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Wars of Position:
A Social Network Analysis of Political Podcasts

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Abstract

Ideological echo chambers on digital media platforms have been the subject of extensive research by computational social scientists. Current debates focus on the role of user choice and algorithmic recommendation feeds in creating these echo chambers. In this thesis, I argue that content creators can work to create echo chambers through collaborations with other ideologically aligned creators. Adopting a Gramscian theoretical framework, I argue that these homophilic collaborations are tools of hegemonic struggle, analogous to the "wars of position" described by the late political theorist Antonio Gramsci. To validate my claims, I perform a social network analysis of collaborations between the 250 most political podcasters in the United States. My network analysis reveals that collaborations are much likelier between podcasters of similar ideological alignments, and these probabilities are the largest for left-wing podcasters. My research also shows that collaborations are highly unequal, adhering to power law distributions observed commonly across a wide range of social phenomena. My results advocate for a renewed focus on engagement between content creators on social media platforms as a potential driver of political polarization.

Introduction

Political polarization in the United States has long been a subject of study for political scientists, who have primarily divided their attention between elite and mass polarization (Fiorina & Abrams, 2008). The widely popularized view is that intense electoral competition in a 2-party system has created a highly polarized electorate, vulnerable to the manipulations of media pundits and political leaders. Although the evidence for elite polarization is well documented by scholars, research identifying similar patterns amongst the median votes has yielded inconclusive results. Scholars have since shifted their focus to environments where elite opinions have successfully cascaded over into the political views of the masses.

One significant area in which this dynamic seems to have successfully played out is on digital media platforms. Highly partisan structures combined with clusters of highly-engaged users have created ideological echo chambers on these social networks (Conover et al., 2011). And while the number of users remains small relative to the size of the electorate, their impact on the broader political climate is undeniable. Contemporary perpetrators of political violence, such as the Christchurch mass shooter, routinely cite prominent Twitter personalities as critical influences in their manifestos. These platforms have also revitalized old conspiracy theories like the anti-vaccine movement while facilitating the spread of new ones like Q Anon.

Scholars have quickly labeled these developments as emblematic of the novel threat to democracy posed by technology companies. They point to the ability of social media platforms to deliver misinformation and disinformation with unprecedented velocity and volume, allowing extremists to distort political discourse. Subsequent research has maintained a razor-sharp focus on the role of algorithmic recommendation systems in shepherding users into partisan echo chambers where they consume an endless stream of sensationalized content. While scrutiny of companies like Twitter and Meta and the technologies they deploy is warranted, this parochial focus on modern platforms has neglected to consider the agency of content creators. It has also failed to situate contemporary online polarization within the broader historical relationship between media, technology, and politics.

In this thesis, I argue that, regardless of the influence of algorithms, political content creators can collaborate with one another to create ideological echo chambers. These collaborations continue the historical struggle for dominance between the major political ideologies in the United States. Using Gramsci's theory of cultural hegemony as a theoretical framework, I perform a network analysis on a dataset of the 250 most popular political podcasts across Apple, Spotify, and Google to identify the presence of ideological echo chambers on podcasting platforms. I then build statistical network models to test the hypothesis that ideological homophily is the primary determinant of these collaborations and substantiate my claims.

My results identify ideological homophily as a significant predictor of collaborations between podcasts after considering different platforms, distribution networks, sensationalist rhetoric and the background of the podcasters. In doing so, I offer an alternative explanation to the common assertion by extant scholarship that the spread of polarizing content is primarily the product of recommendation systems. By collaborating with ideologically aligned hosts, podcasters can expose and implicitly recommend their users to similarly themed content without relying on algorithms.

Additionally, my results also reveal that homophily is strongest between right-wing podcasts, a pattern that has been observed in previous scholarship investigating similar phenomena in talk radio, cable news, and political blogs (Ackland, 2005; Guardino & Snyder, 2012; Mort, 2012). I also demonstrate that despite increased access to content creation afforded by technological advances, podcast networks are highly unequal and continue to adhere to the power law distribution commonly observed across a wide range of social phenomena (Kwak et al., 2010).

I focus on podcasts as a digital medium for three reasons. First, they continue the conversational format popularized by traditional media such as talk radio and late-night television. This allows me to situate them within the broader history of political content creation across these older media forms while still considering the impact of modern platforms on their creation and dissemination. Second, podcasts are a fast-growing medium that is immensely popular and underinvestigated relative to social media platforms like Twitter and Facebook. And finally, podcasts are unique in their ability to foster collaboration between content creators by virtue of their low barriers to entry and the ease of facilitating guest appearances using recording technologies. These factors, when combined, allow for podcasts to serve as a vector for the sustained transmission of information from elites to the masses in elites' quest for hegemonic consensus.

This research paper makes three significant contributions to the current scholarship on political culture. First, it provides a comprehensive overview of the network of the most popular political podcasts, which is invaluable for researchers and policymakers alike. Regardless of the scope of their ambitions, contemporary content analyses can only ever hope to capture a small section of digital content. Providing practitioners with a network map will improve subsample selection for future empirical work.

Second, this project further develops the theory of cultural hegemony by empirically investigating the broader structure involved in cultural production (Lears, 1985). The meteoric rise of populist forces in the United States and subsequent "culture wars" being waged across online spaces are analogous to Gramsci's "wars of position". Mapping spaces of cultural production thus provides a practical means of exploring these intersections within the superstructure, identifying how different groups in the dominant class seek to influence public discourse through the construction of ideological echo chambers and consequently maximize the dissemination of ideas (Crehan, 2002). Regardless of how valuable a medium podcasts actually are for ideological conversion, they are perceived as such by political content creators who engage in bitter contests for influence. This perception allows scholars to probe the extent to which current political discourse can be conceived of as representing a largely monolithic interest of a ruling class (Crehan, 2002).

Third, this research paper will also yield significant methodological contributions. The increasingly popular large-scale content analysis approach often fails to consider the structures from which content is generated (Larson, 2021). As mentioned above, podcasting has been difficult to analyze since its primary format is audio and transcriptions are often inaccurate. Analysis of the linkages between podcast hosts can bridge these gaps partially and re-emphasize the importance of network modeling approaches. Hence, podcasts present a perfect case with which questions about content creators' role in creating ideological echo chambers can be answered.

This thesis provides a novel perspective for policymakers looking to understand the current era of increased polarization and content creators' role in facilitating its creation. It urges a renewed focus on the actions and incentives of opinion leaders in our current information ecosystem. Additionally, I advocate for scholars to move beyond the analysis of short-form content on Facebook and Twitter and consider the impact of longer-form audiovisual platforms such as Apple Podcasts and Spotify.

Theory & Literature Review

Gramsci's Theory of Hegemony

Social media platforms are essentially avenues for aggregating and transmitting information at scale. As a political tool, actors can leverage them to advance support for a particular political figure or belief. This continues the battle for public opinion waged across older media forms like print, radio, and television. This form of non-violent contestation stands apart from coercive exercises of power, which has long been theorists' focus.

Antonio Gramsci was the most astute among these observers of power's non-coercive face. Gramsci conceptualized politics as a dynamic struggle centered around the efforts of a single interest group to achieve ruling class status, which he defined as hegemony. Hegemony is achieved when the masses spontaneously consent to this ruling class's prevailing values, norms and beliefs. Cultural institutions, like the media and academia, function to legitimate the ruling class's dominance, and ideological battles are waged by competing factions for control of these institutions and, consequently the attainment of ruling class status. By giving cultural activity equal weight to political and economic modes of organization, Gramsci sets himself apart from his peers in his argument that ideas could serve as the precursor to social change.

Cultural Discourse as the Site of Hegemonic Struggle

Gramsci conceptualized cultural discourse as reflective of an ongoing hegemonic struggle, with "organic intellectuals", as cultural and opinion leaders of their respective ideologies, serving as foot soldiers in this battle for public opinion. Hegemony, once achieved results in a specific worldview dominating the cultural discourse, of which political discourse is a distinct subcomponent. Stewards of the resulting hegemonic consensus are no longer organic but "traditional intellectuals", referring to non-partisan academics, media elites, religious leaders, etc., who exist to reinforce the existing order. Yet this dominance is not permanent. As ruling classes undergo periods of instability or crises, new political projects can emerge alternating between lightning-fast "wars of maneuver" or siege-like grinding "wars of position".

Gramsci viewed the former as synonymous with open and direct confrontation, consisting of strikes, riots, and mass upheaval between classes vying for hegemony. Wars of maneuvers are characterized by periods of drastic social change where the old order is wholly destabilized, and new ideas achieve consensus under the stewardship of a new ruling class. This stands in contrast to wars of position, which are extended periods of struggle. Groups vying for hegemonic consensus must achieve it by infiltrating existing civil society. Through their diffuse actions and interactions, organic intellectuals disseminate their ideas and vie for control of existing factors of cultural production.

Gramsci also adopted a multi-leveled view of this ongoing struggle. There are thus multiple simultaneously open fronts across various institutions such as education, the media, and the arts for ideologies to wage battle over. Consensus can only be achieved by a broad-based

movement that can co-opt all institutions to serve a political project successfully. While Gramsci's writings were primarily motivated by a desire to understand Italian Communism's defeat to Fascism, his works have been successfully adapted to analyze developments across various polities across differing periods (Mayo, 2020).

Like Marxists, the Gramscian view is heavily cyclical, alternating between hegemonic stability and crisis periods. Each period necessitates the emergence of a traditional and organic intellectual class that will then engage in wars of position or maneuver. Gramsci, however, argued that the current age of capitalist hegemony meant that a war of maneuver was no longer tenable. Instead, he believed that future political struggles would be diffuse and covert movements to wrest control of civil society.

The Struggle for Cultural Hegemony in the United States

From a Gramscian perspective, the United States is currently under the hegemonic control of liberal democratic capitalism, upheld by its vanguard of traditional intellectuals (Bowles & Gintis, 1982). Its politics reflected this hegemony, with bipartisanship being a valued quality amongst elected officials, willing to operate from a shared commitment to upholding a balance between democratic values and free market principles. Scholars have extensively debated the nature of this consensus, but overall do agree that for decades it reflected a widely accepted worldview (Baradat & Philps, 2017; Fukuyama et al., 1993).

Over recent decades, this moderate coalition has steadily eroded. On the right, the emergence of the tea party movement has sparked a growing trend toward an increasingly reactionary strain of conservatism. This movement's alliance with the religious right, The Libertarian Party, and other extremist groups have created a sizeable populist wing within the American right (Baradat & Philips, 2017). On the left classical liberals and contemporary liberals, once associated with the Democratic Party, have also diverged to create a progressive movement that is more open to embracing more explicitly left-wing ideologies such as Democratic Socialism (Baradat & Philips, 2017).

This growing schism has manifested itself in 2 visibly noticeable dimensions. The first is in electoral politics, with the rise of populist candidates such as Donald Trump and Bernie Sanders. Populist here is used in the context of candidates having platforms that appeal to the electorate because the existing establishment has disregarded them. The second, which is heavily intertwined with the first, is an increasingly polarized media environment. These political developments empower new media actors on the right and left, while older, less partisan actors are pushed to pick sides in the fast-evolving political culture war (Lewis, 2020; Fiorina et al., 2008).

From the standpoint of hegemonic theory, these are the signs of a hegemonic crisis. The populist actors emerging from the extreme ends of the political spectrum represent the organic intellectuals looking to infiltrate current discourse in this new war of position. Meanwhile, the traditional center, consisting of moderates, defends the status quo with its vanguard of conventional intellectuals. From this theoretical perspective, my analysis of political discourse and its relationship to digital media commences.

Hegemony and Ideological Echo Chambers

Successful hegemonic struggle depends on the ability of intellectuals to transmit their ideas to the masses successfully. From Gramsci's perspective, transmission is primarily achieved through

control of the printing press and other legacy media forms to deliver a sustained critique of the status quo. Additionally, as a Marxist who viewed systems of production as systems of social relations and a linguist, Gramsci argued that isolated organic intellectuals could not create counter-hegemonies. Instead, counter-hegemonies arise from engagement between intellectuals in counter-hegemonic discourse that delivers sustained criticism and constructs new meanings to challenge the status quo (Smith, 1997; Mayo, 2020). More broadly, in any contestation for hegemony, a Gramscian perspective argues that different factions must effectively organize their intellectuals to succeed (Mayo, 2020).

Gramsci's argument of how cultural battles can be won aligns perfectly with the modern conceptualization of the ideological echo chamber. Current scholarship on social media polarization defines them as ideologically homophilic subgroups that feed users with streams of biased content (Bisgin et al., 2010; Bisgin et al., 2012; Garimella et al., 2018). This mode of transmitting ideas via homophilic networks is highly Gramscian and not unique to the current digital era. Historical scholarship on the relationship between the media and politics in the United States also points to the creation of syndicated radio networks and cable tv platforms that feed their audiences with a rotating panel of ideologically aligned commentators (Peck, 2022).

The advent of digital media platforms has changed this dynamic in three significant ways. The first is by drastically expanding the velocity and volume at which individuals consume information (Marwick & Lewis, 2017). This constant consumption requires content creation at an unprecedented scale to match and dramatically increases the competition faced by content creators for audience share.

The second is by shifting ownership of the means of cultural production from legacy media conglomerates to technology companies. Attempts by ideological factions to create alternatives to Facebook and Twitter, such as Rumble a social media network for conservatives, have largely failed to achieve comparable margins in audience numbers (Gerard et al., 2023). Ideological factions, thus, have to operate within a digital media environment they have very little control over.

The third is by lowering the barriers to content creation. Since creating a social media account and uploading content on platforms such as YouTube or Twitter requires very little upfront investment, digital media platforms have facilitated the rise of "alternative media", independent outlets wholly owned by their creators and not subject to the gatekeeping function exerted by traditional media conglomerates (Fenton & Barassi, 2011; Fuchs, 2010).

Digital content creators have responded to these new environments with various strategies. For example, targeted advertising boosts their profiles' visibility on recommendation feeds (The Markup, 2021). However, while useful in maximising initial clicks, individual market interventions are insufficient to retain audiences for a prolonged period. Given the difficulty of creating enough competitive content, digital creators instead turn to collaborations with one another to create echo chambers. Collaborations introduce different groups of audience members to one another and allow creators to present themselves as willing to engage in debate without having to engage heavily in cross-partisan collaboration (Lewis, 2020).

This preference for homophily stands in contrast to the arguments made by technology companies that their platforms facilitate greater cross-partisan dialogue. And this pattern of greater in-group interactions has been observed in extant scholarship on political blogs, YouTube channels, and Twitter feeds (Ackland, 2005; Lewis, 2020; Lewis, 2018). More

specifically, scholars have observed the continuation of right-wing media dominance observed in legacy media formats such as talk radio and news networks. Personalities and organizations such as Rush Limbaugh and Fox News are notable examples of creators who have successfully captured a sizable share of political discourse (Stroud, 2011). This dominance traces itself to the dawn of the tea party movement and its backing by wealthy donors such as the Mercer and Koch families. Their funding of various think tanks and media personalities has created a successful right-wing influence operation (Baradat & Phillips, 2017; Lewis, 2018).

This phenomenon is best exemplified by a YouTube livestream between 2 white nationalists discussing the presence of biological differences between races in 2018 (Lewis, 2018). Their live debate became the #1 trending video worldwide during the period it was broadcasted (Lewis, 2018). Both of these individuals had channels that were primarily dedicated to informal political commentary. They did not run independent news channels and were simply casual pundits with sizeable followings.

That such a controversial and informal discussion, akin to 2 racists talking at a bar, could achieve instantaneous global outreach would have been unthinkable in prior decades. Investigative journalism eventually revealed that both these creators gained prominence by being regularly featured on the YouTube and podcast channels of popular right-wing content creators sponsored by the same right-wing megadonors (Lewis, 2018). That trend has not abated, and today the most famous content creators, such as Joe Rogan, regularly host right-wing creators on their channels and expose them to a broader audience of millions. This has resulted in massive subscription boosts for conservative podcasters and YouTubers (Lewis, 2018).

Real World Spillovers

The January 6, 2020, events best encapsulate the implications of these technological and historical developments. The world watched in shock as supporters of former president Donald J Trump stormed the heart of the symbolic heart of the current neoliberal hegemonic consensus, the United States Capitol Building, to overthrow the results of the 2020 presidential elections. The complete disengagement from an empirically verifiable fact, that there was no electoral misconduct makes January 6 emblematic of the erosion of public trust digital platforms can facilitate (Bond & Neville-Shepard, 2021). Even now, the belief that Trump was the rightful winner continues to hold strong amongst a sizeable portion of his base (Bond & Neville-Shepard, 2021).

Current Scholarship

Extant empirical scholarship has devoted much attention to understanding how echo chambers are created. However, they view echo chambers as a novel phenomenon, not part of a historical struggle for hegemony. They also do not attempt to quantify the role of collaborations between creators in creating them.

One branch of scholarship argues that consumers self-select themselves into like-minded communities. Since the internet offers users more freedom of choice in consumption, consumers can seek out and isolate themselves in like-minded communities. Studies of users' browsing histories have validated these claims (Hosseinmardi et al., 2021).

An opposing branch of scholarship has opted to point the finger at social media companies instead of consumers. Since platform revenues are generated by selling user data or hosting ads, users must be kept on these platforms for as long as possible (Hosseinmardi et al,

2021). Unfortunately, content sharing a similar political perspective as the viewer is likelier to pique their interest, leading to more clicks and more time online. Algorithms thus unintentionally end up promoting such material. The core assumption in these algorithmic explanations is that users are unlikely to have sought out this content independently, leaving platforms as the remaining culprit.

Randomized controlled trials testing the effects of various recommendation algorithms on Twitter users have found that platforms can artificially nudge users into consuming increasingly biased content (Wolfowicz et al., 2021). Further research in the network science literature has corroborated these findings, demonstrating that directing users to links that are increasingly congruent with their political beliefs is satisfying to the user and conducive to the concretization of group identities online (Lazer et al, 2013; Santos et al, 2021). Some scholars have also argued that the creation of echo chambers is due to the interaction between users and algorithms via comparisons of over 100 million political posts hosted on Facebook and Reddit (Cinelli et al., 2021).

My thesis contributes to this debate by focusing on potential collaborations between content creators to create ideological echo chambers. The presence of ideologically homophilic subgroups operationalizes echo chambers in my network analysis. I demonstrate that these groups engage with one another more than with opposing ideologies, which I define as cross-partisan collaborations.

Podcasting

I choose to make my argument by analyzing political podcasts due to their proximity to recent historical events and their unique position as a bridge between analog and digital media formats. For example, in the lead-up to January 6, conservative content creators were busy riling their base with calls to action over voter fraud (Jacobson, 2021). One of the chief mediums for the propagation of such content was podcasting, where in the week before the insurrection, over 60% of podcasts in iTunes' "Top 100" list promoted Trump's 'Big Lie' (Wirtschafter & Meserole, 2022). These shows command a combined audience of over 25 million listeners (Wirtschafter & Meserole, 2022). It is not far-fetched to imagine that some of these listeners were on the steps of the Capitol on January 6.

Apart from the link to January 6, podcasts are also crucial to our understanding of modern political culture for three reasons. First, they continue the influential role played by talk radio and late-night television centered around hosts' personalities, transferring them onto the digital realm (Williams, 2020). For decades, pioneers in analog media, from radio jockeys like Rush Limbaugh to late-night hosts like Jimmy Kimmel and television commentators like Bill O' Reilly Jr, have served as opinion leaders for millions of Americans, shaping the political views of their fans in the process (Sobieraj & Berry, 2011).

The scholarship on these traditional mediums has shown a higher tendency for listeners and viewers of these shows to participate in political events. These effects are especially pronounced for audiences of more incendiary personalities like Limbaugh (Barker, 1998; Hofstetter, 1998). At its most extreme traditional tele-communicative networks can even play a direct role in the perpetuation of extremism and the commitment of mass violence, as best exemplified by Radio-Television Libre des Mille Collines' (RTLM) complicity in the 1994 Rwandan genocide (Kellow & Steeves, 1998).

Podcasting combines the influential nature of this pre-existing format with significantly expanded accessibility. With streaming apps, listeners can access a vast library of content on demand instead of waiting for scheduled radio or tv slots. Additionally, some of today's most extremist ideologues, like Steve Bannon and Alex Jones, produce the medium's most popular shows (Ven den Bulck & Hyzen, 2020). For example, Steve Bannon's War Room podcast consistently ranked as the second most downloaded show on iTunes before it being taken down for violating content guidelines (Chartable, 2022).

Podcasts also have lower production costs allowing for long-form shows that can stretch multiple hours. Surveys of digital consumption habits reveal that 37% of Americans listen to podcasts at least once a month, with politics constituting a popular genre (Williams, 2020). Podcasts are a vector for cross-platform content creation, with many hosts also maintaining a presence on other websites such as YouTube and Twitter (Williams, 2020; Wirthschafter & Meserole, 2022).

Aside from their growing popularity, podcasts are unique in their ability to facilitate collaborations between content creators. Podcast hosts are routinely invited to make guest appearances on other hosts' shows, giving them a golden opportunity to promote their content across different podcasts. This host-guest network is essentially a network of collaborations between different podcasts and is the chief mechanism through which users get introduced to new content. Networked interactions between creators with different audiences can allow for the rapid spread of ideas via social contagion (Christakis & Fowler, 2013). Additionally, having a group of ideologically aligned hosts reiterate the same talking points results in a continuous stream of biased information being transmitted from host to listener.

The dynamism, charisma, and popularity of podcast hosts can also create para-social relationships between users and hosts akin to that enjoyed by entertainment celebrities. These factors have been shown to boost political participation, with frequent political podcast listeners likelier to vote and participate in political events (Chadha, 2012). Given their popularity, reliance on collaboration, and centrality to recent political events, podcasts represent the ideal medium to investigate the role of creator collaborations in creating echo chambers.

Hypotheses

Having established my core theoretical argument that content creators collaborate to create ideological echo chambers and win the struggle for cultural hegemony, I now lay out my central hypothesis and simplified causal mechanisms for this paper.

H1: Collaborations between podcasters are primarily motivated by ideological homophily

Observed partisan polarization is the product of ideological echo chambers, measured by the strength of homophilic collaboration. Digital content creators create these echo chambers through partnerships with ideologically aligned content creators.

H2: Right-wing podcasts will demonstrate greater ideological homophily than left-wing podcasts

Given the relative historical dominance of right-wing rhetoric in American political discourse, I expect similar dynamics to replicate themselves in the network. More specifically, I expect ideological homophily to be stronger for right-wing podcasters than other subgroups.

Data & Methods

Data

To test my hypotheses, I first assemble a dataset containing relevant metadata on the most popular political podcasts in the United States. The network analysis requires information on the most popular political podcasts across all major platforms, the podcasters who host these podcasts, the media companies responsible for the distribution and creation of these podcasts, and collaborations between the hosts.

I first identify the relevant podcasts using Chartable. This podcast analytics platform aggregates the 250 most popular political podcasts across Apple, Google, and Spotify in a list that is updated weekly. Since these podcasts are circulated on all three platforms, I use the iTunes API to scrape relevant metadata on these podcasts due to its ease of use and ability to handle a high throughput of connections. Using the iTunes API, I can extract the names of the distributors behind these podcasts and the episode descriptions for the 200 most recent episodes from each podcast.

To validate the names of the distributors, I conducted detailed secondary research on each podcast by visiting their episode websites to determine the owners of their respective distribution rights. Each podcast is then classified as belonging to a distributor/network owning multiple podcasts in the dataset {conglomerate}, a distributor/network holding a single podcast in the dataset but multiple podcasts outside the dataset {single company}, or being independently owned by the podcasters themselves {independent}[1]. This classification allows for my statistical analysis to control for the role of ownership by a common company in influencing the propensity for two podcasts to collaborate.

I also conduct secondary research to identify the names of the podcasters hosting these podcasts. Although this information is readily available on the podcast descriptions provided on their web pages, I also randomly sample older episodes to determine if the host composition has changed. If it has, I include these older hosts alongside current hosts. This allows the network analysis to account for older collaborations.

To identify collaborations between podcasters, I first use a BERT-Large-NER model to perform named entity recognition (NER) on the episode descriptions and identify potential guests. As a model fine-tuned for downstream NER tasks, BERT-Large-NER can accurately determine individuals' names from English sentences (Devlin et al, 2019). Tests comparing the efficacy of Spacy, BERT, and RoBERTa-based NER models on a randomly subsampled selection of episode descriptions resulted in BERT returning the most accurate results. Hence, I decide to opt for BERT.

After identifying names, I link two podcasts together as having collaborated if the full name of a host appears in the episode descriptions for another podcast. After a long period of collaboration, some podcasters start to refer to one another on a first-name basis in the episode descriptions. To account for this, I also include single mentions of the first/last name if the full

[1] For example, a podcast like "Political Gabfest", whilst featuring a rotating series of political pundits as host is owned by Slate Magazine. While, another show like "X22 Reports" is wholly owned by the anonymous internet personality known as "Conspiracy Dave". On occasion, podcasts will be owned by their hosts through a limited liability company (LLC) which owns no other podcasts. For example, "Millenials are Killing Capitalism" is owned by a similarly named LLC which exists as an independent entity without affiliations to other podcasts. In these instances these podcasts will be categorised as being under "Independent" ownership, similar to "X22 Reports" above. Meanwhile, podcasts in the dataset belonging to the same media network/company are categorized separately and podcasts belonging to a single company in the dataset are categorized separately.

name of a podcast host has already been identified in the episode descriptions of a partner podcast.

This approach to identifying collaborations is vulnerable to confounding by podcast episodes where another podcaster is the topic of conversation and not necessarily making a guest appearance. For example, republican politician Ted Cruz hosts the 10th most popular podcast on Chartable while also being mentioned frequently by other podcasts. To control for this confounding effect, I qualitatively validate the presence of these collaborations for podcast hosts with a disproportionately high frequency of mentions. I also include, as covariates, the category each podcast host belongs to (political personality, legacy media personality, academic, alternative media personality, religious leader, professional personality) to control for systemic differences in collaborations between these various sources of popularity.

Political personalities are hosts who are nationally recognized political candidates. Legacy personalities are hosts whose fame originally derives from media positions in television, print, or radio before starting podcasts. Religious leaders are hosts who are the heads of religious movements or organizations. Professional personalities are prominent public servants or political operatives associated with politics but have not held political office. Alternative media personalities are podcast hosts whose fame arose due to podcasts or other social media channels such as Twitter or YouTube.

Collaborations may occur more frequently between podcasters who employ similar rhetorical styles. For example, pundits might be more willing to invite other pundits on their show to engage in debates for entertainment purposes. To account for variations in the sensationalist rhetoric employed by these podcasts to attract users, I perform bias classification on the episode descriptions for each podcast in the dataset. I first tokenize each sentence used in these descriptions with NLTK's tokenizer before removing sentences irrelevant to the covered content. These 'stop-sentences' include sentences directing users to paid subscription links.

Next, I use a DA-RoBERTa-BABE model to classify each sentence as biased or unbiased. This model was developed by Spinde et al., (2021) to detect the presence of sensationalist political rhetoric used in sentences. The model utilized a pre-trained RoBERTa model, fine-tuned on an annotated corpus of 3700 statements that address 12 controversial political topics such as vaccines and election fraud (Liu et al., 2019). Each sentence was annotated by a panel of 5 experts in the topic that sentence covers who assess the relative levels of factual accuracy and subjective opinion being represented. The model was demonstrated to outperform previous media bias classifiers and has the added benefit of being trained on contemporary political events, which overlap with the topics covered in my dataset, while including sources across the political spectrum.

Testing the model on a randomly selected subsample of episode descriptions resulted in 99% of sensationalized sentences being accurately identified. Having settled on the model, I then computed the number of biased sentences and the ratio of biased to unbiased sentences used by each podcast in their respective descriptions. This allows me to control for the influence similar content styles (social commentary/punditry vs news reporting) play in shaping collaboration.

Finally, and most crucially, I gather data on the ideological orientations of the podcasters represented in the network. Hegemonic theory primarily distinguishes between the traditional and the organic, which in a contemporary context denotes the status quo and its opponents. To provide a more granular classification of the ideological spectrum present in the dataset that is

grounded in contemporary American politics, I use the Oxford Handbook of Political Ideologies (2013) and Baradat's (2019) typology which traces the historical development of various ideological movements in the United States since its founding.

I then listen to a random sample of episodes from each podcast and conduct secondary biographical research on the identies of the podcast hosts. I also consider the ideological affiliations of the media companies they represent (if a media company distributes their podcasts) before classifying them into one of five categories; {radical, liberal, moderate, conservative, and reactionary}. In the order presented, these categories span the range of movements from far-right to far-left that influence American politics and political discourse. Additionally, six international podcasts do not use English. I assigned these a {NULL} classification.

Radicals and reactionaries fall outside the hegemonic consensus, with the former advocating for extreme progressive change and the latter pushing for regression to societies organized based on racial segregation, religious commandments, market principles taking precedence over democratic norms or the functioning of the state, fascist forms of governance, or any combination of the four. As Baradat argues, much of the populist right-wing movement falls into this category and are classified as such.

Methods

Having assembled my dataset I construct a network graph for network analysis. Each node in the graph represents a podcast, assigned the attributes of ideology {radical, liberal, moderate, conservative, and reactionary}, distributor/network type {conglomerate, single company, independent}, host type {politician, journalist, academic, religious media, alternative media}, normalized number of biased sentences [0, 1], and the ratio of biased to unbiased sentences [0, 1]. Nodes a are linked by a directed edge that starts from the guest's podcast and ends at the host's podcast. Additionally, each edge is weighted by the number of times both podcasts have collaborated.

The first section of my analysis is descriptive. I plot the network graph using the Fruchterman-Reingold Layout (Fruchterman & Reingold, 1991). This algorithmic layout repels all nodes from one another while simultaneously attracting nodes with direct or indirect connections toward one another. Although the algorithm implementation involves high time complexity, the small dataset allows for a rich visual representation that will encapsulate the core themes employed in my analysis.

After plotting the graph, I provide descriptive statistics summarising the relevant aspects of the overall network structure. The first is the distribution of degree centrality, defined as the number of ties each node possesses (Luke, 2015). Since the network is directed, this measure is split amongst in-degree (edges pointing towards the node) and out-degree (edges originating from the node) measures of centrality. In-degree centrality measures the number of guests hosted, while out-degree centrality measures the number of guest appearances. Isolating the podcasts with the highest in-degree and out-degree shows the most active collaborators within the overall network.

The second measure is the distribution betweenness centrality, a measure used to identify the nodes most influential in facilitating the transmission of information (Luke, 2015). Betweenness is higher for nodes that more frequently occupy a position 'in-between' two nodes that are not directly connected. In this context, this allows for identifying podcasts that indirectly facilitate collaborations between podcasts. Apart from these summary statistics most central to

providing context to my results, I also include information on the distribution of cross-partisan collaborations.

The second part of my analysis looks to validate if the various observed distributions adhere to similar patterns observed across other social networks. Empirical scholarship on homophily and the composition of relationship networks have consistently identified the presence of power-law distributions. To test my hypothesis that podcasting, despite its claims to democratizing access to content creation, replicates the same inequalities observed in legacy media formats, I fit my degree distributions to a power-law curve and test the goodness of fit for these curves.

The final part of my analysis tests the hypothesis that collaborations are primarily influenced by ideological homophily. I perform a Monte Carlo simulation using exponential random graph models to determine if homophily is a statistically significant predictor of edge formation between 2 nodes. Standard statistical tests do not work with network graphs since data points are not independently distributed (networks, by definition, are relational entities). Hence, Exponential-Family Random Graph Models simulate null networks similar in composition to the observed data (Cranmer et al., 2011; Hunter et al., 2008; Morris et al., 2008).

With the ergm package in R, I use a Monte Carlo process to approximate a Maximum Likelihood Estimator for the observed data and test for statistical significance. The model outputs create a log-odds ratio for a tie between each node for a one-unit increase in each covariate, holding other covariates constant. I include the covariates present in my dataset whilst also including node and edge-based covariates, such as degree distribution, to simulate null networks that are as similar as possible in terms of their overall structure. This allows the model to determine if observations are due to chance or if there is a systemic difference in collaborations between ideologies. I also present goodness-of-fit diagnostics in the Appendix section for further evaluation.

Results and Analysis

Dataset Composition

Ideological Distribution of Podcasts	
Reactionary	79
Conservative	26
Moderate	53
Liberal	60
Radical	25
NULL	6
Total	250

The table above presents the overall dataset composition. Reactionary podcasts are the largest category, while radicals and conservatives are the smallest. There are more right-wing podcasts than left-wing podcasts; right-wing podcasts are disproportionately reactionary, while left-wing podcasts are disproportionately liberal. This aligns with contemporary observations of the American right being increasingly captured by reactionary movements.

Network Plot

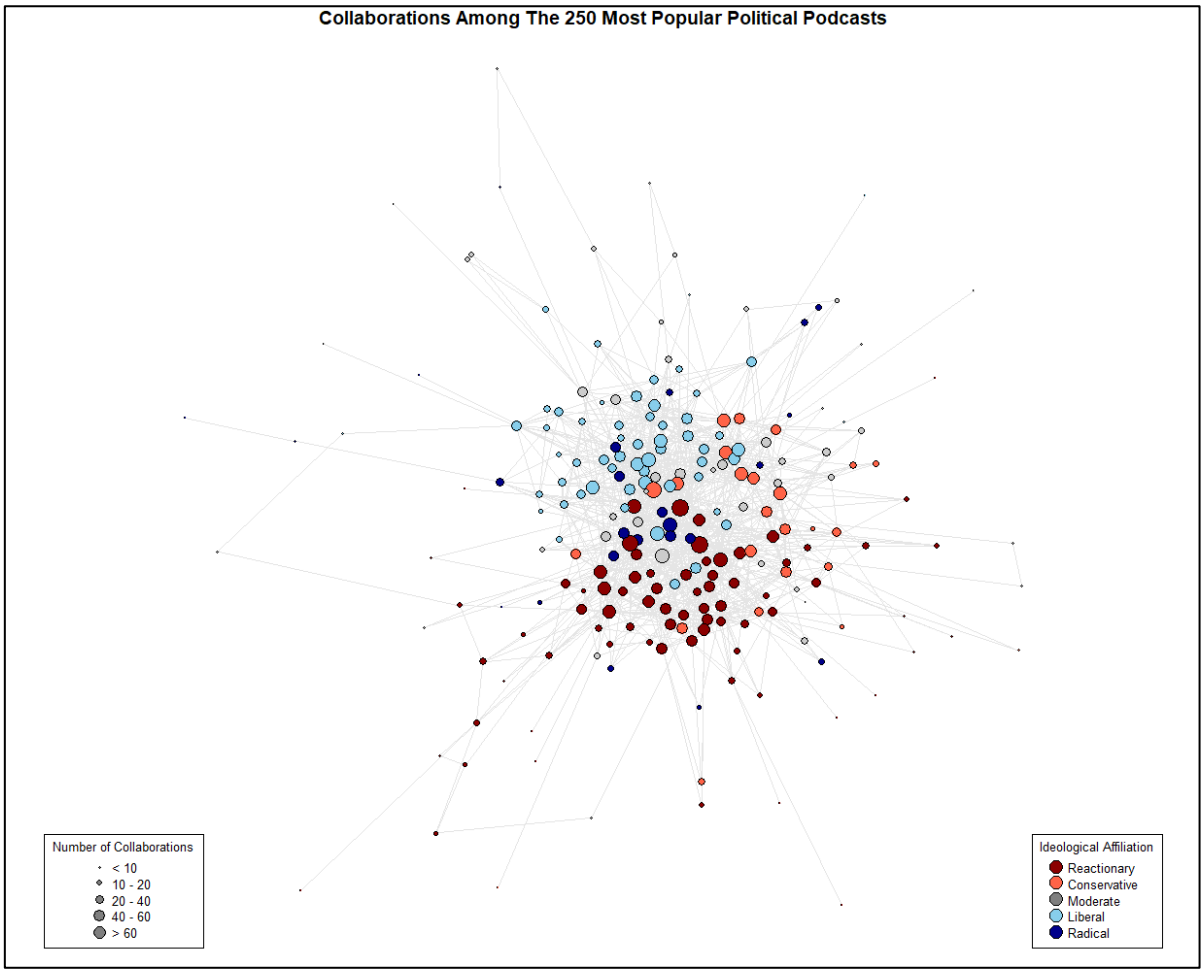


Figure 1: Network Plot of Podcast Collaborations

Figure 1 presents a visual representation of the network object with dark red, light red, grey, light blue, and dark blue used to denote the various ideological categories from right to left, respectively. The plot demonstrates clear clustering between reactionary podcasts in the bottom left quadrant, liberal podcasts in the top left quadrant, and conservative podcasts in the right quadrants. Interestingly, radical podcasts are split between reactionary and liberal, indicating a greater willingness to engage in cross-partisan collaborations. Additionally, there are smaller clusters of conservative and reactionary podcast collaborations in the bottom right and some cross-partisan interactions between liberal and conservative podcasts close to the center.

Degree Distributions by Ideology

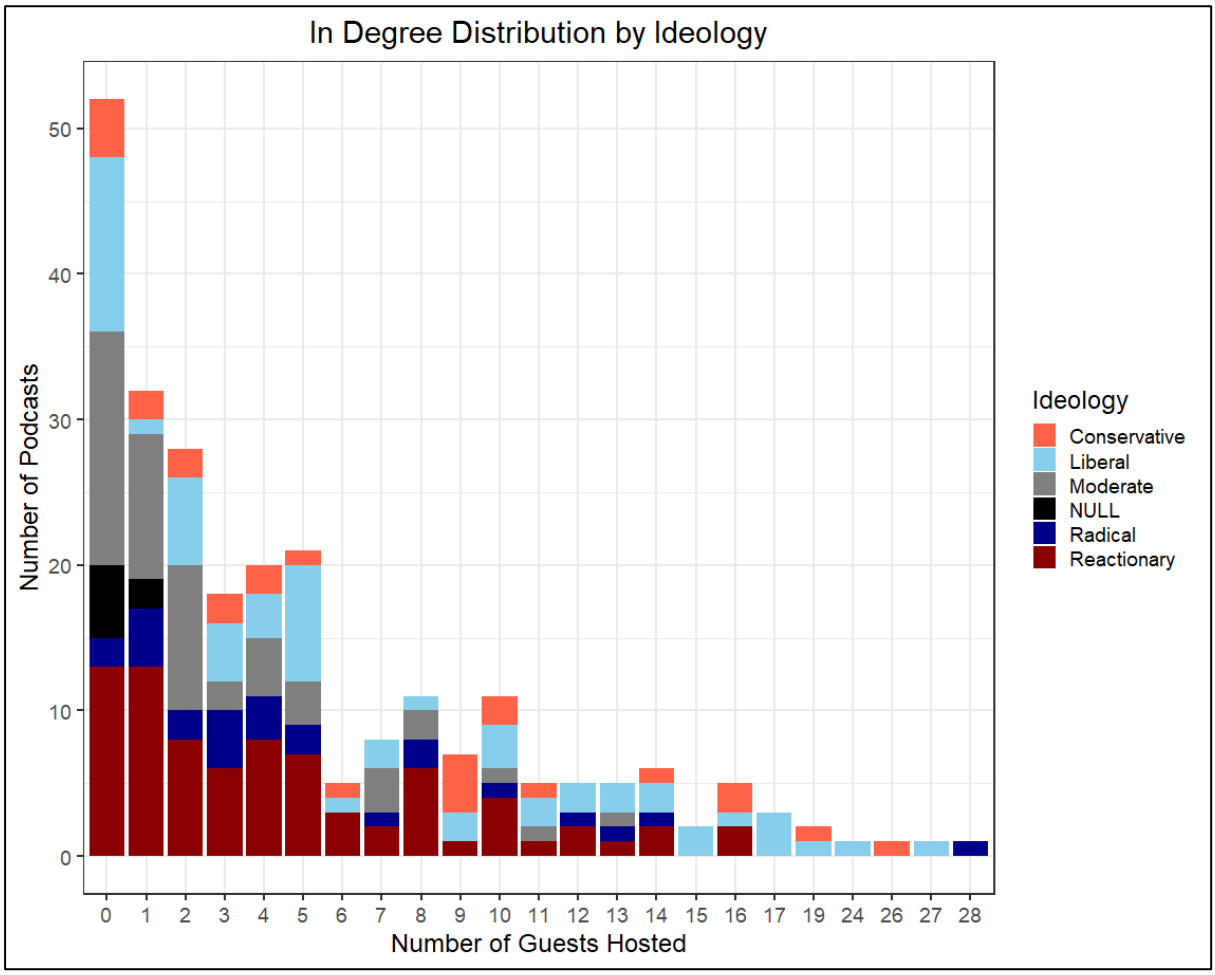


Figure 2: Indegree Distribution by Ideology

The in-degree distribution in Figure 2 operationalizes the number of guests hosted by podcasts in the dataset, grouped by their ideological affiliation. It ranges from a low of 0 to a high of 28, with a median of 8 and a mean of 9. Thus, most podcasts do not host guests, and almost all moderate podcasts are situated within the left tail of the distribution. Reactionary and liberal podcasts dominate the middle half of the distribution while the tails are comprised of liberal podcasts. This indicates that left-wing podcasts are likelier to host more guests than their right-wing counterparts.

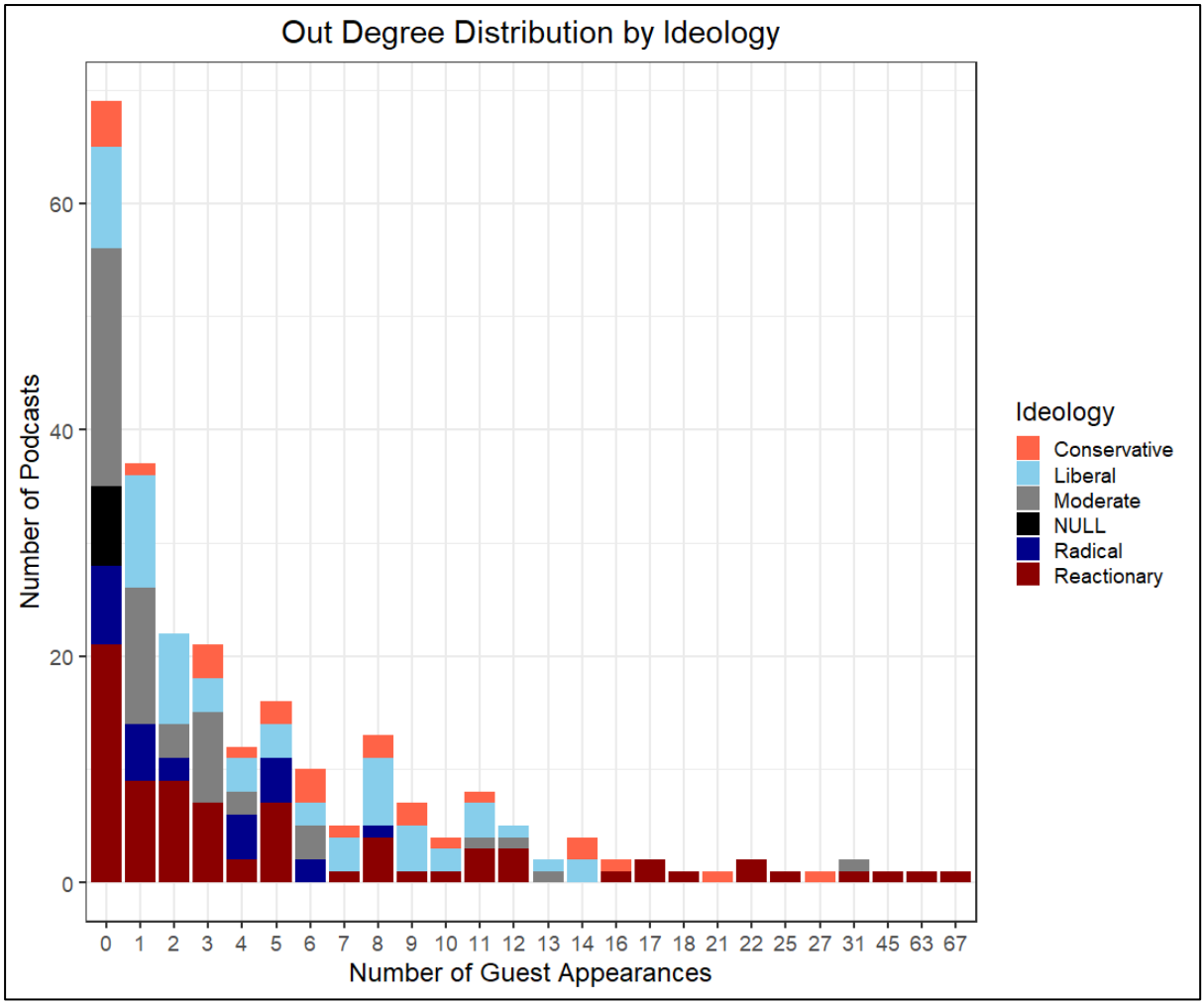


Figure 3: Out Degree Distribution by Ideology

Figure 3 presents the out-degree distribution, which operationalizes the number of guest appearances by podcast hosts from podcasts in the dataset grouped according to their ideological affiliation. The out-degree ranges from 0 to 67 with a median of 8 and a mean of 9. There is a broader range of guest appearances, but most podcast hosts do not engage in outward collaboration. However, the composition of the distribution is drastically different from Figure 2. The right tail is dominated by reactionary and conservative podcasts indicating that right-wing podcasts are likelier to make guest appearances on other podcasts than their left-wing counterparts.

Betweenness Centrality by Ideology

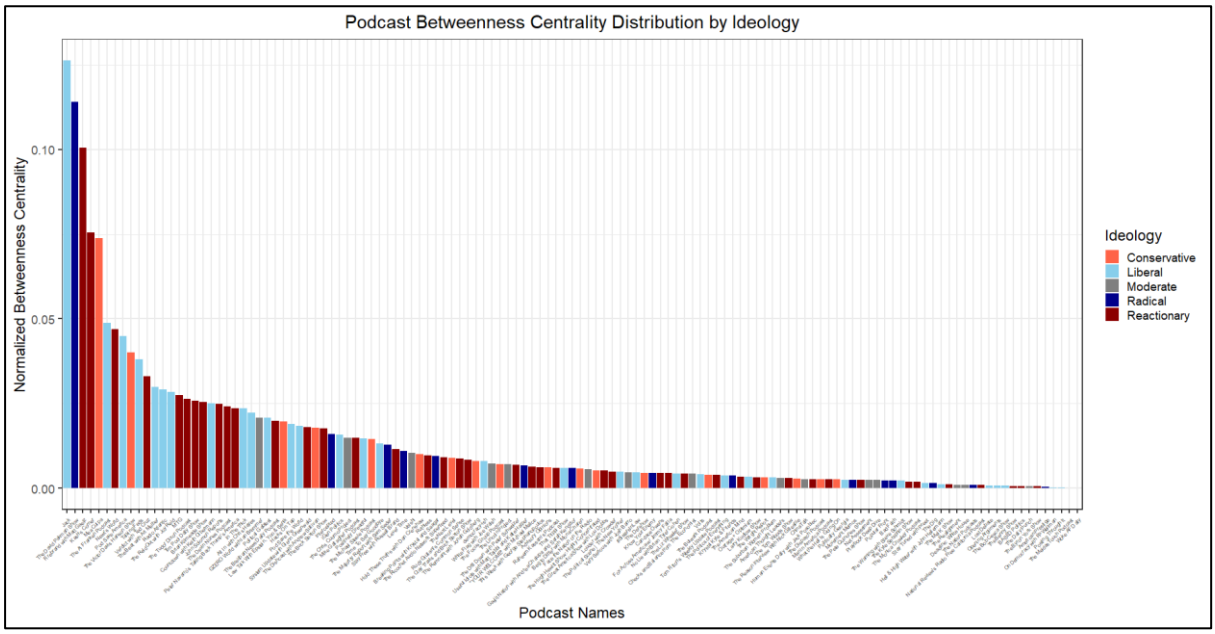


Figure 4: Betweenness Centrality by Ideology

Betweenness centrality operationalizes the level of influence each podcast possesses in facilitating indirect connections between podcasts. Assuming that guest appearances motivate listeners' consumption choices, these would represent podcasts that are the most common intermediaries bridging the gaps between 2 podcasts that have not directly collaborated. The distribution has a heavy leftward skew indicating a highly unequal distribution. The leftmost section is dominated by liberal and reactionary podcasts, which disproportionately constitute the overall dataset's left and right-wing compositions. Thus, this measure has intense competition, with no broader ideological group achieving dominance.

Cross-Partisan Collaborations

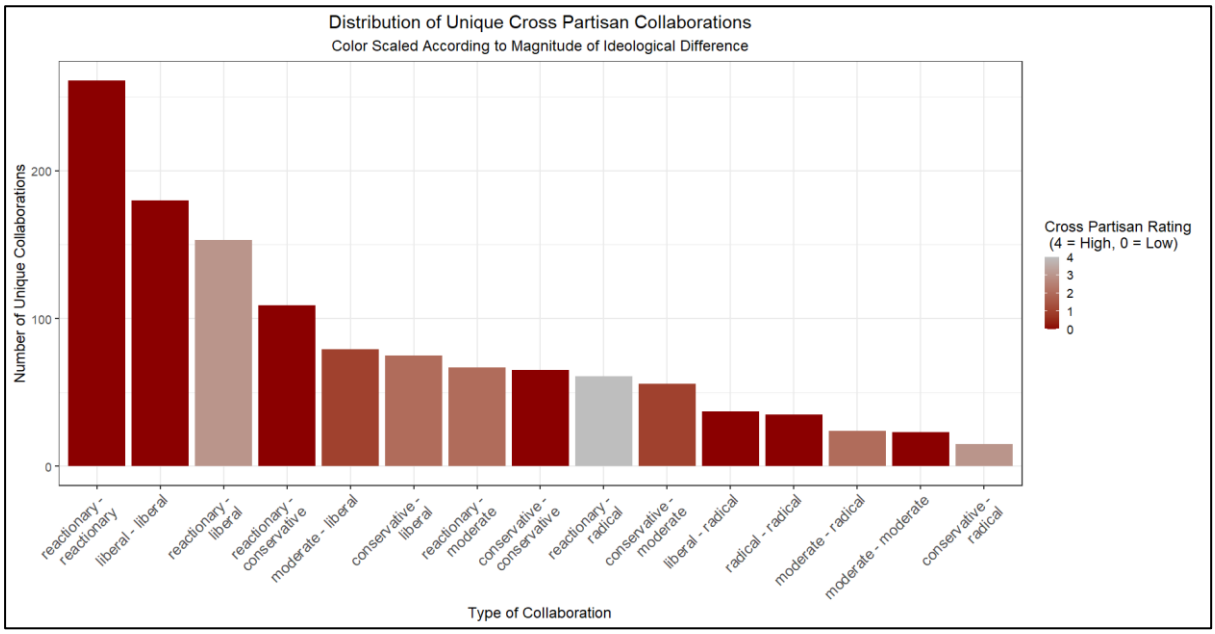


Figure 5: Unique Cross Partisan Collaborations

Figure 5 presents the frequency of unique collaborations (excludes repeat guest appearances) between podcasts in the dataset, grouped by the ideological alignment of both podcasts involved. The colors are scaled according to the magnitude of the ideological difference between both sets of podcasters (0 = none, 4 = max). Overall, the distribution suggests that collaborations with the highest frequencies, concentrated on the left of the plot, are highly homophilic, except for interactions between reactionary and liberal podcasts. This strange observation is surprising and might indicate that podcasts facilitate cross-partisan dialogue that weakens the insularity of established echo chambers.

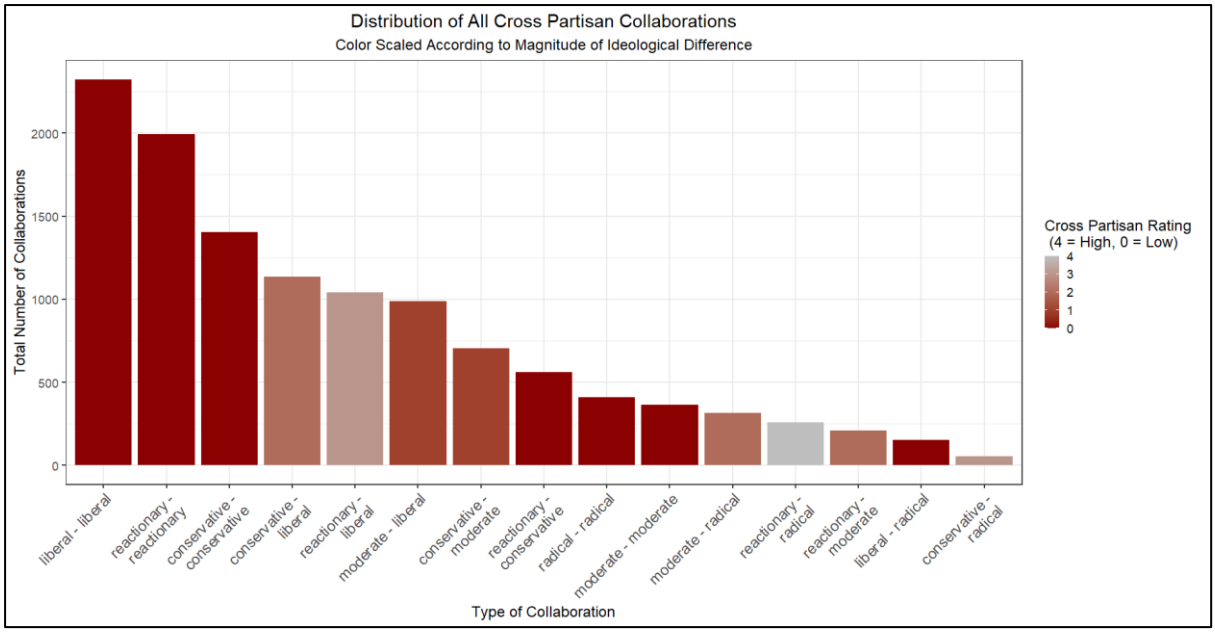


Figure 6: All Podcast Collaborations

Once repeat collaborations are included, the distribution skews more heavily towards ideological homophily. In particular, conservatives, liberals, and reactionaries demonstrate the highest levels of homophily, while most cross-partisan engagement occurs between the right wing and liberals. There is very little engagement with radical podcasts. Differences between Figures 6 and 5 are likely due to occasional cross-partisan collaborations that are overshadowed by a vastly larger frequency of homophilic interactions.

Power Law Fits

To understand how aligned the distributions presented above are with empirical findings from prior scholarship in social network analysis across a range of phenomena, I perform a power law analysis on the centrality and cross-partisan collaboration measures. The results are presented on the next page.

Power Law Fit on In Degree Distribution

Fit	alpha	xmin	logLik	KS.stat	KS.p
Reactionary	3.120888	6	-15.611225	0.1533310	0.9965702
Conservative	3.370761	2	-7.771363	0.1362759	0.9983901
Moderate	1.801150	2	-21.221794	0.1851788	0.9466829
Liberal	2.391217	2	-24.718784	0.0633723	1.0000000
Radical	2.843976	2	-8.791595	0.1098867	0.9999960

Power Law Fit on Out Degree Distribution

Fit	alpha	xmin	logLik	KS.stat	KS.p
Reactionary	1.753123	1	-43.891745	0.0865225	0.9975299
Conservative	3.999316	3	-2.571572	0.0978381	1.0000000
Moderate	1.639565	2	-18.234130	0.2028436	0.9659160
Liberal	2.547867	3	-20.055532	0.1448716	0.9846805
Radical	3.456098	4	-5.857113	0.1140595	1.0000000

Power Law Fit on Betweenness Centrality Distribution

Fit	alpha	xmin	logLik	KS.stat	KS.p
Betweenness	1.736006	0.0024938	339.5301	0.1080547	0.1846106

Power Law Fit on Unique Cross-Partisan Collaborations

Fit	alpha	xmin	logLik	KS.stat	KS.p
Betweenness	2.631312	56	-49.78813	0.1399152	0.9896177

Power Law Fit on All Cross-Partisan Collaborations

Fit	alpha	xmin	logLik	KS.stat	KS.p
Betweenness	1.779169	211	-100.1882	0.1907516	0.7314954

Figure 7: Power Law Fits on Various Distributions

The power-law fits for the overall distributions return statistically insignificant Kolmogorov-Smirnov (KS.p) probabilities, thus failing to reject the null hypothesis that the underlying probability distribution adheres to a power law. Correspondingly the KS statistics (KS.stat) returned are low, indicating high goodness of fit. However, the estimated parameters have log-likelihoods (logLik) that are extremely high in magnitude, meaning a poor estimation of the parameters shaping the power-law curve. Given the small size of the dataset, this result estimation is expected. However, the fit's overall significance indicates that even among the most popular podcasts, a minority of creators account for a majority of collaborations.

ERGM Models

Finally, I perform ERGM simulations to determine if my descriptive observations are due to chance or indicate substantive differences in collaborative behavior between ideological subgroups. I fit 2 ERGM models. The first tests for homophily within subgroups and the second controls for cross-partisan collaborations. I include relevant covariates mentioned in the data section and also include endogenous features of the network such as the degree distributions, number of edges present, and the presence of mutual relationships between nodes. My simulation results are presented below.

ERGM Models			
Covariates	**Model 1**	**Covariates**	**Model 2**
Number of Edges	**-4.08*****	**Number of Edges**	**-4.03*****
	(0.16)		(0.11)
Reactionary	**1.31*****	**Conservative >> Reactionary**	**-0.67*****
	(0.15)		(0.17)
Conservative	**0.79*****	**Moderate >> Reactionary**	**-1.64*****
	(0.18)		(0.21)
Moderate	0.09	**Liberal >> Reactionary**	**-2.47*****
	(0.25)		(0.26)
Liberal	**1.17*****	**Radical >> Reactionary**	**-2.61*****
	(0.15)		(0.42)
Radical	**2.00*****	**Reactionary >> Conservative**	-0.13
	(0.27)		(0.14)
Difference in In Degree - Conservative	**0.19***	**Conservative >> Conservative**	**0.89*****
	(0.09)		(0.13)
Difference in In Degree - Moderate	**0.24****	**Moderate >> Conservative**	**-0.47***
	(0.08)		(0.21)
Difference in In Degree - Liberal	**-0.28****	**Liberal >> Conservative**	**-0.81*****
	(0.11)		(0.21)
Difference in In Degree - Radical	**-0.40***	**Radical >> Conservative**	**-1.78*****
	(0.16)		(0.51)
Difference in Out Degree - Conservative	**1.11*****	**Reactionary >> Moderate**	**-1.16*****
	(0.15)		(0.17)
Difference in Out Degree - Moderate	**0.37***	**Conservative >> Moderate**	-0.39
	(0.15)		(0.20)
Difference in Out Degree - Liberal	**1.01*****	**Moderate >> Moderate**	**-1.14*****
	(0.13)		(0.22)
Difference in Out Degree - Radical	**0.96*****	**Liberal >> Moderate**	**-0.84*****
	(0.15)		(0.17)
Ratio of Biased to Unbiased Statements	**0.42*****	**Radical >> Moderate**	**-2.36*****

	(0.09)		(0.50)
Host is a political figure	**0.31*****	**Reactionary >> Liberal**	-0.15
	(0.07)		(0.11)
Host is a legacy media figure	**-0.14****	**Conservative >> Liberal**	-0.08
	(0.04)		(0.16)
Host is a alternative media figure	**-0.18*****	**Moderate >> Liberal**	**-0.92*****
	(0.05)		(0.18)
Host is a relgious leader	**-1.37****	**Liberal >> Liberal**	**0.31****
	(0.49)		(0.09)
Host is an academic	**-0.21****	**Radical >> Liberal**	**-1.21*****
	(0.08)		(0.26)
Independent Podcast	**0.22*****	**Reactionary >> Radical**	-0.23
	(0.06)		(0.15)
Podcast owned by a Single Company	0.07	**Conservative >> Radical**	**-0.72***
	(0.08)		(0.31)
Podcast part of a Distribution Network	**0.25****	**Moderate >> Radical**	**-0.68****
	(0.08)		(0.23)
0 Guest Appearances	**11.91*****	**Liberal >> Radical**	**-0.91*****
	(0.52)		(0.23)
1 Guest Appearances	**9.01*****	**Radical >> Radical**	**0.35***
	(0.49)		(0.17)
2 Guest Appearances	**6.67*****	**Ratio of Biased to Unbiased Statements**	**1.16*****
	(0.47)		(0.14)
3 Guest Appearances	**5.31*****	**Presence of Reciprocal Collaboration**	**1.87*****
	(0.44)		(0.13)
4 Guest Appearances	**3.67*****		
	(0.44)		
5 Guest Appearances	**3.16*****		
	(0.39)		
Presence of Reciprocal Collaboration	**1.74*****		
	(0.13)		
AIC	10212.55	11104.11	

BIC	10482.01	11346.63
Log Likelihood	-5076.28	-5525.06
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$		

The coefficients in the table represent the log odds ratio of observing a tie between 2 nodes with the same covariate value holding all other covariates constant. The model was built sequentially, with each successive covariate decreasing the AIC and BIC scores, indicating that each added covariate improved the quality of the model fit.

Holding all other covariates constant, there was a statistically significant ($p < 0.001$) difference in the odds of homophilic collaboration between reactionary (OR = 1.31, 95% CI = [2.76, 4.97]), conservative (OR = 0.79, CI = [3.14, 1.55]), liberal (OR = 1.17, CI = [2.40, 4.32]) and radical podcasts (OR = 2.00, 95% CI = [4.35, 12.5]) compared to the simulated null models. The confidence intervals are for the estimated probabilities computed using the Odds Ratio and Standard Errors. The odds of collaboration are greatest for radical podcasts followed by liberals, reactionaries, and conservatives. Moderates do not display homophilic collaboration. These findings validate my first hypothesis but contradict the second.

For further robustness, the second model includes the direction of collaborations and the entire matrix of possible homophilic and cross-partisan collaborations. However, since the directionality of collaborations is now included, the inclusion of other covariates related to degree centrality results in a high amount of multicollinearity. Additionally, due to the small number of observations, the simulations degenerate with the addition of additional covariates. Given these constraints, I include as control covariates the presence of reciprocal collaborations, the number of edges, and the presence of sensationalized rhetoric since these are not correlated with the direction of collaboration. Similar to model 1, this model was built sequentially, with each successive covariate decreasing the AIC and BIC scores, indicating that each added covariate improved the quality of the model fit. The odds ratio for each collaboration are calculated relative to collaborations between 2 reactionary podcasts.

Most notably, the odds ratios of cross-partisan collaborations were all negative compared to collaborations between reactionary podcasts, indicating a relatively lower probability of cross-partisan collaboration. Additionally, the odds of homophilic collaboration between conservative (OR = 0.89, CI = [1.89, 3.14]), liberal (OR = 0.31, CI = [1.13, 1.64]), and radical podcasts (OR = 0.35, 95% CI = [1.02, 1.98]). The confidence intervals are for the estimated probabilities computed using the Odds Ratio and Standard Errors. Thus homophilic collaboration for reactionary, liberal, conservative, and radical podcasts is likelier than cross-partisan collaborations. This finding further weakens the argument for the ability of digital media platforms to facilitate greater cross-partisan dialogue. Furthermore, collaboration is the greatest for conservative podcasts when split along edge directions. These findings partially validate my second hypothesis, given that liberal and radical podcasters collaborate more frequently than podcasters on the far right.

The goodness of fit diagnostics for each model are visualized in the appendix. Overall, the null networks successfully simulate the distribution of collaborations between podcasts based on ideology. However, they struggle to account for the heavy leftward skew in degree distributions. Since the number of observations is small, attempting to include the leftmost in and out-degree values as covariates results in the monte carlo simulation failing to converge.

Because most of the observations have low degree centrality, forcing the model to control for these low values leaves too little freedom to generate comparable simulations. Thus, the precision of the estimated coefficients is likely to suffer. However, since the purpose of the analysis is for relative comparisons, this does not diminish the overall utility of the results obtained.

Analysis

The descriptive statistics presented lead to two major insights. The first is that there is a large amount of ideological homophily observed in podcast collaborations. Assuming that listeners are likelier to listen to a podcast if they have been exposed to it via a guest appearance in another podcast, homophilic collaborations will result in users consuming more podcasts with similar ideologies. Collaborations could thus be a potential means of creating echo chambers.

Second, the broader ideological divide on a left-right spectrum pits liberal podcasters against reactionary podcasters. Liberal podcasters are likelier to make guest appearances on other podcasts, while reactionary podcasters are likelier to host other podcasters. This is well substantiated by existing scholarship on digital media. Right-wing podcasters have been observed to prefer hosting, allowing them to stage sensationalist attacks on their often less prepared guests while claiming an openness to free and fair debate. These exchanges are then selectively edited and uploaded for their audience to consume. My findings build on this work by suggesting that liberal content creators are conversely more willing to engage and facilitate indirect engagements between different podcasts, as observed from the betweenness centrality distribution.

Additionally, these liberal and reactionary subgroups are overrepresented compared to their respective radical and conservative counterparts in the left-right spectrum. Meanwhile, engagement amongst moderates remains extremely low. This is substantiated by existing scholarship on legacy media forms, noting a gradually dissolving center in favor of a more polarised media environment.

Next, my power law reveals that despite expanding access to content creation, digital media networks continue to replicate inequalities observed across other media forms and human social networks. Across all ideological subgroups, a minority of podcasters are responsible for a majority of homophilic and cross-partisan collaborations. Assuming that collaborations influence discourse, these findings indicate that a minority of creators are shaping a majority of the content being produced due to collaborations.

Finally, my ERGM fits result in two major conclusions. The first, from Model 1, is that homophily significantly predicts collaborations between hosts across all ideological subgroups. This relationship is meaningful after accounting for the type of distributor, the occupations of podcast hosts involved in collaboration, the use of sensationalist rhetoric, and structural features such as reciprocal ties, the number of edges, and degree centrality. This validates my first hypothesis that echo chambers are a product of homophilic collaborations.

The second, from model 2, is that the probability of collaboration between reactionary, conservative, liberal, and radical podcasts is statistically significant and greater than all other combinations of homophilic and cross-partisan collaborations. This affirms my first hypothesis and partially supports my second hypothesis that conservative and reactionary podcasts will demonstrate a greater homophilic tendency.

These findings demonstrate that despite the ability to engage with one another on digital media platforms, content creators will engage with other ideologically aligned creators instead. This creates ideological echo chambers for listeners who are likelier to be exposed to similarly themed content. This contributor to polarization is distinct from extant explanations of algorithmic biases and listener choice. While the results do not disprove the validity of the latter two branches of scholarship, they demonstrate the limitations of these explanations that do not consider the creators' agency. Additionally, the results provide a fuller picture of the pathways through which echo chambers are created, and polarization is consequently deepened.

Collaboration between ideologically aligned creators is not a new phenomenon, and has been documented across various legacy media formats in the United States. From conservative talk radio to cable television, media companies, and networks have often sought to capture market share and advance ideological agendas by exposing viewers to a constant stream of similarly themed content. This phenomenon is well accounted for in Gramsci's theory of cultural hegemony, which conceptualizes political discourse as a battleground among intellectuals from different ideological factions.

Traditionally this has occurred under the umbrella of common ownership by legacy media conglomerates, whose rotating staff of commentators, reporters, and journalists engage with one another within the same newspaper, radio network, or television station. With digital media formats, outright control of the means of cultural production is no longer possible because technology companies own platforms. These platforms allow content creators to operate independently without being syndicated by a significant legacy network. Hence, collaborations between content creators become an essential tool by which ideological echo chambers are created. This has been well documented in studies of political blogs and is similarly observed in my network analysis of political podcasts (Ackland, 2005).

However, despite the democratized access to content creation enabled by technological advances, these new digital formats are subject to the same inequalities in outcome observed across other social networks. And in line with broader political trends, right-wing movements are more effective than creating these echo chambers than different ideological subgroups.

Future Work

Future work on this subject should focus on expanding the analysis in 2 ways. The first is to create a dynamic network model that considers fluctuations in the popularity of podcasts, content style, and collaborations over time. The current Chartable dataset is updated weekly, and each iteration results in large shifts in popularity. While the overall composition remains similar, the large change in relative rankings suggests that temporal variations within the dataset warrant inclusion in future models.

The second is to focus on computational text analysis of the podcast content. With advances in computation processing large amounts of episode transcripts to identify semantic similarity, common n-grams, and stylometric similarity can be used to better model the intertextuality of generated political discourse. This will allow an accurate identification of ideologically aligned hosts that scales beyond the qualitative methods employed within this paper.

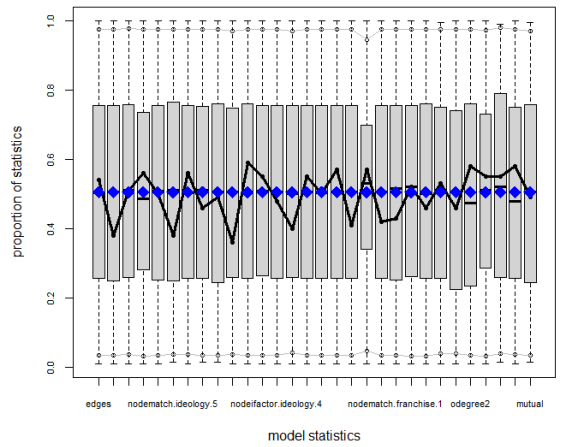
Both these suggestions, when paired with an extended dataset that also includes influential but non-political podcasters who make guest appearances on the podcasts in the

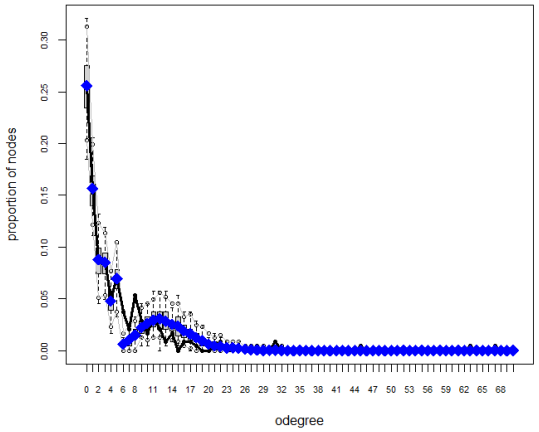
dataset, will result in more robust results. Political content is not limited to explicitly political content creators. Many famous podcasters like Joe Rogan regularly provide political commentary to their millions of subscribers. Scaling the network to include these creators will give a fuller picture of collaborations and, consequently, the formation of echo chambers.

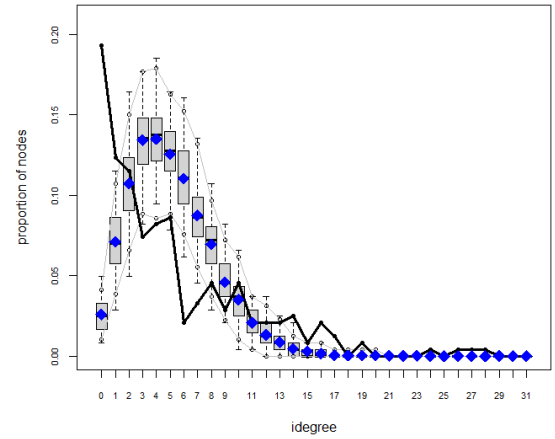
Appendix

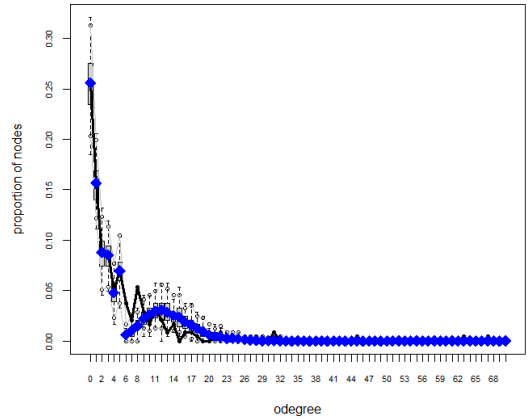
Goodness of Fit Plots

Model 1

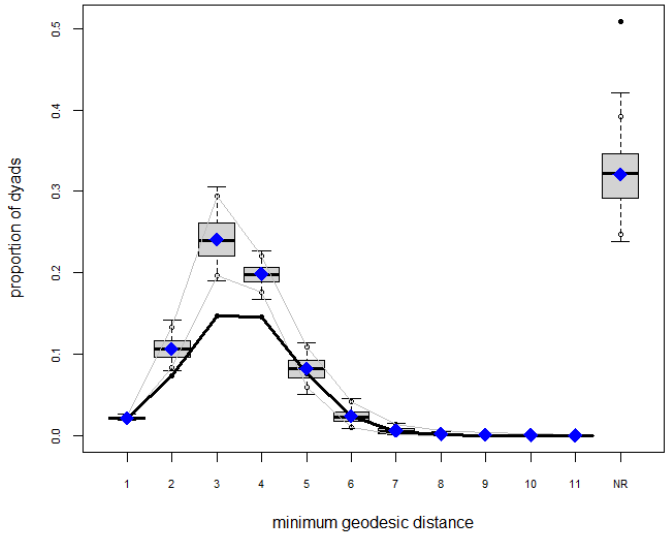




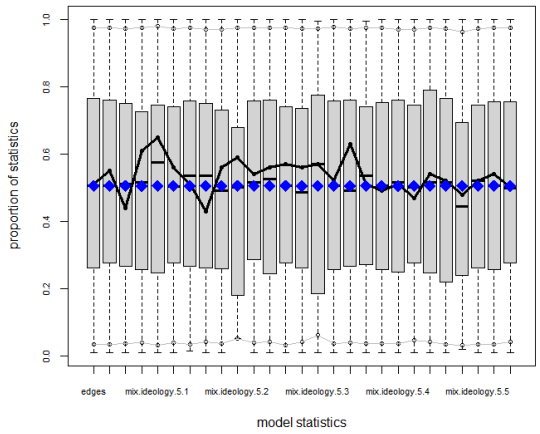


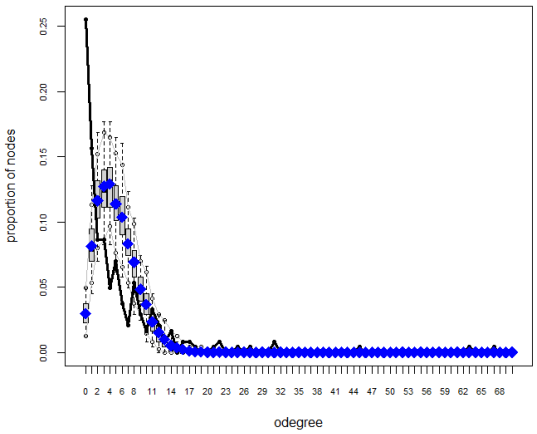


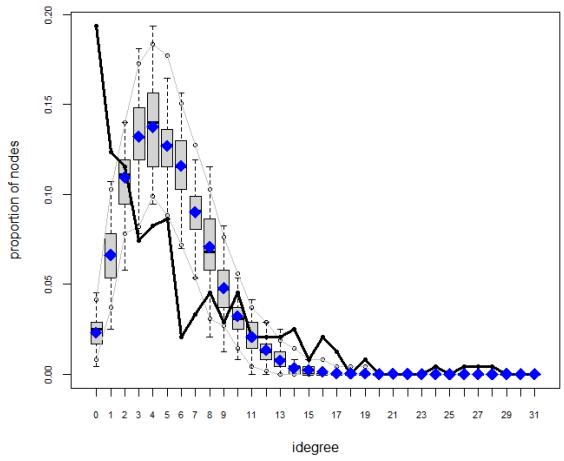
Goodness-of-fit diagnostics

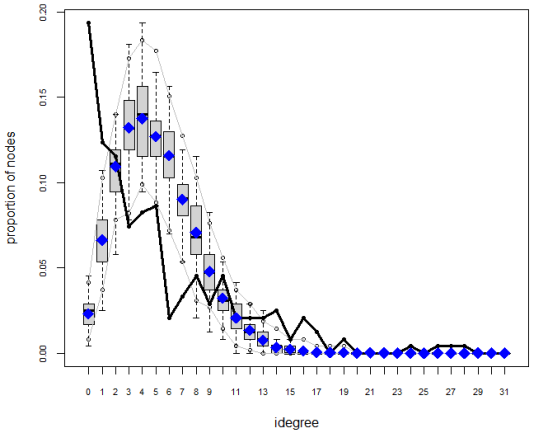


Model 2

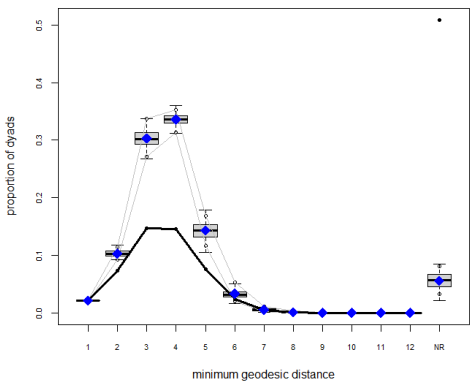








Goodness-of-fit diagnostics



Data and Code Availability Statement

The datasets analysed during the current study are available in the replication-materials repository hosted here:

https://github.com/thesis- replication-materials-Thiyaghessan

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