Measuring Partisan Segregation in Political Media Consumption

Abstract

Despite the amount of research on the topic, there are few direct measurements of partisan segregation in media use. Instead, indirect evidence, like coefficients in multiple regression models, is typically used to indicate the presence or (more typically) absence of partisan segregation. The few methods that do approximate a direct measure require dichotomizing partisanship of people and sources, which is problematic in the United States and unworkable in many other democracies. I suggest using a method originally designed to measure residential segregation to quantify the amount of balkanization in media use at the country, party, and individual levels. To show the potential of the measure, I use data from a nationally representative survey to describe the amount of partisan segregation in media consumption in the United States.

Keywords: selective exposure, network analysis, partisan media, segregation

Measuring Partisan Segregation in Political Media Consumption

Concerns about the influence of partisan media in the United States have come to dominate both academic and lay discourse on potential pitfalls of the current political environment (e.g., Levendusky, 2013; Sunstein, 2001). Research to date has mostly dispelled the notion that the typical partisan is isolated from mainstream or contrary views (Bakshy, Messing, & Adamic, 2015; Flaxman, Goel, & Rao, 2016; Gentzkow & Shapiro, 2011), though equally strong evidence shows partisans prefer in-group or ideologically friendly media while giving more scrutiny to counterattitudinal claims (Garrett, 2009b; Garrett, Carnahan, & Lynch, 2013; Taber & Lodge, 2006). Less clear are the criteria by which researchers can and should evaluate patterns of political media consumption for the presence or absence of such balkanization, especially as media systems and political norms change over time.

Although there is an impressive array of work arguing persuasively for the lack of so-called "echo chambers" (in the words of Sunstein (2001)), it is worth considering what sort of evidence would be compelling in their favor. As a first step, I review some of the evidence that has been levied against claims of partisans occupying political echo chambers. I will argue that this evidence by and large fails to get to the core of the question because it is fundamentally a descriptive task requiring some assumptions and excluding others. Next, I propose a general approach, conceptualizing audience fragmentation as analagous to segregation and using analytical techniques derived from research on social networks, to add to this literature. This approach is put into practice using representative survey data from the United States. Although there is no smoking gun in the search for echo chambers, the set of measures proposed should leave researchers prepared to address future developments or related problems in a principled, rigorous way.

This study builds on previous efforts to use network analytic approaches to this problem (Fletcher & Nielsen, 2017; Webster & Ksiazek, 2012; Weeks, Ksiazek, & Holbert, 2016) by using a richer set of media sources and focusing specifically on quantification of partisan segregation. The benefit of approaching media fragmentation from a network perspective is the ability to explicitly — and statistically — consider interdependencies between viewers, sources, and the characteristics of each. When one looks at the aggregate characteristics of the audiences of political media outlets, it is difficult to understand how the audiences of one source relate to another; are they in competition with one another, does all of one's audience exist as a subset of the other's, or something in between? Although individual-level data can help to alleviate some of the issues in aggregating audience data, what tends to be done instead is aggregation by individual. This provides some insight (like the proportion of one's media diet that is congenial) but still results in some loss of information, especially when the goal is to make inferences about both people and the sources. This is not to say that all research on selective exposure and/or partisan media should eschew some of the aforementioned methodologies. Instead, it is this particular question — is political media use characterized by partisan or ideological segregation, and how much? — that invites this approach.

Reviewing Evidence of "Echo Chambers"

Regression Modeling

Garrett et al. (2013), one of many examples of this type of approach, use survey data with measures of media use in partisan categories. Their key tests take the form of a series of regression models, each predicting use of a category of political media sources. With sources trichotomized into mainstream, liberal, and conservative, the authors find in two separate national surveys that the use of ideologically consistent sources *positively* predicts use of ideologically discrepant sources, which certainly runs counter to the idea of partisan (or in this case, ideological) enclaves. An implication is people who consume partisan media are just generally heavier media consumers and do not avoid all unfriendly sources, all else being equal. The results are compelling in the context of selective exposure theory, showing that while people do appear to select congenial media, they do not seem to actively avoid uncongenial media. Similarly, Holbert, Hmielowski, and Weeks (2011) document a suppression effect in the three-variable relationship between ideology, MSNBC consumption (acting as a proxy for liberal media use), and FOX News consumption (acting as a proxy for conservative media use). While there is near-zero correlation between the consumption of the two sources, the introduction of ideology and other exogenous covariates in a multiple regression context reveals the relationship between the consumption of those two sources to be positive, all else being equal.

That being said, one should remember that for the question of whether political media audiences are fragmented, all else is *not* equal. The theoretical and statistical approaches in Garrett et al. (2013) and Holbert et al. (2011) are wholly appropriate for researching the social and psychological mechanisms of selective exposure. The use of controls for ideology, for instance, allows one to engage in the counterfactual thinking required for causal inference. This standard social scientific approach allows us to ask questions like: If we could hold a person's political views and congenial media consumption at some constant level, how much uncongenial media would they consume? In the context of establishing why people choose the sources they do, this question is important. For the related but distinct question of whether media consumers are insulated from contrary views (and how much), it becomes more important to describe things as they are, even if it comes at the expense of insight into causal processes. The counterfactual in which conservative ideologues become moderates and so on will not be realized; whether the state of affairs is driven by partisanship, political interest, or something else is not as important for the specific goal of characterizing what the state of affairs is.

Tracking Data

Bakshy and collaborators (2015) begin by categorizing web links as liberal, neutral, or conservative on the basis of the balance of liberals and conservatives who share the link on Facebook. They describe the proportion of content available to users on their Facebook News Feeds that are “cross-cutting”, i.e. liberal links for conservative users and vice versa. They find liberals to be exposed to 22% cross-cutting content and conservatives 34%, with 21% and 30% of outgoing clicks to cross-cutting content, respectively. The authors note this is considerably more closed off than what would be expected if exposure and selection were random, in which case the proportions would be 45% (for liberals) and 40% (for conservatives). They conclude, “our work suggests that individuals are exposed to more cross-cutting discourse in social media than they would be under the digital reality envisioned by some” (p. 1131). This was followed by a Sunstein (2007) reference and another to Bennett and Iyengar (2008), who in their article stated that in the near future, “most media users will rarely find themselves in the path of attitude-discrepant information” (p. 724).

The study does well to take data from what has long been believed to be a potential hotbed for partisan enclaves (Facebook) and leverage a descriptive analysis to explore the claim. One danger with the particular approach applied, however, is defining what is “liberal” and “conservative” based only on those who share the content. There is an implicit assumption that one can deduce the extent to which the content of a source is partisan/ideological based on who is exposed to the source. In the American context, this is a common and often defensible assumption, at least in general, but it is not unfathomable that partisans could be exposed to different sets of non-partisan sources. Perhaps most important, however, is the lack of a standard against which to compare. The only inferential test offered is one that suggests liberals and conservatives are exposed to significantly less cross-cutting content than expected under a null, no-fragmentation model. Despite a conclusion noting the findings fall short of the somewhat dystopian possibility raised by Sunstein, one could marshal this study's findings as evidence in *favor* of the existence of echo chambers of a degree less severe than the most extreme predictions. Barberá, Jost, Nagler, Tucker, and Bonneau (2015) provide some more nuance, analyzing retweets on Twitter. For political topics, they characterize the interaction patterns as consistent with segregation: 38% of retweets about the 2012 U.S. Presidential election, for example, involved one "extreme conservative" retweeting another and another 28% among "extreme liberals," groups that characterized just 16% of users analyzed. On less political news topics, however, attention shifted to moderate sources. Breaking news events, like the Newtown shooting, started with non-segregated retweeting behavior but over time became segregated.

Gentzkow and Shapiro (2011) take yet another approach, in this case using proprietary data from a web traffic tracking firm. The firm, which installs software on users' browsers to track the sites panelists visit, asked a subset of users to describe their ideology. The researchers continuously rated the ideology of each of over 100 sources on the basis of the ideology of its visitors. For another group of people, the researchers accessed individual-level browsing data along with their ZIP codes, which were used to derive an estimate of ideology via local presidential vote share. Another purpose-built survey asked about a small number of offline sources (i.e., newspapers and TV channels). They introduce a useful construct to quantify and reason about fragmentation: segregation. Using a measure better known for measuring residential racial segregation, the quantity is interpreted roughly as the average conservativeness of the sources consumed by conservatives minus the average conservativeness of the sources consumed by liberals, in effect yielding the ideological difference in the media diets of those two groups. On the internet, this quantity (bounded at 0 and 1) was .075 and smaller for offline sources. This design shares with Bakshy et al. (2015) the weakness of defining source ideology by a source's audience, something that is not a challenge faced in the studies of racial segregation for which the measure was designed. Nevertheless, Gentzkow and Shapiro's operationalization offers a fairly intuitive interpretation and a principled theoretical justification.

Flaxman et al. (2016) use a similar procedure with web tracking data, though without user-level information on ideology or partisanship. They generate an overall segregation estimate of 0.11, although for certain content types and methods of access the estimate goes as high as 0.20 and as low 0.07. Another useful insight from Flaxman et al. (2016) is the finding that most people in their sample had little ideology diversity in their media use; they only avoid high segregation because the typical person's media consumption is not on the ideological extremes. That being said, they offer as a point of reference the explanation that a segregation level of 0.20 corresponds to the difference between liberal site The Daily Kos and conservative news behemoth Fox News. The authors describe this as being substantial but not outside the "mainstream political spectrum" (p. 313). This is of course literally correct, but those examples are — in this author's opinion — essentially on the poles of that spectrum. The finding of segregation that large, however, did only apply to a subset of the content under study (opinion news accessed via search engines).

Network Approaches

Inherent in the idea of media segregation is the idea of information diffusion. The normative concern about balkanized patterns of media consumption tends to revolve around facts and perspectives being confined within partisan or ideological groups. Network analysis is well-suited for questions of this kind due to its ability to factor in the relations between entities. An important precedent in this area is Weeks et al. (2016), who drew on National Annenberg Election Study (NAES) data from the 2008 presidential campaign as a basis for network analysis. The authors took the responses to questions about where participants got their news from and constructed a set of sources for analysis, focusing primarily on mainstream versus partisan sources. This built on Webster and Ksiazek (2012), who used market research data to analyze this general question with very similar techniques.

The Weeks et al. (2016) article is also instructive as an example of how survey data may be treated as a network. Each source selected from the NAES responses was treated as a node while links between source nodes represented the co-consumption of the two sources by one or more respondents. The links have a strength attribute, with more strength going to those outlets with more respondents co-consuming them. For instance, The Daily Kos could be linked to both MSNBC and Fox News, since there is at least one person who consumes both pairs of sources. But if there are 100 who use both The Daily Kos and MSNBC and only 5 who get news from The Daily Kos and Fox News, the strength of the tie between MSNBC and The Daily Kos is 20 times stronger than the tie between The Daily Kos and Fox News. This is important since in large samples that have anything less than complete partisan segregation in media consumption, all possible pairings of media sources will be realized at least once. Weighting allows the analyst to keep all the information while still emphasizing the links that are realized the most frequently in the data. It is worth noting that this is not a feature of the influential Webster and Ksiazek (2012) piece, likely due to lack of availability of analytical tools to handle weighted-edge network data.

The key analyses in Weeks et al. (2016) categorize sources according to their "coreness" (Borgatti, 2005), focusing on the centrality of the sources. This is in and of itself a worthwhile approach for certain research problems but does not give much evidence for how fragmented media audiences are, instead just showing which sources connect the possibly isolated communities of sources. Comparing the co-consumption networks of Republicans and Democrats along these lines was closer to getting at the key underlying questions, but still more can be done to try to *quantify* the degree to which anything resembling echo chambers exist.

A subsequent entry in this literature came from Fletcher and Nielsen (2017), who cite Weeks et al. (2016) and Webster and Ksiazek (2012) as key predecessors. Their focus, however, is on comparison of media systems in different countries and not on partisan differences. Acquiring data from multiple countries required some compromise on measures, resulting in a small number of sources for each country. Their inferences focus on the density of each network, which does get at the question of audience overlap. Rather than use weighted edges in the analysis, the researchers took a recommendation from Webster, Phalen, and Lichty (2006) and only included edges when the amount of shared audience between a pair of sources was greater than expected under a null model (using a p value cutoff), thereby enabling more conventional network analytic techniques.

Convergent Evidence

Overall, the evidence against widespread balkanization in media consumption tends to point in the same direction regardless of method. In some cases, however, one must exercise some judgment to interpret the evidence as such. A reasonable interpretation of the Facebook data from Bakshy et al. (2015) is that is evidence in favor of balkanization; it only fails against the Sunstein (2001; 2007) standard, which may be intentionally overstated for effect and at any rate needs not be enshrined as the best or only such standard. The takeaway from designs like that of Garrett et al. (2013) and Holbert et al. (2011) is less clear when the counterintuitive finding relies on statistical models that may not be well-suited to *describing* the information environment. Using this reasoning, Gentzkow and Shapiro (2011) make perhaps the most compelling case against the widespread existence of partisan media enclaves on the basis of their analytic approach and results. That being said, their data involves several major compromises and is now the most out of date among the reviewed data sources. Flaxman et al. (2016) is another rigorous study that utilizes the segregation construct but their findings, as they admit, provide evidence both for and against the existence of something like echo chambers. There are of course other efforts in the research literature that address or purport to address this question, but they generally resemble one of the aforementioned in terms of their strengths and weaknesses.

Conceptualizing Partisan Segregation

The extant literature should allay the fears articulated by Sunstein (2001; 2007) and Bennett and Iyengar (2008). These ideas of a media environment in which news consumers are almost entirely isolated from unfriendly viewpoints are easily falsifiable even with imperfect evidence. The more difficult question is whether some amount of selective media use, between the extremes of no diversity and complete diversity, may be problematic. For instance, research shows that partisan media use increases polarization (Garrett et al., 2014; Stroud, 2010) and may also promote belief in misinformation (Del Vicario et al., 2016; Garrett, Weeks, & Neo, 2016). If it is the case that segregation has some kind of continuous relationship with outcomes like these, then it is important to measure it continuously rather than engage in binary thinking about the existence or non-existence of echo chambers and the like.

This extends to the level of analysis. Some people can experience very segregated media environments even if the media environment, in aggregate, is not characterized by rampant segregation. There may also be partisan or other group-based differences in segregation that can be investigated. If balkanized media use is believed to be a predictor in theoretical models, it is best to measure it directly rather than surrogates like counts of sources. In the coming pages, I describe such a measure that generalizes to the individual, source, party, and society levels. Unlike its most similar predecessors, this measure also easily accommodates multi-party systems.

A Network Analytic Approach

Two-mode networks

A commonality among the reviewed studies that use network analysis in this domain is the usage of survey responses to generate network data. Survey responses of this kind — in which individuals indicate whether they use a set of media sources — are not obviously suited to network analysis. Researchers operationalize a tie between two sources as the sharing of an audience member (or for Fletcher and Nielsen (2017), audience overlap above a certain threshold). This is sensible, but effectively omits a step. The most natural operationalization of survey responses in a network format is the tie between the survey respondent and the media source, given this is the most direct extrapolation from the raw data.

Networks in which there are two types of nodes, like people and media sources, are known as two-mode networks or alternately bipartite or affiliation networks (Borgatti & Everett, 1997). That is, the network can be represented as a $n \times m$ matrix A where n is the number of survey respondents and m is the number of media sources and a_{ij} is 1 if respondent i is a viewer of source j and 0 otherwise. What these previous studies have done is use what Everett and Borgatti (2013) call the "conversion approach," taking the two-mode network and *projecting* it to a single mode, in which all the nodes are of the same type (media sources). This means what is analyzed, using this matrix representation, is $A^T A$, a symmetric $m \times m$ matrix in which the rows and columns are both sources. Analyses of these networks can also use the other projection, AA^T, which defines relations between respondents.

The alternative is directly analyzing the two-mode network. The rather serious downside of directly analyzing the two-mode network is the fact that many analytic methods make assumptions about the nodes that are untrue for two-mode networks (e.g., that all nodes could potentially be tied to one another). The concern with the conversion approach, on the other hand, is the possibility of lost information in the process of creating the network projections. And while previous work has focused on the relations between sources, there are clear theoretical reasons to care about the relations between people as well: Are groups of people, especially politically-significant groups like parties, consuming fundamentally different sets of sources? The advice of Everett and Borgatti (2013) suggests not being afraid of using the conversion approach, at least when both projections are used; between the two of them, information is not typically lost.

This study takes some steps forward in this vein. I take the conceptual contribution from Gentzkow and Shapiro (2011) and attempt to quantify segregation, which has several operationalizations in the networks literature. And unlike some previous efforts in this research area, I do this for both the sources and respondents network projections in an effort to use all the information in the data and demonstrate the usefulness of doing so.

Measuring Segregation in Networks

Before proceeding, a clarification of terms is needed. Homophily refers to the widely observed phenomenon of greater likelihood of ties among entities — usually people — with similar characteristics (e.g., race, gender, partisanship) across many social contexts (McPherson, Smith-Lovin, & Cook, 2001). As the term suggests, much research on homophily either assumes or explicitly investigates preferential attachment. In other words, homophily as typically understood implies a tie formation process in which the decision to form a tie (or maintain existing ties) is influenced by the similarity between nodes. There is a clear conceptual link to selective exposure in this regard, but it should be noted that homophily contains elements of both selective approach and selective avoidance (in the terms of Garrett, 2009a). The other main explanation for homophily (other than spuriousness) is social influence, in which it is not the tie formation process that causes entities to be similar to one another but instead the fact of being tied causes conformity within the network.

For conceptual clarity, I follow the lead of Bojanowski and Corten (2014) and focus instead on *segregation*. In terms of the empirical strategy for observational network analysis, there is no meaningful distinction between homophily and segregation. But to emphasize the goal of description — knowing the process by which partisans become segregated is not required for measuring whether and how segregated they are — I will generally avoid using the term homophily going forward due to the way the term is usually understood to imply a particular causal process (see also Henry, Mitsche, & Prałat, 2016 for a similar distinction). Whether audiences sort along partisan lines because of partisanship or some other reason is not as important as establishing whether and how much they have sorted for the goals of this study. The term segregation better fits this framework, in that it more clearly connotes both the descriptive goal and the potential consequences of isolation.

Although there are a number of different measures of segregation, designed for different purposes and with different properties, I will focus on just one. It is the spectral segregation index (SSI; Echenique & Fryer, 2007), which was derived with racial segregation in mind. It is highly correlated with the isolation index (White, 1986) used by Gentzkow and Shapiro (2011) and is correlated to varying degrees with other commonly used measures. The SSI has several desirable properties for this research question. In addition to being suited to network data in general, it can accommodate the weighted edges expected in the projections of two-mode network data. Furthermore, the measure can be applied at the node, group, and network levels, providing a means to describe the media environment overall, the groups within it, and the distribution of segregation at the person level. Furthermore, it does not require dichotomous categories, permitting multiple parties and/or a non-partisan category. No other measure of segregation has this combination of attributes (see Bojanowski & Corten, 2014 for a listing and overview).

The quantity ranges from 0 — meaning all ties are between, rather than within, groups — to 1, except in exceptional cases in which it can exceed 1 (especially at the individual level as I will show later). The number roughly corresponds to the proportion of links that bind same-group members, making it important to bear in mind the size of the relevant group since the largest groups have the greatest likelihood of having within-group ties even in the absence of any preference or influence. Another property of the SSI worth mentioning is, in addition to considering whether a tie is between same-group members, the measure incorporates the level of segregation of the nodes who are tied. For example, if Person A is a Democrat and so are persons

B and C, the effect of adding B and C to A's network may not be equivalent. If B is very segregated and C is not, then the connection to B would increase A's SSI more than a connection to C. Doing so makes full use of the interdependence inherent in networks and empirically taps into what the notion of echo chambers is about.

Methods[1]

Data

Survey data come from the first wave of Pew Research Center's (2017) American Trends Panel, which began collecting data in March 2014. The panel wave used for this study occurred between March 9th, 2014 and April 29th, 2014 for Pew Research Center by Abt SRBI. Panelists were recruited via random digit dialing (RDD) surveys of landline and cell phone users in the United States. Those who agreed to participate and were internet users took the survey online while non-users of the internet could choose between computer-assisted telephone interviews and mail formats. In all, 3,308 respondents completed the wave that is the basis of this study.[2] The

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[1] Code and data to reproduce analyses are available at https://osf.io/dvfwt/?view_only=1c050304d2e24fc8bfd65f6facba9f54. Those materials are blinded and so can be reviewed anonymously. I cannot distribute Pew's data, but it can be obtained easily through their website. The OSF repository contains the processed data so reproducibility is possible.

[2] Reporting a response rate for such a complex design is not straightforward. The response rate for the RDD recruitment survey was 10.6% (yielding 10,004 responses). Among those contacted in the recruitment survey, 54.4% (N = 5,339) agreed at that time to participate in the American Trends Panel. Finally, 62.0% of those who agreed to participate completed this wave of data collection.

target population for the sample was non-institutionalized residents of the United States who are 18 years old or older. Although Pew provides weights to allow for statistical estimates to better resemble the population, they are not used in this study due to the lack of research into how to incorporate these into network analysis.

Participants had the following age distribution: 15.3% were between 18 and 29, 27.6% between 30 and 49, 32.6% were between 50 and 64, and 24.5% older than 65. 50.5% of participants described themselves as female. 77.4% were white and not Hispanic, 7.8% were black and not Hispanic, 7.7% were Hispanic of any race, and 6.0% were another race. 51.1% are college graduates. Those who identify as or lean towards Democrats make up 50.2% of the sample, Republicans/Republican leaners 42.0%, and those with no partisanship or leaning 7.8%

Measures

The key portion of the questionnaire implements a variation of the so-called "program list technique" (Dilliplane, Goldman, & Mutz, 2013), in which respondents are presented with a series of media sources in list format. In this questionnaire, respondents were first asked whether they had heard of each source, regardless of whether they ever used the source. Afterward, a similarly formatted follow-up, including only the sources the respondent had heard of, asked to indicate which the respondent "got news from about government and politics in the past week." Some of these sources were television stations: ABC, NBC, CBS, PBS, FOX News, MSNBC, and CNN. If respondents selected any of these TV channels, they were allowed to select individual programs from these stations in a follow-up question.

The measure is imperfect (Prior, 2013), but is the state of the discipline in self-reported media use, largely thanks to its simplicity that does not require respondents to make cognitively difficult estimates of media use frequency. This survey offered 66 relevant sources[3], which were a mixture of television programs, websites, newspapers, and radio shows. Rather than use a data-driven procedure to decide whether the sources were partisan — in which the partisanship of sources is determined based on its audience — categorizations from Long, Eveland, and Slater (2019) and Dilliplane (2011) are used instead, where possible. There are three categories: Democrat-favoring, Republican-favoring, and non-partisan. Long et al. (2019) used expert ratings to categorize sources, falling back on the Dilliplane (2011) method when the ratings did not sufficiently agree. Dilliplane (2011) details this fallback method, which relies on how news articles and television transcripts refer to the sources as liberal/conservative and/or Republican/Democrat. Sources not categorized by either of the aforementioned articles were placed into a group based on the author's judgment of their fit[4]. Source classifications are included in Table 1. Respondents chose 5.49 programs on average (SD = 5.15)[5].

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[3] Google News is omitted as a source despite appearing in this list because it is a news aggregator, pointing users to external sites such as those included elsewhere on the list.

[4] The following sources were classified by the author: Buzzfeed (Democratic), Colbert Report (Democratic), The Daily Kos (Democratic), The Guardian (Democratic), Mother Jones (Democratic), The New Yorker (Democratic), Slate (Democratic), thinkprogress.org (Democratic), Breitbart (Republican), The Blaze (Republican), Al Jazeera (non-partisan), BBC (non-partisan), Bloomberg (non-partisan), Crossfire (non-partisan), New Day (non-partisan), Politico (non-partisan), The Economist (non-partisan).

[5] Respondents who chose 0 sources (N = 531) are excluded from analysis as is one respondent who selected nearly every source. They are included in the calculation of the descriptive statistics, including the mean number of media sources used.

Table 1:

Classifications of political media sources

Democratic Sources	Republican Sources	Non-partisan Sources
All In	Breitbart	20/20
Anderson Cooper 360	Drudge Report	60 Minutes
Buzzfeed	Fox and Friends	ABC World News
Colbert Report	Glenn Beck (Radio)	Al Jazeera
Daily Kos	Hannity	BBC
Ed Schultz (Radio)	Huckabee	Bloomberg
Erin Burnett Out Front	Kelly File	CBS Evening News
Good Morning America	O'Reilly Factor	CBS This Morning
Guardian	On the Record	Crossfire
Hardball with Chris Matthews	Rush Limbaugh (Radio)	Face The Nation
Huffington Post	Sean Hannity (Radio)	Frontline
Meet the Press	Special Report	NBC Nightly News
Melissa Harris-Perry	The Blaze	New Day
Morning Joe	The Five	New York Times
Mother Jones	Wall Street Journal	Nightline
New Yorker	Your World with Neil Cavuto	NPR
Politics Nation		PBS News Hour
Rachel Maddow Show		Politico
Situation Room		The Economist
Slate		This Week
Tavis Smiley		USA Today

The Daily Show	Washington Post
The Ed Show	Yahoo
The Last Word	
thinkprogress.org	
Today	

Network Description

The network is represented in two ways. These are the projections of the two-mode network, so one in which all nodes are survey respondents and another in which all nodes are media sources. In all cases, the network is treated as undirected. The projections have weighted edges; the weights represent the count of respondents who got news from both sources (for the sources projection) and the count of sources both respondents got news from (for the respondents projection).

Because the validity of the analysis of media sources is so dependent on proper categorization of the sources, I also report some analyses in which algorithmically-defined labels are used instead. That is, I use the multi-level modularity optimization algorithm (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008; recommended by Yang, Algesheimer, & Tessone, 2016) on the sources network projection and use those communities, which happen to map fairly well onto the Democrat/Republican/non-partisan human labeling scheme (see Table 2 for a summary), although it struggles somewhat to differentiate Democrat-favoring and independent sources. The list of these categorizations is included in the appendix. Recall that the algorithmic labels are not based on any information about the content of the sources, just the co-consumption patterns; the labels would not map well onto partisanship if co-consumption does not as well. This also means that these labels are likely to correspond with the maximum level of segregation possible in these data. Treating both the human and algorithmic methods as raters, the Krippendorff's α (Hayes & Krippendorff, 2007) is 0.58 when the labels are treated as nominal and 0.69 when treated as ordinal. This means there is some substantial disagreement between the two classification methods, but they are agreeing much more than would be expected by chance. If the human labels are treated as ground truth, these values can be interpreted as indicating that partisanship of source clearly promotes selection but there are also other factors at play (e.g., medium, timing, topics, format, etc.). Note that the validity of these labels does not affect the estimates of segregation for the individual respondents.

Table 2:

Cross tabulation of algorithmic and human labels of political media sources

	Algorithmic Label		
Human label	Democrat	Independent	Republican
Democrat	19	7	0
Independent	10	13	0
Republican	1	0	15

Note. Rows represent the human labeled categories and the columns represent the algorithmic categories.

Table 3: Descriptive statistics of the network representations

	Two-mode network	Sources projection	Respondent projection
# Nodes	2842	65	2777
# Edges (unweighted)	18172	2053	1868307
# Edges (weighted)	18172	169412	7227150
Diameter	5	42	3

To give a general impression of the observed network, I have plotted the sources projection in Figure 1. The visual suggests at least some segregation along partisan lines at the source level, particularly for Republican sources. There are also clearly some number of people with highly varied media diets, leading to the weak (signified by small, translucent edges) connections between some of the sources. Figure 2 is the same data with the exception of the labels, which are instead those derived from the multi-level modularity community detection method. It does seem to comport better with the data, but there are also some sources that are probably mislabeled. Of course, only so much can be learned from these visualizations, which can be interpreted quite differently depending on the arrangement of the nodes and other design decisions.

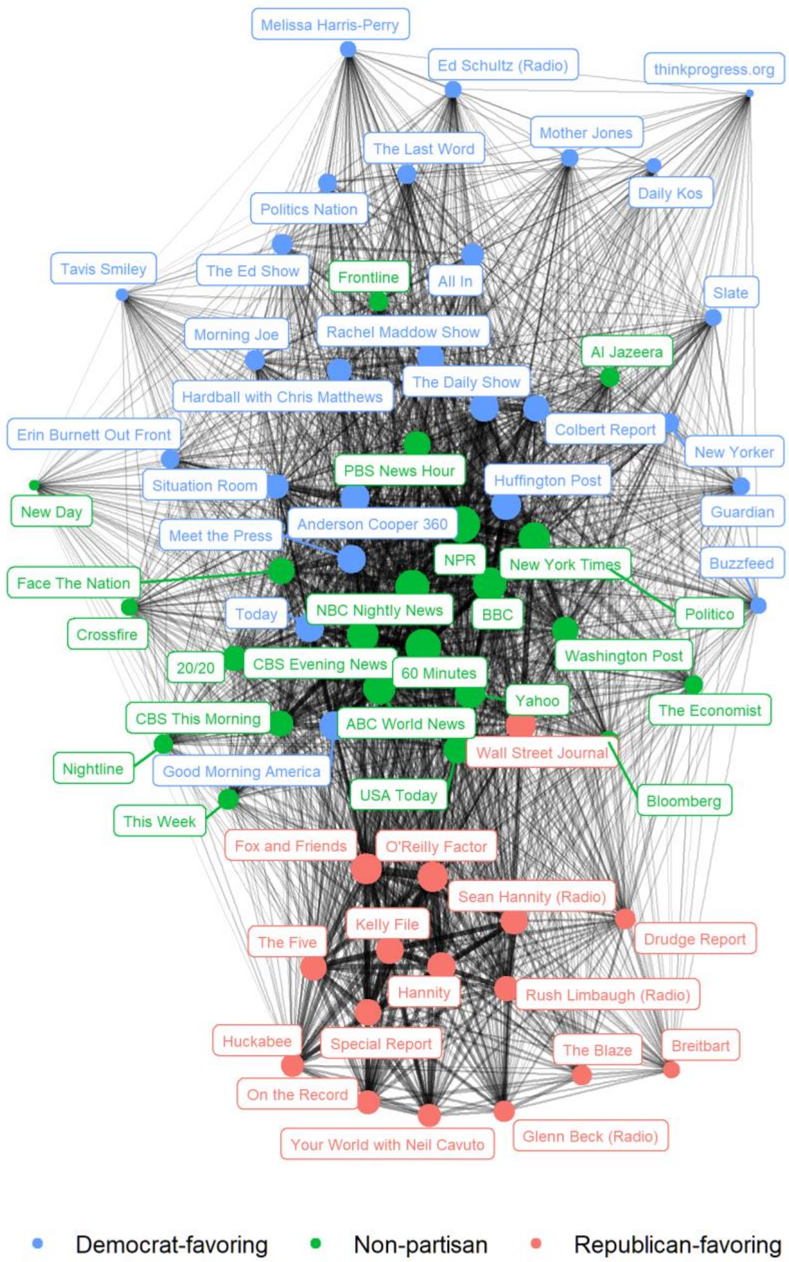

Figure 1: Sources projection labeled by partisanship. Node size is scaled by degree centrality and edges are scaled by weight.

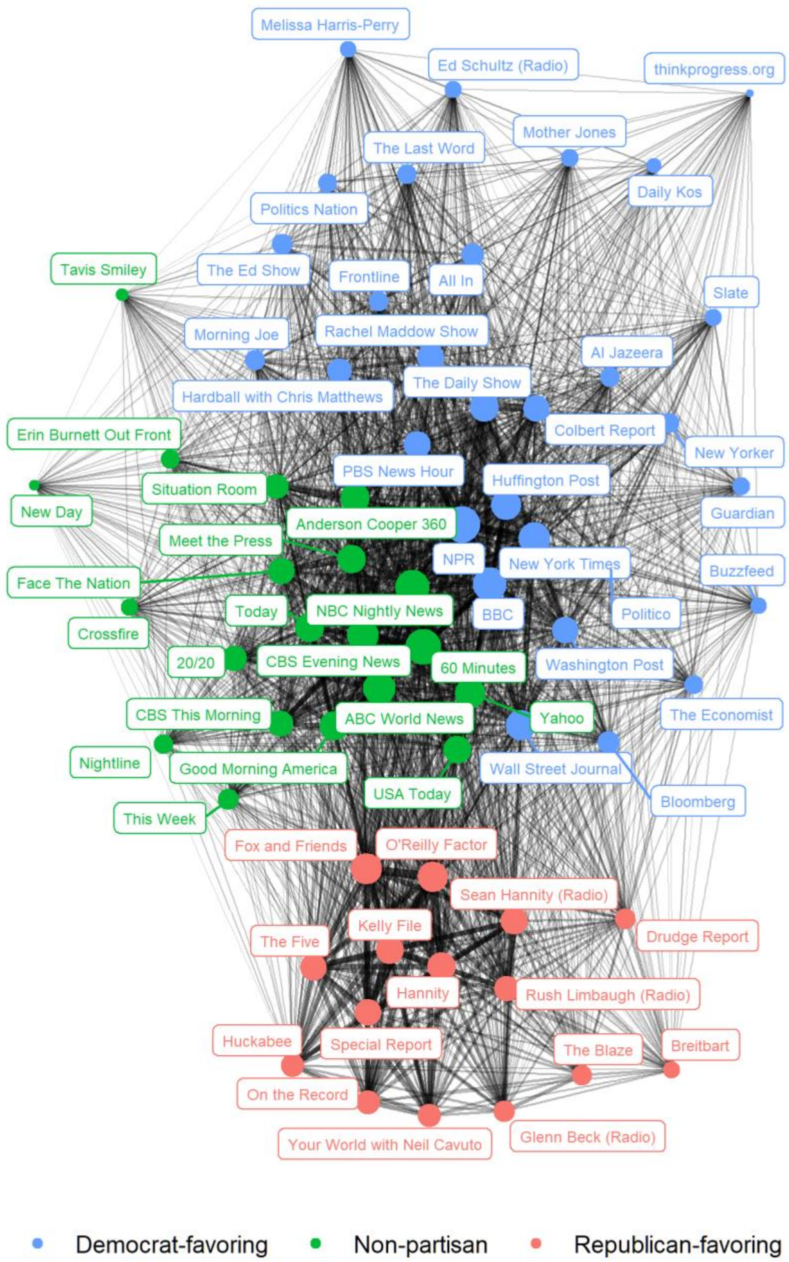

Figure 2: Sources projection labeled by algorithmic communities. Node size is scaled by degree centrality and edges are scaled by weight.

Results

To calculate the SSI, I wrote a function for R based on the one in the `isnar` R package (Bojanowski, 2018) with changes to accommodate weighted networks as well as to improve speed and memory usage with large networks. The code is included in the replication materials. The SSI generates quantities at the node, group, and network levels of analysis. Of most interest are the group- and network-levels, which are simply means of the included nodes. The SSI is not readily interpretable if computed for the two-mode network representation, so instead it is calculated for each of the projections. When comparing groups, the most useful heuristic reference point is the proportion of the sample comprised by the group. For instance, we can see in Table 3 that political independents (who make up 7% of the sample) have an SSI of .07. This suggests independents do not have media diets that are highly similar to fellow independents. The more the SSI is in excess of the group's sample proportion, the greater evidence of segregation (Echenique & Fryer, 2007).

To more formally test the extent to which these quantities demonstrate greater segregation than would be expected given the groups' sizes, I conduct 1000 simulations[6] in the vein of Echenique and Fryer (2007), who show the relationship between group size and a "null" SSI is not quite linear. For each simulation, I hold constant the number of sources each respondent

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[6] The relatively small number of simulations is due to the computational difficulty in calculating the SSI for a network that has 2777 nodes and 1868307 edges (7227150 with weights) as the respondents projection does. Calculating the SSI once for the respondents projection on a quad-core 8th generation Intel Core i7 processor with 8GB RAM can take well beyond an hour. The [blinded] supercomputer was used for these computations.

selects and the overall distribution of selections per media source. Empirically, this means each respondent's media choices are replaced with a random sample of media sources of equal size without replacement (a respondent can't choose the same source twice in the same simulation). The probability of selection for the media sources is weighted according to the sources' popularity; in other words, the most popular source (NPR) has the highest likelihood of being selected, which is about 10 times higher than the least popular source (Think Progress). The goal of this procedure is to assess the level and variability of the SSI when it is known that any segregation is purely due to chance.

Additionally, since the distributional properties of SSI are not known, I do a series of 1000 bootstrap replications to quantify the uncertainty in the SSI estimates. In this case, I simply sample survey respondents with replacement and re-run the analysis.

Table 4: Spectral segregation index measures for the respondent projection

	SSI	Null SSI	SSI - null	Reps. ≤ null
Democrats	0.63	0.50	0.13	0.00
Republicans	0.66	0.43	0.23	0.00
Independents	0.07	0.07	0.01	0.06
Network	0.61	0.44	0.17	0.00

The interpretation for the respondents and sources projections differ. For the respondents projection (see Table 4), the segregation measure is literally a reflection of the strength of ties to co-partisans compared to out-partisans. The ties are sources the respondents both got news from, so substantively the respondent-level segregation is tapping into the similarity of the media diets within parties. To be clear, segregation can be high regardless of the source content; if Democrats only used Republican sources and Republicans only used Democratic sources, they would have high segregation by this measure. If there are highly distinct patterns of media consumption within groups, this may make segregation seem low when in fact the groups are not sufficiently granular. Nevertheless, in this case there appears to be at least modest levels of segregation, with Republicans slightly more segregated than Democrats — Republicans have a higher SSI in 94.40% of bootstrap replications (M = 0.03). On the other hand, given their relative frequency in the data, Republicans are in excess of the null by quite a bit more than Democrats (M = 0.10, 100% of replications). Independents are clearly the least segregated and only barely more segregated than the point null estimate. Democrats and especially Republicans are well beyond the null level of segregation, however. At the network level, the observed level of segregation is also clearly larger than the point null estimate from the simulations.

To further explore the individual-level information, I have plotted the density of SSI values by partisan affiliation in Figure 3. This shows very little variation around the mean level of segregation for independents and more variation for Democrats, some of whom are relatively low in segregation and others with values near 1. Republicans, on the other hand, have segregation values that are distributed in an unusual way. The modal segregation value is fairly low, around 0.25, but the distribution is very wide and almost bimodal. There is a substantial group of Republicans whose SSI is just under 1.5, representing exceptional amounts of segregation. There is an approximately uniform distribution of SSI values between the two modes at around 0.25 and 1.4. This suggests Republicans as a group are by far the most internally inconsistent in their media habits. Some get news from a mixture of sources that are widely used by non-Republicans but there are many others with highly and even extremely segregated patterns of media consumption.

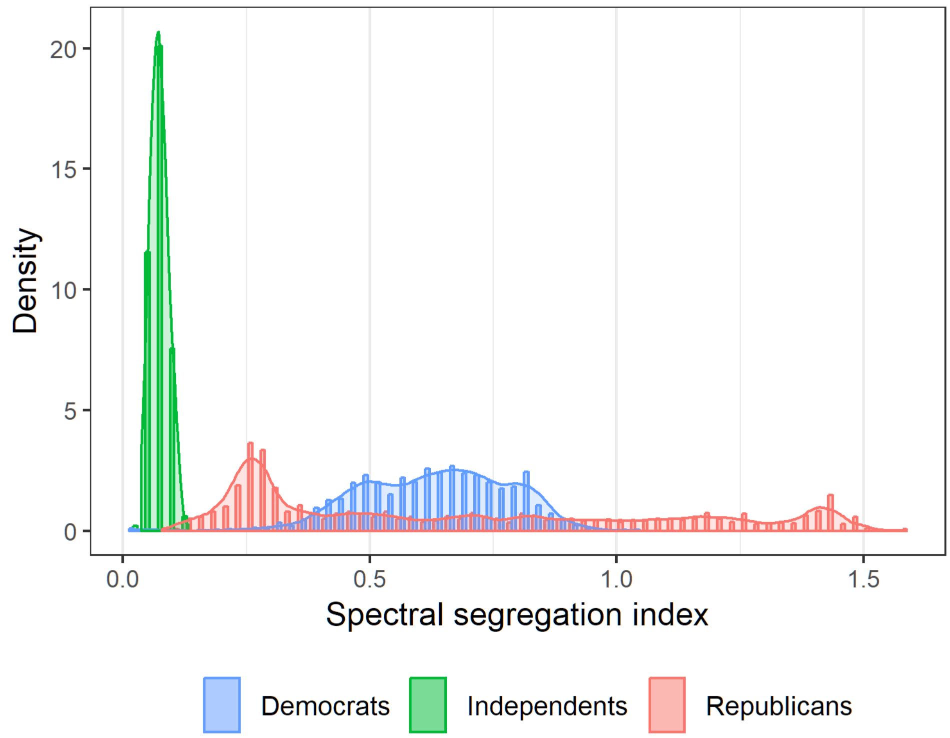

Figure 3: Distribution of segregation values by partisanship.

The sources projection tells a slightly different story. The ties in the sources projection represent sources sharing an audience member. Stronger ties represent greater audience overlap. The segregation measure, then, reflects similarity in audiences among sources of the same type. It becomes apparent (see Table 5) that Republican sources display considerable segregation. Substantively, this means the audiences of Republican sources typically consume much more Republican media than any other kind of source. What is likely being captured here, compared to the respondents projection, is how certain high-consumption respondents within each party have highly selective media diets (as with the Republican respondents who have very high SSI values).

Table 5: Spectral segregation index measures for the sources projection

	SSI	SSI (algorithmic)	Null SSI	SSI - null	Reps. ≤ null
Democrats	0.56	0.61	0.32	0.24	0
Republicans	0.66	0.65	0.36	0.29	0
Independents	0.44	0.50	0.28	0.16	0
Network	0.54	0.58	0.33	0.21	0

Discussion

Whether the level of segregation observed here is mere, harmless human nature or the sign of a problem is open for debate. The original concerns about echo chambers were envisioning a very strong form of them — one would expect almost no overlap in media usage between Democrats and Republicans. In the true echo chamber scenario, it would not take much effort to quantify segregation because one would simply look for the existence of any countervailing exposure. It is clear that this is not the norm in American politics. Perhaps there is a threshold of segregation that, once crossed, turns the influence of the political media environment from helpful or benign into one that drives democratic dysfunction. This would require careful study of how to best quantify this segregation, which this study has helped to do, and how to identify the amount of segregation that corresponds with major social problems.

If there is no threshold and segregation has a continuous type of effect on individuals, groups, and/or society, then it is important that researchers measure it and the same general tools likely apply. Future work trying to anticipate consequences of selective media consumption could use simulation, like agent-based modeling, to test how different levels of segregation are likely to affect other outcomes. By using a network analytic approach, one-to-one comparisons are possible between segregation in media use and interpersonal networks (as attempted in Gentzkow & Shapiro, 2011 with a different empirical strategy). Future researchers should bear in mind that the data demands for interpersonal networks are relatively high. For egocentric network data, the analyst needs to know the partisanship of both the alters and the alters of the alters to make the most of the SSI. Whole networks are ideal, but difficult to obtain. Applying SSI to media consumption is comparatively simple, since one needs only a diverse survey sample and a relatively comprehensive program list.

Although I have used the echo chambers hypothesis as a point of reference throughout this study, as is hopefully obvious I find it useful only because it is such a commonly understood benchmark and not because it is a gold standard. It is not difficult to see why the existence of echo chambers in their strong form would likely be harmful; it is also unlikely they come to fruition any time soon in free societies. Deriving a more realistic benchmark, or figuring out if one exists at all, is a more important goal. It is clearly true from prior research that political media consumers do not necessarily take great pains to avoid identity-discrepant information, but it remains to be determined if that discrepant information can have any impact if it is effectively drowned out by the use of identity-affirming media. A related question to be answered is whether highly segregated media use is only a problem if it becomes the norm. Perhaps a relatively small group of partisans, growing ever more extreme in their media consumption, can exert a socially meaningful effect even as most of their peers are more balanced in their exposure. This could manifest in primary elections, for example, where a small group of fairly strong partisans determine the candidate choices for the entire population. The group of Republicans with extreme values of SSI in this study may be responsible for the lay perception that partisans occupy echo chambers, since the data show that a number of Republicans clearly do.

The SSI has several uses. First, it offers a fairly intuitive interpretation and comparability with some of the other research in social domains that use the measure. Furthermore, the SSI has the considerable advantage of generalizing to multiple levels of analysis. Research that is not interested in the question addressed here — measuring partisan segregation as a goal in and of itself — can use the SSI as an individual-level predictor or dependent variable in more conventional regression-type analyses. One potential use is to explore what is going on with the subset of individuals with very high levels of segregation, who may provide a useful test case of what happens when people create balkanized media environments for themselves. As previously mentioned, research using other (perhaps social) networks can use the SSI to have a measure that is equivalent across contexts as well.

A benefit of the SSI is it generalizes fairly easily to multi-party systems. To demonstrate this, I have included a third category for both the sources and the respondents, reflecting more accurately the real variation in party affiliation, which is indeed categorical but not necessarily binary. In contrast, Gentzkow and Shapiro (2011)'s segregation measure required moderate/independent respondents to have their partisanship imputed because the measure did not sufficiently accommodate that sort of multicategorical structure. Although there is a small enough population of non-partisans in the United States to have inferences not greatly affected by this sort of adjustment, there is no option to dichotomize partisanship in many countries. Adopting the measures suggested in this study should alleviate those concerns and permit cross-national comparisons.

There are some drawbacks to this approach. First, for relatively large sample surveys like the one used as an example here, calculating the SSI for the respondents projection can be computationally intensive. To generate a null distribution like I have for comparison, high-performance computing resources will be necessary. To generate the SSI for sources, researchers must be able to label the sources, which is not always straightforward and can be labor-intensive. Using community detection algorithms may reasonably approximate human raters, although in these data the algorithm struggle somewhat in differentiating Democrat-favoring and non-partisan sources. That being said, for some research questions one can just calculate the SSI for the respondents only and ignore the sources projection. Although the SSI conceptually suits interpersonal networks quite well, it is unusual in research on political behavior for sufficiently complete network data to be collected for the SSI to be calculated. For ego networks, it would not provide more information than simpler approaches unless data on the networks of alters is also collected.

Despite some ambiguity in the meaning of the substantive results of this study, it is clear there is some level of partisan segregation in the United States. Moreover, I have laid out some statistical and conceptual principles that should be helpful as researchers continue to investigate these and related issues. Potential shortcomings of this study can be addressed without any change to the analytic procedures; for instance, data collected via digital trace data can be fashioned into a network format and the same type of measures taken. Surveys that are newer, use another list of sources, or occur in another country or countries could all add more insight.

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Appendix

Table A1:

Algorithmic classifications of political media sources

Democratic Sources	**Republican Sources**	**Non-partisan Sources**
Al Jazeera	Breitbart	20/20
All In	Drudge Report	60 Minutes
BBC	Fox and Friends	ABC World News
Bloomberg	Glenn Beck (Radio)	Anderson Cooper 360
Buzzfeed	Hannity	CBS Evening News
Colbert Report	Huckabee	CBS This Morning
Daily Kos	Kelly File	Crossfire
Ed Schultz (Radio)	O'Reilly Factor	Erin Burnett Out Front
Frontline	On the Record	Face The Nation
Guardian	Rush Limbaugh (Radio)	Good Morning America
Hardball with Chris Matthews	Sean Hannity (Radio)	Meet the Press
Huffington Post	Special Report	NBC Nightly News
Melissa Harris-Perry	The Blaze	New Day
Morning Joe	The Five	Nightline
Mother Jones	Your World with Neil Cavuto	Situation Room
New York Times		Tavis Smiley
New Yorker		This Week
NPR		Today
PBS News Hour		USA Today

Politico	Yahoo
Politics Nation	
Rachel Maddow Show	
Slate	
The Daily Show	
The Economist	
The Ed Show	
The Last Word	
thinkprogress.org	
Wall Street Journal	
Washington Post	