Comparing membership interest group networks across space and time, size, issue and industry*

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Abstract

We compare and contrast the network formation of interest groups across industry and issue area. We focus on membership interest groups, which by virtue of representing the interests of voluntary members face particular organizational and maintenance constraints. To reveal their cooperative behavior we build a network dataset based on cosigner status to United States Supreme Court amicus curiae briefs and analyze it with exponential random graph models and multidimensional scaling. Our methodological approach culminates in a clear and compact spatial representation of network similarities and differences. We find that while many of the same factors shape membership networks, religious, labor, and political organizations do not share the same structure as each other or as the business, civic and professional groups.

Keywords: *interest groups, membership organizations, coalition strategies, amicus curiae briefs, exponential random graph models, multidimensional scaling*

That interest groups coordinate to pursue shared political objectives—thereby forming coalitional networks—is hardly surprising. Furthermore, that interest groups often do so within their industry and issue area has been well documented (e.g., Berry (1977), Berry & Wilcox (1989), Schlozman & Tierney (1986), Hula (1995), Hojnacki (1998), and Whitford (2003)). Networks allow interest groups to share resources, disseminate information, and signal broad support (Mayhew, 1974; Kingdon, 1981; Holyoke, 2003; Esterling, 2004; Mahoney, 2004). However, little is known about how interest groups structure their relationships. For instance, do all interest groups value the same attributes in their partners? And to what extent are the structures of networks in one industry similar to those in another?

 In this study, we focus on *membership* interest group networks. Because these advocacy groups are comprised of voluntary members they face additional

organizational constraints that are likely to impact the formation of their coalitions. A networks perspective on membership interest groups motivates more micro-level considerations of the structure and composition of their coalitions. The division of labor across industries varies as might the collaborative appeal of different interest group qualities within each industry. Thus an explanation of membership networks naturally gives way to more specific questions about which organizations are the most attractive partners; that is, which group characteristics are sought out as complements and which are considered threatening to cooperation. Most pointedly for this paper, we consider whether the answers to these questions differ across industries.

To do so we build a network dataset based on membership groups' cosigning behavior on United States Supreme Court amicus curiae briefs. Among the desirable characteristics of our data is its comprehensiveness, capturing all groups active in the first 10 years of the millennium. This rich data allows us for the first time to compare and contrast variance in network structure not only across coalitions but entire industries. Thus we build on previous work that endeavored to compare seemingly diverse networks "across space and time" (Faust & Skvoretz, 2002).

In what follows, we extend existing methods to compare membership group networks. We begin by discussing the particular organizational and maintenance concerns of membership groups with respect to interest groups at large, before exploring the basic network structures of groups in different industries. We then move to a more comprehensive process of comparison that takes place in two stages. First, we estimate exponential random graph models (ERGMs) for each of the industry-based membership networks. Next we conduct a multidimensional scaling analysis on the models' parameters to gauge the relative similarity across the networks and place them in spatial dimensions. We conclude with a discussion of the implications for understanding interest group networks and how they operate in the US's representative democracy.

1 Membership association networks

While much of the early literature on networks predominantly concerned a single network, studies of interest groups have long recognized the different kinds of interest group communities and the different organizational constraints faced by them (e.g., Olson (1971) and Walker (1983)). We are particularly interested in membership associations because of their unique role in American politics. These groups are a central component in the system of representation because they are accountable for policy output to their members (Walker, 1983). While all interest groups have policy goals by definition, membership associations also have to devote time and resources to group formation and maintenance (Salisbury, 1969; Olson, 1971; Moe, 1981; Walker, 1983). They need to demonstrate policy change (or at least be a participant in the voice for more informal social change) and simultaneously maintain contact with their members (i.e., recruit them and keep them enrolled) as well as their patrons (which may be the same or different from the membership depending on the group).

Membership groups stand in contrast with business establishments and industrial groups that do not depend on voluntary membership. As such, the activities of

membership groups are especially costly and critical to their success. Walker (1983, 391) contrasts the "personal trade-offs facing prospective group members and the larger social dilemma over the provision of public goods" as a core aspect of membership associations. However, as Walker also points out, there is a dearth of comprehensive empirical work and instead the literature is primarily descriptive, focusing on "the history of a single group, or more often, with small clusters of groups in a single policy area." Despite more recent and insightful understandings of membership associations (see Cook 1984; Hansen 1985; Leighley 1996), this is still true of most of the interest group literature. By examining all membership groups that participated in the amicus curiae process from 2000–2009, we provide a more comprehensive perspective.

Why organizations, and membership organizations in particular, form and how they stay in existence has been an important question in American politics (Truman, 1951; Edelman, 1964; Salisbury, 1969; Wilson, 1973; Olson, 1971). Their ability to survive and the variation in strategies is tied to broad questions of how groups work with other groups, that is, coalitional politics. The more complicated roles and duties of membership groups make them a particularly interesting focus for studies of coalitional behavior since they have more than the ordinary amount of organizational pressure and greater incentives to demonstrate political returns for their membership. Such may motivate these groups to cooperate—that is, to share resources and signal support—in different ways depending on the type of association and their goals. Therefore, we should expect to see differences in how membership organizations' coalitions are structured. It is not hard to imagine that business membership groups could have a more centralized or top-down structure than labor groups, or vice versa, perhaps. Similarly, we might expect civic/social membership groups to be more likely to cooperate with other civic/social groups based on different characteristics than those that bring political groups to work with one another. To these ends, we compare the factors that contribute to the formation of membership networks and the resulting structure of these networks across industries.

In examining the coalition formation of membership interest groups, we engage a general theory of homophily. That is, are interest groups like *birds of a feather*, joining forces with similarly equipped groups in their industry? Do common socio-economic characteristics, like size or profit, make groups more attractive partners? In line with prevailing views of homophily in various networks (see, e.g., McPherson et al. (2001), Wimmer & Lewis (2010), Lewis et al. (2008), Bearman et al. (2004), and Powell et al. (2005)), we expect assortative mixing based on the interest group's characteristics. However, we note that the alternative is equally plausible. Perhaps membership groups are more likely to seek out resources that they do not have in their partners, leading to heterogeneous coalitions. Indeed, if the principle of homophily were to fail within the vast array of interest group coalitions, it should be among membership groups who face the greatest resource demands in balancing membership and policy concerns. We shed light on why networks are likely to form between these groups by testing the likelihood that socio-economic attributes are more or less predictive of coalition formation in different industry and issue areas. Ultimately, then, our goal is to provide a simple picture of how coalition strategies of membership interest groups resemble or differ from one another across industries and issue areas.

2 Comparing and contrasting networks

To examine our questions about network similarity, we use a novel measure of coalitional networks from interest group activity on amicus curiae or "Friend of the Court" briefs. Specifically, our measure of interest group coalitions is based on cosigner status to United States Supreme Court amicus curiae briefs from 1930 to 2009 (Box-Steffensmeier & Christenson, 2014). Briefs before the United States Supreme Court may be submitted in support of the petitioner, respondent, or in some cases neither. Importantly, cosigners coordinate the content and signatories.[1]

A large percentage of amicus briefs come from interest groups attempting to affect a case outcome (Collins, 2008). Collins (2004) and Wasby (1995) argue that groups may join amicus briefs specifically to build and maintain relationships with similar groups. Thus ties between interest groups based on cosigner status provide a measure of purposive, coordinated action ideally suited to examine questions about network similarity.[2] The dataset is the only purposive and coordinated measure of interest group networks that we are aware of that also captures the virtually complete population of interest groups across industry areas and time. It is not based on surveys, samples, or indirect linkages, and has been used to examine the relative power of interest group networks on judicial decisions (Box-Steffensmeier et al., 2013b), the progress of bills through the legislative process (Box-Steffensmeier et al., 2013a) and the duration of executive nominations (Box-Steffensmeier et al., 2013d).[3]

The data in this paper are limited to the first decade of the 21st century for which a range of covariates, or interest group attributes, are available to test our primary concerns of whether socio-economic factors contribute to the likelihood that interest groups form coalitions with each other. The covariates were gathered using business and lobbyist directories, including Associations Unlimited (Gale, 2010) and the Million Dollar (D&B, 2010) databases.[4]

From them, we use the Standard Industrial Classification (SIC) codes to categorize different interest group networks based on industry and issue areas. The SIC codes are based on the principal end product of the firm and classify economic as well as public interest activities.

SIC codes denote firm categorizations down to four levels. When the last digit of the code is removed, the organizations are aggregated into broader, but similar groups (Fertuck, 1975; Grier et al., 1994, 1990, 1991). The highest level is that of SIC Divisions. There are ten divisions, which includes headings such as, Agriculture,

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[1] The term "cosigners" is sometimes used to distinguish the individual or group that initiated the brief from others that signed onto it. We use the term here to refer to everyone on the brief (see also Gibson (1997)).

[2] Our research also complements the work of Koger & Victor (2009), LaPira et al. (2009), and Scott (2007) who similarly study interest group networks, but with alternative measures of those networks based on campaign finance and the Lobbying Disclosure Act (LDA) data.

[3] Heaney (2014) defines influential interest groups by leveraging network analysis while (Heaney & Lorenz, 2013) investigates interest groups that join multiple coalitions, both in the domain of health care policy.

[4] The interest group characteristics data come primarily from Gale's Associations Unlimited (Gale, 2010) and Dun and Bradstreet's Million Dollar (D&B, 2010) databases for interest group characteristics. Information that was missing from both databases was subsequently searched for in Lexis-Nexis Reference USA, by a Google web search and finally directly by phone and/or email correspondence when contact information could be found (see Box-Steffensmeier & Christenson 2014).
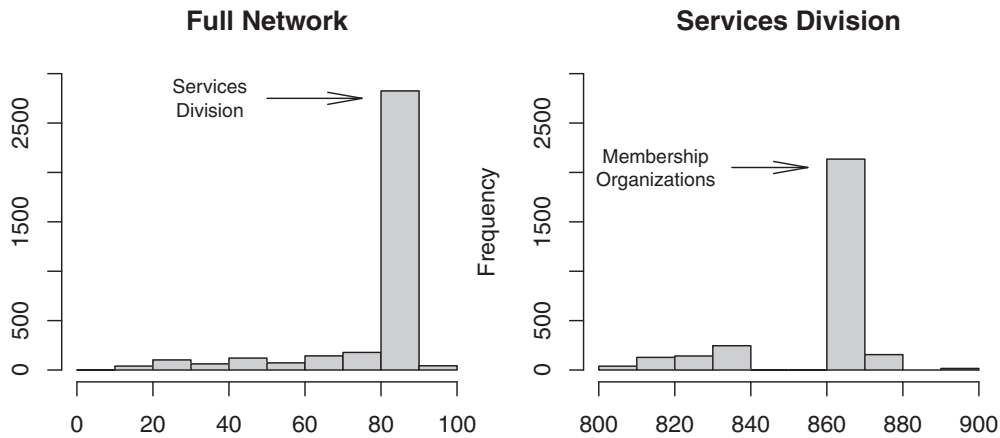
Fig. 1. Interest group network composition, 2000–2009.

Mining, Construction, Manufacturing, and Services. Within the Divisions, there are ninety-nine Major Groups. For example, one of the Major Groups is Membership Organizations under the Service Division. Figure 1 shows that service organizations, category values with SIC numbers from 70–89, are the primary categorization in the full interest group network. When moving to the three-digit level in Service, as shown in the right side of Figure 1, membership associations dominate, which begin with 86 as the SIC number.

Looking within the Major Group of Membership Organizations, three-digit codes indicate seven Industry Groups for Membership Associations: Business, Professional, Labor Unions, Civic, Political, Religious, and finally Unclassified. We use these seven divisions to compare and contrast interest group networks. The four-digit codes within each of these seven detail the type of groups included. Within Business Associations, there are Better Business Bureaus, Real Estate Boards, Trade Associations, and Chambers of Commerce. The definition is membership organizations that engaged in promoting the business interests of their members. Professional Associations include Bar, Medical, and Engineering Associations that are organized for the advancement of the interest of their profession. Labor Unions are organized for the improvement of wages and working conditions and include Trade Unions, local or national, and other collective bargaining units. Civic Associations include Alumni Associations, Community Membership Clubs, and Veteran's Organizations. The Political Organizations are established to promote the interest of national, state, or local political parties or candidates and include Political Action Committees (PACs), Political Campaign Organizations, and Political Fundraising. Religious Organizations are defined as those operating for worship, religious training or study, administration of an organized religion, or for promotion of religious activities and include churches, convents, and shrines. The Unclassified Associations include Art Councils, Athletic Councils, Farm Bureaus, and Humane Societies.[5]

Figure 2 presents the network structures of the seven Industry Groups for Membership Associations independently, as well as the network of the combined set

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[5] See the Occupational Safety and Health Administration (OSHA), United States Department of Labor for more details at http://www.osha.gov/pls/imis/sic_manual.html.
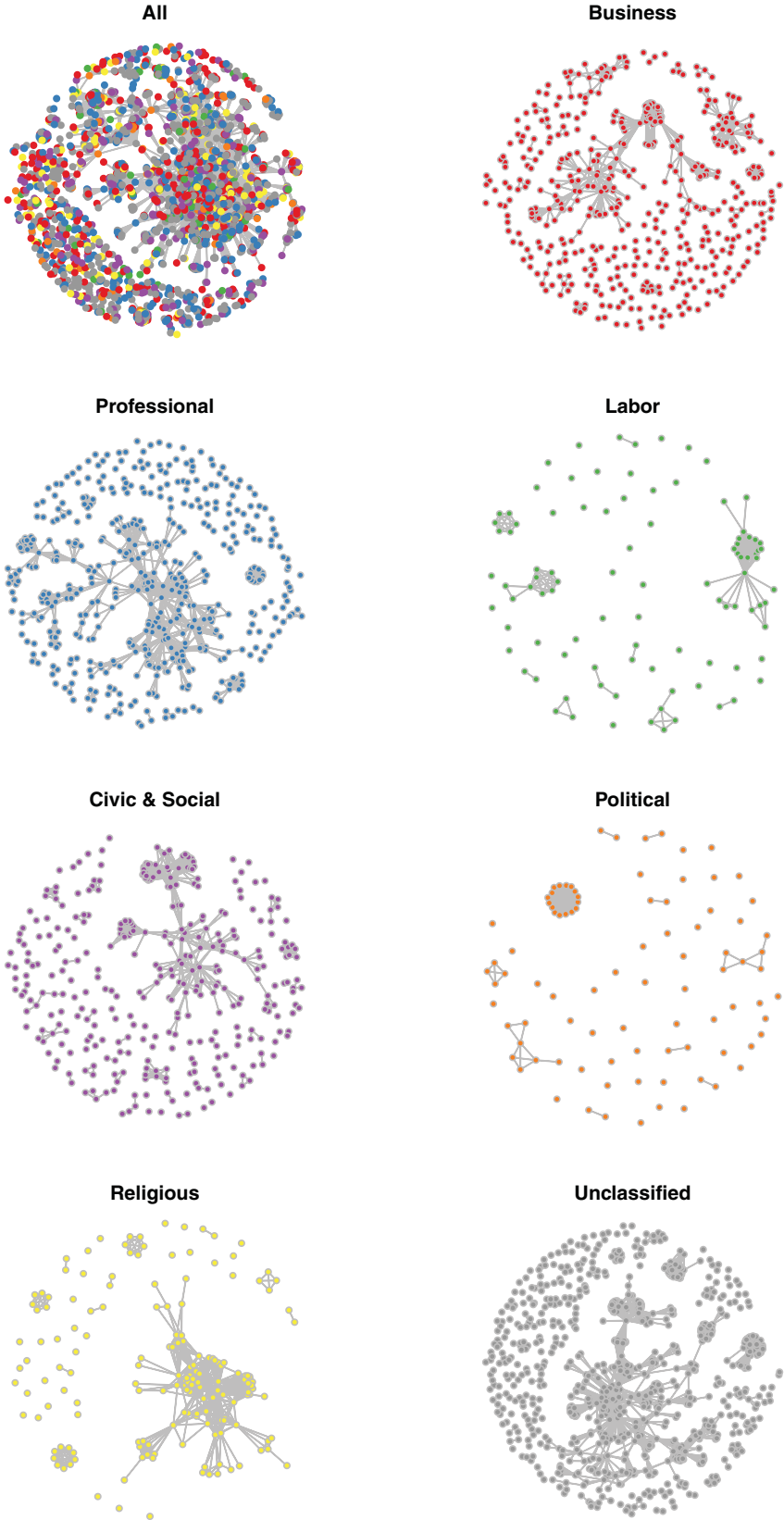
All

Business

Professional

Labor

Civic & Social

Political

Religious

Unclassified

Fig. 2. Membership association interest group networks. (Color online)

Table 1. *Network statistics for membership interest groups networks.*

	SIC	Vertices	Edges	Density	Transitivity	Centralization	Isolate ratio
All membership	86	2610	15818	0.008	0.715	0.063	0.129
Business	861	504	1893	0.027	0.850	0.151	0.260
Professional	862	526	1520	0.019	0.689	0.104	0.241
Labor	863	96	179	0.101	0.897	0.281	0.375
Civic	864	358	806	0.025	0.768	0.173	0.285
Political	865	90	149	0.151	0.991	0.199	0.500
Religious	866	169	734	0.079	0.699	0.345	0.189
Unclassified	869	867	4010	0.017	0.776	0.087	0.198

of membership groups. For the distinct membership group network plots here—as well as for the analyses below—we subset all of the organizations by their primary membership group and allow all intra-group ties. That is, the grouping is mutually exclusive and any cross-group ties are discarded. Although a number of options for defining the subnetworks exist, defining them this way brings us closest to our objective of comparing the network structures across industries. The Fruchterman and Reingold algorithm used to plot the networks places connected nodes closer to each other. While some differences appear to exist in the structure of the networks— for example, the tight grouping of high density players in the political and religious networks or the abundance of isolates in the former—such visual tests are too subjective to be of much use in networks of this size.

Faust & Skvoretz (2002, 273) define similarity as two networks that "exhibit the same structural tendencies, to the same degree." As such, basic network statistics offer some leverage in quantifying and comparing the topology or shape of different networks. Indeed, Bhadra et al. (2009, 48) argue that very simple network properties are the most useful for between-system comparisons since they "help us to study the dynamics of complex systems and to make predictions about the behavior of such systems and their components." Thus we begin our analyses by looking at the density, transitivity, centralization, and the isolate ratio for the membership association networks.[6]

As a point of comparison, Table 1, row 1, provides the network structure properties for the full network of membership interest groups in 21st century. The subsequent

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[6] We use a one mode projection of the data for substantive and theoretical reasons, though we recognize that alternative approaches would also be interesting to explore, including valued-regression, if we collapsed in time and projected while keeping the edge weights, or bipartite regression, if we collapsed over time, but did not project (Wang et al., 2009), or tERGMs if we projected, but did not collapse over time (Cranmer & Desmarais, 2011), or used clustering coefficients in two-mode networks (Opsahl, 2013). Furthermore, we have chosen to only link those interest groups that have signed the same brief. Alternative approaches might link all interest groups that sign a brief in the same direction (i.e., for respondent or petitioner or neither), or consider positive and negative ties that are defined by being on opposite sides of a case. Both approaches would create denser networks based on both issue area and ideological direction; however neither would signify any sort of coordinated action on the part of the signers, which we find unsatisfactory. Coordinated action is central to our beliefs about interest group networks, because it denotes a deliberate link between organizations. While interest groups undoubtedly interact broadly, an interest group network based on amicus briefs suggests, at a minimum, a regular contact, or a "weak tie" (Carpenter et al., 1998; Box-Steffensmeier & Christenson, 2014).

rows break the network apart by industry as classified by the SIC code. The measures of density, transitivity, centralization, and isolate ratio help describe the network.[7] The density of the network is the number of edges divided by the number of possible edges in the graph. In substantive terms, we may think about density as the connectedness of the entire network of interest groups. The density measure for the full network is a low score of 0.008, which suggests that many of the interest groups are not connected to as many of the others as they could be. That is, membership interest groups do not coordinate with all stake holders. Instead of many weak ties, the network appears comprised largely of factions. Contrarily, the Political membership associations are the most connected (after removing the isolates). They have the highest density measure of 0.151. Labor associations are second with 0.101. While professional and unclassified associations have the lowest density at 0.019 and 0.017, which is still higher than that of the full network.

A measure of clique, or transitivity, moves us to considerations of indirect relationships. It calculates the extent to which two interest groups that are indirectly linked by a third interest group, are also directly linked themselves.[8] This is almost always the case in the interest group networks, which has an overall transitivity value of 0.715. It appears that in membership interest group networks being a *friend of a friend* also means *you are a friend*. Among the subnetworks, political associations have the highest value. The measure of transitivity for political associations is 0.991. Labor are second with 0.897, followed closely by business associations at 0.85. The lowest value is for professional associations with 0.689.

The general centralization score provides an average value of the centrality of all the interest groups in the network. More formally, it is the difference between the maximum and mean node centrality score conditional on the number of nodes. Here the centrality scores for most of the interest groups are quite similar, resulting in a low centralization index for the total network of 0.063. Religious associations have the highest value for centralization with 0.345 and labor the second with 0.281. The lowest values are again for unclassified and professional organizations.

The isolates ratio provides a measure of groups in the industry that do not collaborate. Political groups have the highest isolate ratio of 0.5 followed by labor with 0.375. Religious and unclassified groups have the lowest isolate ratios of 0.189 and 0.198, respectively. While the literature on membership groups has generally considered isolates as anomalies, this table makes it clear that there is important variation in these organizations across the industries.[9]

Figure 3 provides further analysis of the centrality by plotting the range of eigenvector centrality scores for each interest group in the network as a histogram, excluding isolates. Eigenvector centrality complements the earlier descriptive measures by showing the importance of each interest group in the network relative to the

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[7] The isolates are included in the number of vertices but removed from the network when calculating the other statistics as these may be overly responsive to their presence. Their removal may better capture the coalition formation in the core of the network. In practice, the statistics and histogram presented later did not vary much regardless of the exclusion of the isolates.

[8] Transitivity is a triadic, algebraic structural constraint. In its weak form, the transitive constraint corresponds to *a* is a friend of *b* and *b* is a friend of *c*, then *a* is a friend of *c* (see Wasserman & Faust (1994)).

[9] Prakash & Gugerty (2010, 19) collective action approach towards membership coalitions provides a useful theoretical backdrop to consider this more fully in future research.
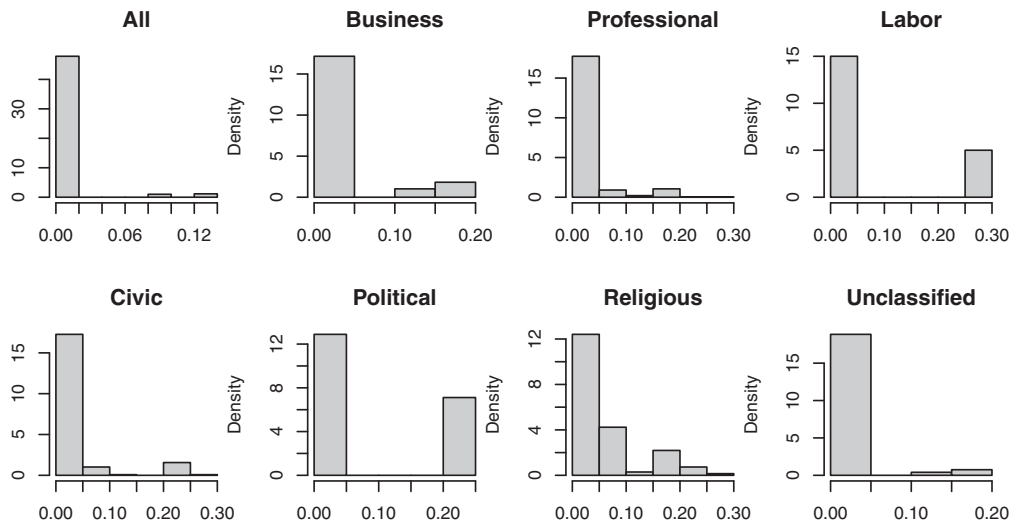
Fig. 3. Eigenvector centrality histograms for membership interest group networks.

connectedness of its neighbors (Wasserman & Faust, 1994). For all the subnetworks, and especially the full set of membership groups, the bulk of interest groups have low degree centralities. Thus most interest groups in both the full membership network as well as the industry specific subnetworks are not well connected to other high centrality groups. Contrarily, we see a large positive skew with a long tail of increasingly central groups for the religious subnetwork. Religious associations exhibit a *rich get richer* pattern: as centrality or influence in the network increases the number of groups with it decreases gradually.

The other apparent commonality across the subnetworks is a bimodal distribution. The business, labor, civic, political and unclassified networks all have their largest portion of groups with low centrality, very few to almost none in the middle range, but a great deal more with higher eigenvector centralities. That is, a few interest groups in each of these subnetworks are immensely more influential than the rest of the groups in their respective networks.

3 Exponential random graph models

Our goal is to shed light on why networks are likely to form among particular interest groups. While the descriptive statistics above demonstrate some similarities and differences, a stochastic approach offered by ERGMs provides a more detailed comparison of the factors that impact network formation for the membership association networks. ERGMs are particularly useful for interpreting the effect of substantive covariates, of primary concern to social scientists, on network formation because they explicitly model non-independence and can include structural parameters to account for dependence among ties. That is, we expect some assortative mixing of interest groups based on interest group characteristics as well as structure. We therefore include both graph-theoretic and interest group characteristics in the ERGMs.

The graph-theoretic characteristics model the structural effects of the network. Our model focuses on a couple of basic and commonly used graph-theoretic measures,

Table 2. *Summary statistics.*

Variable	Mean	Std. Dev.	Min.	Max.	N
Budget	1.08e + 07	3.01e + 07	0	4.50e + 08	671
Employees	579	8,381	1	276,886	1,283
Sales	3.41e + 07	5.60e + 08	0	1.67e + 10	1,340
Founding year	1,957	38	1,620	2,009	1,946
Members	252,646	3,379,117	5	1.00e + 08	1,074
Office/plant size	19,675	52,336	0	900,000	1,447

which have been shown to capture the full interest group network (Box-Steffensmeier & Christenson, 2014). Edges is a count of the number of edges in the network that assesses whether interest groups are connected and the density of the entire network. We also include an isolates term to account for interest groups that are not connected.

To capture the more complicated dependencies we rely on two geometrically weighted parameters introduced by Snijders et al. (2006) and amended by Hunter & Handcock (2006): GWD and GWDSP. Together these terms help to model the degree distribution and transitivity in complex networks. The GWD accounts for the decreasing degree distribution, while GWDSP models the number of dyads with shared partners. Thus the latter models the natural clustering in our network where dyads share multiple partners.[10]

The interest group characteristics are the substantive explanatory variables that may explain the formation of the network. Table 2 list descriptive statistics for the covariates in the full model. These covariates are typical characteristics reported by associations and business organizations. They tap the relative strengths and weaknesses of organizations' most common resources and organizational considerations.

The *number of employees* reflects the general size of the interest group as does *number of members*. The latter is more likely to be reliable for membership associations, which we focus on here. We test whether groups of the same size are more likely to work with each other, showing a united front of groups of similar resource strength. If large groups are more likely to work with small groups, it suggests a leadership strategy, such that small groups might independently follow the lead of bigger groups. The *office/plant size* captures the size of the facility in square feet. The *Year Founded* of the group simply captures how long the group has lasted. Older, more established groups may be more likely to serve as a connector and be more attractive coalitional partners. Of course, size and longevity are likely to be dependent (Hannan & Freeman, 1977, 1984; Baum, 1996).[11] The group's *budget* and *annual sales* taps into the group's resources. Similarly, size and budget are expected to be related (Baum & Mezias, 1992; Baum & Singh, 1994b,a; Greve, 1999; McPherson, 1983). Finally, the full model includes *Industry* to capture shared interests. Specifically, we use the SIC code at the three-digit level to specify the industrial focus of the interest groups.

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[10] We also attempted modeling the networks with geometrically weighted edgewise shared partnerships (GWESP) at different decay values along with combinations of the other covariates, which largely resulted in degeneracy.

[11] The organizational ecology literature provides a rich backdrop for the substantive characteristics (e.g., Hannan & Freeman 1977 and Hannan & Freeman 1989).

3.1 Explaining network formation

We begin by using ERGMs to compare and contrast the membership networks (see, e.g., Johnson et al. (2012)) and then extend it by using Mahalanobis distance and multidimensional scaling to provide a simplified spatial comparison of them. Table 3 presents the results of the ERGM estimation for the full membership network and the seven Industry Groups included under Membership Associations.[12] The interpretation of the model coefficients is similar to that of logit models; when a parameter estimate is positive (negative), the probability of a link between two interest groups is larger (smaller) than the probability they are unlinked (linked), conditional on all other parameters in the model. All interest group attributes are coded categorically and result in a uniform homophily statistic when the respective attribute is shared by two edges.

The information criterions, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), can be compared with lower values demonstrating an increase in model fit. While the information criterions have been shown to be consistent with model fit, because the appropriate sample size is unknown and because the observations are not independent and identically distributed, they are still lacking (Hunter & Handcock, 2006). In addition, our desire to compare these networks and thus maintain the same model across subtypes impacts these values.[13]

Before comparing the membership networks, we note that there is one additional covariate for the model of the full network, *Industry*, which accounts for the field (SIC classification) of the group. This factor is not needed for the industry subnetworks as they are divided by this variable and therefore uniform within each network. *Industry* is positive and statistically significant in the full network model, which indicates that interest groups working in the same industry also influence the formation of the larger network. Along with descriptive statistics and referenced literatures above, this finding validates the distinctions in industry area and subsequent industry-based network analyses. Moreover, the full membership network ERGM serves as a comparative baseline for the subnetworks.

The graph-theoretic properties are extremely important for explaining network formation, as expected. Almost all of the parameters are statistically significant across the models and quite powerful in terms of the information criterions.[14] The

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[12] We conducted the ERGMs with the `statnet` package in `R`.

[13] We arrived at the final model specification both by comparing information criteria (AIC and BIC for nested models) as well as visual inspections of goodness of fit tests for over 300 specifications. That is, the ERGMs allow us to apply likelihood-based inference on the formation of relatively large networks such that it is possible to consider how well the model fits the observed data (Hunter et al., 2008; Goodreau et al., 2009). Contrary to most papers that utilize ERGMs, our objective is not simply to find the best fitting model for each network but to find a model that balances theoretical motivations for including substantive parameters with graph theoretic parameters and does so across seven different networks. Such is a nontrivial task and necessarily means that the model fit will vary across the networks. Thus we sought a model specification that performed well enough for all of the networks, even when that sometimes meant it did not do as well as a different specification for a single network. This involved trying combinations of a host of terms, as well as a range of values for the α on the geometrically weighted terms, beginning with $\alpha = 0.1$ and increasing until the log-likelihood stops improving (Goodreau et al., 2008).

[14] While the distribution of the ratio of the estimate to its standard error is not known, the literature uses the approximate t-distribution (Robins et al., 2007a; Snijders & Van Duijn, 2002). In addition, a one-sided test is appropriate for some higher order parameters, re: 1.65 times the standard error at the 5% level (Robins et al., 2007b).

Table 3. Exponential random graph model (ERGM) results.

				Networks				
	All (1)	Business (2)	Professional (3)	Labor (4)	Civic (5)	Political (6)	Religious (7)	Unclassified (8)
Edges	1.392***	2.325***	3.587***	8.749***	4.745***	45.536***	3.245***	2.296***
	(0.030)	(0.110)	(0.131)	(1.092)	(0.251)	(7.521)	(0.171)	(0.068)
GW DSP ($\alpha = 1.5$)	−0.148***	−0.194***	−0.240***	−0.584***	−0.322***	−3.219***	−0.242***	−0.213***
	(0.001)	(0.006)	(0.006)	(0.055)	(0.012)	(0.534)	(0.009)	(0.003)
GW Degree ($\alpha = 1.75$)	−8.139***	−5.485***	−6.684***	−7.658***	−6.350***	−26.489***	−5.205***	−5.916***
	(0.050)	(0.094)	(0.120)	(0.679)	(0.169)	(4.090)	(0.182)	(0.070)
Isolates	−2.163***	−0.273**	−0.610***	0.181	−0.350**	−0.538	−0.286	−0.552***
	(0.091)	(0.137)	(0.152)	(0.385)	(0.161)	(0.638)	(0.279)	(0.114)
Budget	−0.262***	−0.207***	−0.211***	−0.176	−0.526***	−0.028	−0.263**	−0.497***
	(0.022)	(0.077)	(0.076)	(0.377)	(0.107)	(0.452)	(0.111)	(0.053)
Employees	0.050**	−0.099	−0.012	0.619**	0.099	−0.121	0.291**	0.066
	(0.024)	(0.082)	(0.079)	(0.310)	(0.109)	(0.441)	(0.118)	(0.055)
Sales	−0.250***	−0.077	0.075	−0.051	−0.105	0.031	−0.693***	−0.164**
	(0.028)	(0.090)	(0.092)	(0.350)	(0.134)	(0.525)	(0.143)	(0.066)
Founding Year	0.051**	0.101	−0.068	0.699**	0.113	0.106	−0.108	0.337***
	(0.021)	(0.075)	(0.068)	(0.273)	(0.098)	(0.422)	(0.113)	(0.048)
Members	0.060*	0.375***	0.163**	0.672**	0.037	0.198	0.178	0.077
	(0.023)	(0.079)	(0.080)	(0.333)	(0.108)	(0.454)	(0.116)	(0.054)
Plant/Office Size	0.070**	0.194**	0.113	0.106	0.276**	0.886*	0.283**	0.043
	(0.028)	(0.090)	(0.087)	(0.338)	(0.112)	(0.483)	(0.141)	(0.064)
Industry (SIC)	0.658***							
	(0.021)							
Akaike Inf. Crit.	94,717	7,768	9,303	546	4,361	260	2,999	17,679
Bayesian Inf. Crit.	94,857	7,865	9,401	610	4,452	323	3,074	17,788

Note: * p < 0.1; ** p < 0.05; *** p < 0.01

positive edges parameter, which link the groups in this non-directed network, tells us that ties are common. For our non-directed network, an isolate is defined to be any node with degree zero. The isolates term captures the network structure by accounting for groups that do not cosign. The isolates term is negative and statistically significant for some of the groups. In looking across the models for patterns, political groups are quite unique. When we look graphically, we see that they are a relatively simple and small network primarily built of isolates with one tightly connected team within the graph (see Figure 2). The graph theoretic parameters do a particularly good job explaining the network formation of political associations.

The more complicated dependencies are captured by the global structural terms, geometrically weighted degree (GWD) and geometrically weighted dyadwise shared partnerships (GWDSP). Recall that these terms help capture the degree distribution and clustering. The models contain α decay parameters fixed at 1.5 and 1.75 for GWDSP and GWD, respectively. Both terms are negative and statistically significant for all models. A negative and statistically significant coefficient for a geometric term indicates that that the distribution of degree and dyadwise shared partnerships (DSP) in the observed network leads to the likelihood of a tie that is less than would happen by chance (see, e.g., Harris (2014)).

In addition, several of the interest group covariates appear statistically significant, in the expected direction, and consistent across most of the different membership associations. Interest groups with a large number of members, a larger number of employees and founded long ago are more likely to be linked to groups that also have a large number of members, a large number of employees, and were founded long ago. Business, professional, and labor groups are more likely to form a network with groups that are similar in membership size. Labor and religious groups are more likely to form a network with groups that employ a similar number of people. Labor and unclassified groups are more likely to form networks that were founded around the same time. This indicates that there is not a level playing field. However, most groups work with others that have differential budgets and sales. That is, large budget groups form networks with small budget groups.

Structurally, the full network and membership association subnetworks have several similarities. We see statistical significance across most of the structural network terms. The groups that stand out the most from this perspective are political, and labor associations. In particular, there is not much explanatory power for the isolate terms in the ERGMs after accounting for global structural characteristics for political, labor, and religious associations as the network is well explained without them. Likewise, political networks appear less dependent on the socio-economic covariates. A relatively small number of groups identify themselves as political and we would argue that all of the membership groups have a political orientation to impact policy. Of those that are categorized as political (by the SIC), they have a unique network structure.[15]

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[15] Political and labor groups are also the most likely to benefit from estimation with the frailty ERGM, a recent modeling innovation that incorporates a frailty term into the ERGM to account for unobserved heterogeneity, since they are likely to be impacted the most by ideology, which is unmeasurable for such a large number of organizations (Box-Steffensmeier et al., 2013c).

Compared to the full network, business and professional networks seem the most similar as they are primarily explained by the budget and number of members. However, the size of the office/plant is important for business networks, but not for professional networks. The covariates that are most likely to impact network formation across all types of associations are the budget and plant/office size, which are obviously correlated for most groups.

Ultimately, it is difficult to generalize about which groups are the most similar and which are different by looking across so many different structural and substantive parameters. That is, how does one decide which networks are more or less similar? Looking more closely and comparing, for example, professional and civic associations, both have a similar effect for budget. In addition, employees, sales, and founding year are not statistically significant for either. However, some differences stand out. Members impact network formation for professional groups with large groups working with other large groups. There is no such effect for civic groups, yet their coalitions are impacted by plant/office size. Of course, the magnitude of structural and substantive coefficients needs to be considered as well. Thus, in order to arrive at a big picture assessment for comparing networks a methodology is needed.

We gain a more systematic and objective perspective of the similarities and differences in the interest group networks by using multidimensional scaling, principal coordinates analysis (Gower, 1966), of the ERGM results.[16] The idea is to reduce all the structural and substantive parameters in the ERGM down to a manageable set of dimensions for a clearer analysis of similarities and differences. The breakthrough of Faust & Skvoretz (2002) use of correspondence analysis is that their method for comparing networks was the first to provide an index that quantifies the degree of similarity between networks. They included information about structural parameters to calculate similarity regardless of variability in network structure. Likewise, Desmarais & Cranmer (2012) use scaling after stochastic actor-based models (SABMs) to compare inferred positions and parameter estimates. Similar to these approaches, we offer a method for summarizing what is more complex and harder to discern across several sets of coefficients.

The process is straightforward. We begin by assembling the parameter estimates from our ERGMs of the seven membership networks. The coefficients and standard errors from the ERGMs are reduced to a dissimilarity matrix via Mahalanobis distance. Then we perform classical multidimensional scaling to discern the similarity of the networks in lower dimensions.

Figure 4 presents the results of the ERGM parameter scaling in three dimensions. The unique groups are instantly clear: religious, political, and labor membership associations are all more distinct according to the factors that impact network formation, though in different ways. That is, the underlying natures of the network structures of all three appear relatively distant from all of the other groups as well as each other. On the contrary, business, professional, unclassified, and civic membership associations have more closely related coalitional structures.

There are three dimensions that align with our substantive understanding. On the political dimension, all the groups cluster to the left of the figure except for political

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[16] To carry this out, the same graph-theoretic terms are needed in all the models. This necessitates a trade-off with model fit.
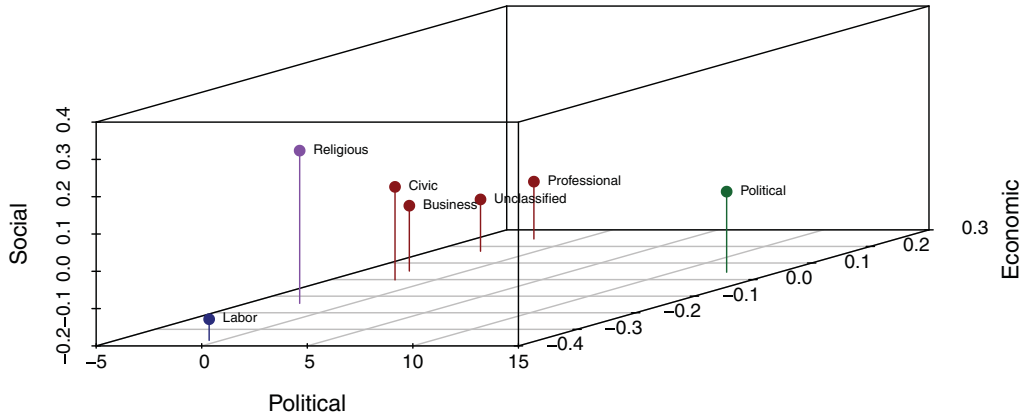
Fig. 4. Multidimensional scaling on membership interest groups. (Color online)

groups. We know that political groups are characterized as having purposive goals with an explicitly political agenda. Their unique positioning is easily seen in the figure. On the economic dimension, we see substantial variance with professional and unclassified groups in the top portion of the figure. In contrast, religious and labor groups are placed nearer the bottom of the economic scale. Political, business, and civic groups make up a middle zone. This dimension captures the extent to which groups are materially driven. The works of Dunleavy (1988) and Bennett & Ramsden (2007) appear to comport with these findings, as the groups near the bottom of this dimension are more focused on pursuing non-excludable benefits. Finally, the third dimension is social. Here religious groups are the highest, followed by civic and political groups. There is a clustering of business, professional, and unclassified groups followed by labor, which is the lowest. The social dimension turns on principled or ideological beliefs versus instrumental concerns (Keck & Sikkink, 1998; Goldstein & Keohane, 1993).

What makes the four networks so similar? Andrews et al. (2010) point to distinctions in how associations are organized, the purposes for which they are organized, and the ways they exercise influence as factors to consider when making comparisons. It may be that business, professional, civic, and unclassified associations are more broadly involved in politics. That is, the focus on achieving a potentially broader range of policy goals is the primary motivation for formation of each of these four groups. These groups are more likely to have a highly centralized decision making structure and to have the work done by hired employees. In addition, the membership often does not choose the leaders or decide policy (Knoke, 1994; Smith, 2000; Wilson, 1973). Baumgartner et al. (2009) point out, for example, the wide array of issues that civic associations are called upon to become involved in.

In contrast, the religious and political associations in particular are more likely to have narrow or even a single issue focus. They tend to focus on positional issues, which include topics such as abortion or gun control. Indeed there are single-issue groups focusing on these topics under political groups and others under religious groups. That is, the positional topic foci overlap these two categories, which may make the networks for religious and political groups outliers from the others, yet

they are structured differently from each other as well. These findings are consistent with Grossmann (2013) who finds issue domain differences in governing networks.

According to Andrews et al. (2010) criteria, civic and religious membership associations are unique (see also Skocpol et al. 2000). Religious associations often have explicit policy goals that are effectively achieved through politics, but the primary rationale for religious associations are decidedly not political, but rather religiously based. A similar argument, but to a lesser extent, applies to civic groups, which is the closest association to religious groups shown in the figure. Considering motivations centered around shared moral values rather than instrumental gains (Risse, 2010), religious, political, and to a lesser extent civic associations again stand out from the others. When considering how membership associations are organized, specifically by considering whether the leadership is hierarchical (Lecy et al., 2010), religious, political, and civic associations are the least hierarchical, perhaps due to a greater need than other associations to appeal to grassroot members.

4 Discussion

Substantively, this paper builds upon the important work of Lowery (2007) and Whitford (2003) which pushes scholars to examine communities—or networks—of interest groups. We address recent calls to investigate network ties among advocacy organizations engaged in collaborative relationships (Gugerty & Prakash, 2010, 306), and to exploit more comprehensive data to understand similarities and differences in subpopulations of interest groups (Gray & Lowery, 1996). In the broadest sense, this work moves from the focus of much of the literature—concerned with either a single interest group or a single division of interest groups—to examining how vast coalitions and communities of interest groups function and interact across *space and time, size, issue, and industry* (see also Faust & Skvoretz 2002). In doing so, our work moves us to a better understanding of why and when interest groups coalition strategies diverge.

Membership associations are a well-suited domain for comparing and contrasting interest group network structures. They constitute the bulk of interest groups in the United States and are uniquely accountable for both policy representation and membership/organizational concerns. We find that their story is one of similarity for business, professional, civic, and unclassified membership associations, while religious, political, and labor membership associations are distinctively placed in the space created by their network structures. It is interesting that in spite of different interests, four of the groups have commonalities in the factors that impact how they are organized as a network across the three dimensions.

These four similar structures of networks suggest that even diverse industries do not necessarily employ different coalitional network strategies. The variance among the religious and political membership associations suggest instead that the objectives of the groups may be more indicative of the network structure than the issue area. Likewise, the position that groups take on an issue may also turn out to be an overstated concern when it comes to the structure of cooperative behavior that calls for additional examination.

Examining interest group communities of interest sheds light on questions of representation and insight into how different types of membership associations have

responded to the dual pressures of policy representation and membership. How structure is linked to function in networks is an important subsequent topic (Bhadra et al., 2009). For example, Krebs (2002) points out how changes in the shape of the network led to major changes in the functioning of terrorist networks. Our analysis here has aimed to shed light on how different interest groups make use of cooperation within their own industry and on various issues. Another important step for future research is to connect the illuminated variance in network structures here to relevant political outcomes.

Methodologically, we provide an extension for comparing network structures by using ERGMs, Mahalanobis distance, and multidimensional scaling as a way to provide simpler spatial comparisons. Rather than having to compare the statistical significance, sign, and magnitude of parameters across structural and substantive coefficients, our approach culminates in a clear and compact representation of similarities and differences that we expect to be useful for a variety of networks.

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