, and divisive or toxic speech, which are prevalent problems in this space. We investigate the actors who use this medium to engage with an ideologically varied set of alters, building comprehension of those who, on a surface level, are using this medium in a unique way and seem to occupy a social role that may be geared more towards finding common ground or at the very least engaging with a varied set of voices.

This research is not without limitations. First, following an individual on X does not necessarily imply exposure to their posts or that the content one is shown on X is less polarizing when following accounts with a variety of partisan alignments. While following a variety of accounts may indicate that one intends to listen to a variety of viewpoints, it is unclear if the content one pays attention to is also varied. X feeds are constructed based on a variety of parameters, and the accounts one follows do not exclusively dictate the content a user sees. Another limitation pertains to our use of entropy as a bridging metric, and the fact that we remained agnostic to the partisan bent of the ego. The Democratic governor of California started the “This is Gavin Newsom Podcast,” a show featuring debates between himself and prominent conservatives. While the intent of this show is to generate cross-cutting conversations, it would not be classified as a bridging show with our entropy metric. We also note that we did not run multi-topic analysis for each podcast episode, although some guests discussed several topics in interviews. While most guests largely are interviewed for one topic, comparing these results against a multi-topic model is one pathway for future research. Last, the impacts that these cross-cutting conversations have on the audiences of certain podcasts remain unclear, and it is unknown who the bridging actors are reaching, leaving an open avenue for future work.

Our results begin to characterize prominent actors that platform, attend to, and engage with a politically heterogeneous set of alters in an otherwise balkanizing system. Because good-faith, cross-cutting dialogue is becoming rare despite its importance to the maintenance of democratic states, studying these actors may shed light onto certain behaviors that others seeking to lessen partisan dissension may adopt and improve upon. We hope that this work will prompt further investigation into the behaviors of those who sustain cross-party engagement in highly polarized systems.

Ethical Considerations

Throughout this study, we analyze non-confidential data that is available in the public domain. The University of Washington found this research to be exempt from IRB review, as it did not meet the definition for human subjects research by the Common Rule. Public figures were exclusively considered in this research, and none of the individuals in this study were acting in a private capacity. To prevent any political misclassification of named actors as a consequence of using correspondence analysis to estimate their partisan leaning, we cross-validated the political labels for all bridging guests and shows.

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Paper Checklist

1. For most authors...
 - (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes
 - (b) Do your main claims in the abstract and introduction accurately reflect the paper’s contributions and scope? Yes
 - (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes
 - (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? Yes
 - (e) Did you describe the limitations of your work? Yes
 - (f) Did you discuss any potential negative societal impacts of your work? Yes

- (g) Did you discuss any potential misuse of your work? Yes
 - (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes
 - (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes
2. Additionally, if your study involves hypotheses testing...
- (a) Did you clearly state the assumptions underlying all theoretical results? N/A
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 - (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? N/A
 - (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? N/A
 - (e) Did you address potential biases or limitations in your theoretical framework? N/A
 - (f) Have you related your theoretical results to the existing literature in social science? N/A
 - (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? N/A
3. Additionally, if you are including theoretical proofs...
- (a) Did you state the full set of assumptions of all theoretical results? N/A
 - (b) Did you include complete proofs of all theoretical results? N/A
4. Additionally, if you ran machine learning experiments...
- (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? N/A
 - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? N/A
 - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? N/A
 - (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? N/A
 - (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? N/A
 - (f) Do you discuss what is “the cost” of misclassification and fault (in)tolerance? N/A
5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...
- (a) If your work uses existing assets, did you cite the creators? Yes
 - (b) Did you mention the license of the assets? N/A

- (c) Did you include any new assets in the supplemental material or as a URL? N/A
 - (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? Yes
 - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? Yes
 - (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR? N/A
 - (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset? N/A
6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...
- (a) Did you include the full text of instructions given to participants and screenshots? N/A
 - (b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? N/A
 - (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? N/A
 - (d) Did you discuss how data is stored, shared, and de-identified? N/A

Appendix

Node Identification. Prompt for Detecting Guest Names.

To identify any guest names in podcast episode titles or descriptions, we used the following prompt: *Extract the names of the guests who appear in this podcast episode using the following episode title: {episode title}*, and set model temperature to zero to minimize hallucinations. We then ran this prompt on the episode description for cases where the model could not identify a guest name in the title.

Sensitivity Analysis. Since 40.47% of guests were missing data on political leaning, we conducted a sensitivity analysis to assess our results. To do so, we assigned the missing leanings based on the observed distribution of the labeled data. Specifically, we first computed the mean observed distribution of labeled data for more liberal, conservative, and moderate shows; and then, depending on the shows’ leaning, randomly sampled from the corresponding mean distribution of guest leanings to impute the missing labels (Table 6).

To evaluate whether such sampling is suitable, we manually annotated 263 previously unlabeled guests and compared their distribution with that of the imputed labels. Because this was a convenience sample, we focused on comparing the magnitude and direction of the distributions and found that they were closely aligned with the imputed data.

Below, we present the results of our reanalysis for RQ1 and RQ2 using the imputed data.

RQ1. Results do not change between the presented and imputed data. With the imputed data, podcasts show entropy that is 0.103 greater on podcasts compared to X (SE = 0.029,

Group	Lean	Medium	Min	Q1	Mean	Med.	Q3	Max
Guests	More Con.	Podcast	0.8031	1.0613	1.1689	1.1488	1.2516	1.5000
	More Con.	X	0.0000	0.5221	0.7265	0.7738	0.9447	1.5000
	More Lib.	Podcast	1.0613	1.2516	1.2968	1.2516	1.4056	1.5850
	More Lib.	X	0.0000	0.3225	0.5664	0.5554	0.8116	1.5000
Shows	More Con.	Podcast	0.5007	0.8004	0.9664	0.9781	1.1490	1.5000
	More Con.	X	0.4248	0.7187	0.8400	0.8632	1.0052	1.2218
	More Lib.	Podcast	0.3846	0.5813	0.7333	0.6635	0.8728	1.2988
	More Lib.	X	0.3509	0.5796	0.7095	0.6475	0.8379	1.1678

Table 5: Summary statistics of the entropy value the groups shown in Figure 2.

Show Lean	% Lib	% Con	% Mod
More Liberal	90	9	1
More Conservative	32	67	1
Moderate	59	40	1

Table 6: Partisan distribution of guests given a podcast’s partisan lean.

$p < 0.001$). Similarity in the entropy of liberals’ ties on X and their engagements in the podcasting network persists, as well as the finding that that conservative podcasts also are more likely to feature and attend to a more diverse set of alters compared to more liberal podcasters on both media (Podcasts: Effect Size = 0.375, SE = 0.043, $p < 0.001$, X: Effect Size = 0.244, SE = 0.043, $p < 0.001$).

Guest entropy is 0.442 higher on podcasts compared to their entropy on X (SE = 0.23, $p < 0.001$). The interaction between medium and partisan affiliation also is maintained: Liberal guests are significantly more likely to appear on a podcast with a different affiliation compared to conservative guests. Conservative leaning guests had slightly higher entropy on X compared to more liberal guests (More Conservative Podcasts vs. More Liberal Podcasts; Effect Size = -0.128, SE = 0.0251 $p < 0.001$, More Conservative X vs More Liberal X; Effect Size = 0.160, $p < 0.0001$).

RQ2. We find that with the imputed data, the entropy of the guests that podcasts featured was correlated to the entropy of the individuals that a podcast’s host(s) followed on X (Table 7). There was not a substantial difference between results from the presented and imputed data. Additionally, the selected set of the most bridging podcasts from the manuscript did not change.

Overall, in the sensitivity analysis evaluating the relationship between guest entropy on podcasts and X the results do not meaningfully change. More liberal guests continue to show the largest correlation between entropy on the podcasting medium and X (Table 8). Correlation for all other groups continues to be small, although it is of note that the correlations for the overall and conservative categories in both sets of guests are not statistically significant.

Gemini prompt for summarizing guest topics. We used the Gemini-2.0 Flash Model with the following prompt

	Obs. Correlation	Pr($p \geq$ obs)	n
Overall	0.462	0.000*	87
More Liberal	0.481	0.003*	35
More Conserv.	0.225	0.056·	52

Table 7: **Sensitivity analysis.** Correlation of a podcast’s entropy in the podcasting network and the corresponding community on X, generated using imputed data. “*” denotes statistical significance at the 0.01 level, “·” indicates significance at the 0.05 level, measured using permutation tests with 5,000 iterations.

Group	Correlation	Pr($p \geq$ obs)	n
2+ Shows:			
Overall	0.030	0.171	999
More Liberal	0.174	0.000	533
More Conserv.	0.021	0.324	457
4+ Shows:			
Overall	0.697	0.122	271
More Liberal	0.296	0.000*	105
More Conserv.	0.023	0.380	163

Table 8: **Sensitivity analysis.** Observed correlation of guest entropy between podcasts and X for guests featured on more than one podcast and more than three podcasts, generated from imputed data. “*” denotes statistical significance at the 0.01 level, “·” indicates significance at the 0.05 level, measured using permutation tests with 5,000 iterations.

to provide a 200 word summary of the topics a specific guest discussed in a given podcast episode, as many podcast episodes in this dataset feature multiple guests: *You will be given the name of a person, followed by a colon then a podcast transcript. Give me the gist of the topics the named individual discusses in this podcast transcript in less than 200 words. Do not be conversational. Do not discuss ads and do not mention the title of the podcast, the names of podcast guests or the show hosts. If you cannot find evidence that this person was featured in this podcast, return ‘not featured’.* The last sentence accounts for imperfect guest identification using podcast episode titles or descriptions, and allows the

model to indicate that a guest was not featured, in order to minimize hallucinations.

Additional Stopwords. We removed the following words which were common in the summaries of guest episodes returned by the Gemini-2.0 Flash Model: “podcast”, “also”, “feature”, “features”, “featured”, “touches”, “recounts”, “talks”, “topics”, “current”, “events”, “event”, “focusing”, “interview”, “discuss”, “features”, “discussion”, “discusses”, “discussed”, “episode”, “conversation”.

Topics Key. Table 9 shows the keys to the topics depicted in Figure 3.

Topic	Count
-1. Analysis of current political and cultural issues	149
0. Trump and the Republican Party	190
1. Russia-Ukraine	104
2. Gender and culture	58
3. Comedy careers and cancel culture	50
4. Big tech censorship, free speech	48
5. Biden’s economic and energy policies	40
6. Kari Lake campaign	36
7. Covid-19 and vaccines	35
8. US Supreme Court & abortion rights	34
9. Border crisis and immigration	31
10. Race in the US	27
11. American race and identity	24
12. Election integrity	23
13. Sports, shows, women’s issues	20
14. Commentary on current events	19
15. Controversies in sports and culture	15
16. FBI investigation at Mar-a-Lago	14
17. Build Back Better and COVID-19	13
18. Military conflicts, terrorism, and veteran affairs	13
19. Durham investigation, FBI conduct in Trump-Russia case	13
20. Education, school closures, and parental rights	12
21. Ron DeSantis Florida policies	11
22. Bill O’Reilly’s commentary	11
23. Crime, policing, and race	10
24. Steve Bannon, FBI, media coverage, and political issues	9
25. Kyle Rittenhouse	9
26. High profile legal cases	6
27. Current events, politics, and legal cases	6
28. Education, politics, and the US military	6
29. Generational labor trends	5
30. Mass shootings	5

Table 9: Key to topics depicted in Figure 3, as well as the topic frequency in our data.