



The evolution and formation of amicus curiae networks

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ABSTRACT

This paper sheds light on two age-old questions of interest group behavior: how have interest group coalition strategies changed over time and which factors determine whether interest groups work together? Through the creation of a new network measure of interest group coalitions based on cosigner status to United States Supreme Court amicus curiae briefs, we illuminate the central players and overall characteristics of this dynamic network from 1930 to 2009. We present evidence of an increasingly transitive network resembling a host of tightly grouped factions and leadership hub organizations employing mixed coalition strategies. We also model the attribute homophily and structure of the present-day network. We find assortative mixing of interest groups based on industry area, budget, sales and membership.

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1. Introduction

Winning in front of the courts, the legislative arena, or the executive branch is not a solitary act. While interest groups use a variety of techniques to exert influence, coalition strategies are the dominant lobbying technique. That is, interest groups do not work alone. However, how they have worked together over the years and which factors bring them to work together today are less clear.

Interest group coalitions, in particular, are often used to pursue strategic goals at reduced costs, shape public debate by influencing a broader platform, gather information, and receive symbolic benefits (Hula, 1999). Thus it is necessary to understand interest groups as part of a network and the relationships among them. In this paper, we examine a comprehensive interest group network (perhaps the most comprehensive to date) over the last 80 years and what leads to coalitions among the gamut of today's active interest groups.

We make three primary contributions to the study of interest group coalitions. Foremost, we present and utilize a purposive and coordinated measure of interest group coalitions based on cosigning amicus curiae before the Court. The amicus network has a number of desirable properties. It occurs naturally in the function of government activity. Our data is not based on surveys, samples, incidental links or contrived settings, but culled from the actual, purposive and coordinated work of interest groups in front of the Court. It also comes close to a complete network of the population of interest, with an increasing probability of capturing the full

population given longer time spans due to the assumption that interest groups which often work together will eventually sign the same brief. Furthermore, the data we have gathered are longitudinal, which is of fundamental merit for future work on the evolution of complex social networks (Burt, 2000; Christakis and Fowler, 2007; Marsden, 1990; Robins, 1987; Borgatti, 2011).²

Second, we achieve a unique perspective on interest groups by applying network theory and methods. A network perspective provides a lens where the attributes of individuals are no more important than the relationships and ties with other actors in the network. This theoretical perspective is particularly apt for the study of interest groups. After all, the relative strength of interest groups is directly tied to their relationships. Rather than by solitary action, interest groups benefit and suffer by virtue of their ties. For example, network theory suggests that more open networks (weak ties and connections) result in a higher probability of introducing new ideas and opportunities (Granovetter, 1973). Understanding the existence and density of brokers within networks, which serve

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² We supplement our quantitative analyses with a sample of interest group leader interviews selected by network position. That is, we chose groups based on a range of network measures to ensure that groups held various positions in the networks. Our interviews reveal that substantial negotiation and coordination is often required when signing a brief as the details need to be agreed upon by all parties (personal communication, November 2010). The interviews address the work involved in preparing joint and independent briefs, the factors that lead them to work with others, and how they view their position in the networks. Similarly, Heaney (2004) uses original data obtained by interviews and finds that alliance formation is encouraged by previous network interaction, contact with mutual third parties, and having a central position in a network. In addition, he shows how interest groups manage their brokerage roles as dispersed actors in a decentralized system, rather than as central mediators that intervene in a wide range of policy disputes (Heaney, 2006).

as the bridges that fill structural holes, is useful in further characterizing and distinguishing interest group coalitions.

Finally, we use recent innovations in network methods to study the evolution of amicus curiae networks and the factors that lead to their formation. Our analysis has two major components. The first looks at the evolution of the network and node characteristics from 1930 to 2010. The second uses an exponential random graph model to estimate the effects of interest group characteristics (e.g., firm size and annual profits) on network formation from 2000 to 2009, while also estimating parameters that provide a structural description of the network (Hoff et al., 2002; Handcock et al., 2007; Krivitsky et al., 2009).

2. Interest group coalitions

Classic works in the interest group literature have sought to understand why interest group coalitions form. A discussion of resources initiates most scholarly work on this topic. That is, scholars maintain that coalitions serve as an economical and efficient means to form a more powerful bloc (e.g., Berry, 1977; Berry and Wilcox, 1989; Schlozman and Tierney, 1986; Hula, 1995; Hojnacki, 1998; Wasserman, 2003). Hojnacki's (1998) theory of strategic coalition formation summarizes the factors influencing coalition formation as perceived strength of the opposition, previous experience in a coalition, whether the group is pivotal or critical to the success of the coalition.³ Coalitions thus signal broad support to policy makers on an issue (Mayhew, 1974; Kingdon, 1981; Esterling, 2004; Mahoney, 2004).

Social network theory also suggests that alliances form out of the pursuit for access to resources and information (Gilsing et al., 2008). That is, coalitions function as 'pipelines' through which information and knowledge flow. The incentive for interest groups to form networks appears to be similar to that of firms: to share information and to diffuse information more quickly or to enhance the efficiency of cooperation (Teece, 1986; Wasserman, 2003; Gilsing, 2005; Gilsing et al., 2008). In addition, there are control benefits, such as sanctions, reputation, and trust. The social network literature discusses the positive effects of networks on group performance, growth (Powell et al., 1996), speed of innovation (Hagedoom, 1993), organizational learning (Hamel, 1991), and reputation (Stuart, 1998).

Bacheller (1977) emphasizes the importance of both group characteristics and relationships for a complete understanding of the role of interest groups. The interest group literature provides an extensive and thorough examination of individual group characteristics. In spite of strong interest in group relationships (e.g., Heinz et al., 1993; Carpenter et al., 1998a), heretofore, there has not been much empirical work on group relationships. Whitford (2003, p. 46) states that "as recent studies suggest, the network aspects of group coordination – the specific interconnections between groups – may be as important as whether participation occurs at all." Our work brings renewed focus on the interconnections between groups.

Various network measures for interest group coalitions serve to effectively capture group relationships and have great potential to provide substantive insights. Our network characteristic measures may be useful to reexamine important questions previously assessed only with survey data and interviews, which

are the common approaches in the current interest groups literature. For example, Heaney's (2004) analysis showed no statistically significant effect of resource levels on leadership position within coalitions. Our measures of network centrality could be used, arguably as a more objective measures, of leadership position to reexamine this hypothesis. In addition, our measures will be available over longer time spans and across a host of policy areas.

Network hypotheses often focus on the location of groups in the network. If a group has a high measure of centrality they hold a brokerage position between groups. Central interest groups are better informed and more attractive network partners. Network density provides other interesting hypotheses to examine as well (Granovetter, 1973; Clark, 1988; Carpenter et al., 1998b; Burt, 2001). For example, Coleman's (1988) theory states that network closure creates trust in a social structure and secures information flows. Teasing out how different interest groups vary on basic network measures is therefore among the many interesting questions motivated by network theory that have not yet been addressed in the study of interest groups. The amici network data introduced here will be useful to interest group and judicial scholars, as well as those studying Congress and the Presidency.

3. A coordinated and purposive network measure

In Supreme Court cases, various parties with related interests submit briefs to the Court in favor of the petitioner, respondent, or in some cases, neither. Cosigners on amicus curiae briefs coordinate the content of the briefs and signatories.⁴ A large percentage of amicus briefs come from interest groups (see Collins, 2008). We explore the use of this coordinated action as a measure of interest group networks. We argue that amicus curiae cosigning provides a better measure of interest group networks than the existent, yet nascent, literature.⁵

Using coalitions formed by the interest groups themselves when signing onto an amicus curiae brief, we arrive at purposive, coordinated actions by the interest groups better suited for our analyses.⁶ Our interviews with interest group leaders reveal that substantial negotiation and coordination is often required when signing a brief, as the details need to be agreed upon by all parties (personal communication, November 2010).⁷ This comports with (Wasby, 1995) who conveys that groups may not pursue coalitional activities because they can fail to reach consensus and often believe that they are ineffective or will have detrimental effects on their

⁴ 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).

⁵ The earliest papers found that approximately 50% of interest groups indicated in surveys that they have participated in writing amicus briefs when asked about activity in the last two years (e.g., Solberg and Waltenburg, 2006; Scheppele and Walker, 1991). Schlozman and Tierney (1986) ask interest groups about litigation or otherwise using the Courts and reported that over 70% of groups did so. Kearney and Merrill (2000) find that the number is closer to 80% and Almeida (2004) finds 76%. Wasserman (2003) argues that because judicial strategies are high cost efforts, coalitions are optimal strategies, and concludes that the 80% seems reasonable. Our comprehensive list of amicus cosigners will allow us to get as reliable measure as possible because we can compare it to databases of interest groups. We can also track the number of groups participating in the process over time.

⁶ While it is arguable whether the coalitions that are observed on the amicus curiae briefs are specific to those court cases, interviews with leaders in the interest groups emphasize that the amicus curiae coalitions are indicative of coalitions forged to act on issues across different policymaking venues. That is, if they reach agreement on a brief, they are likely to find similar common ground when working on issues in the legislative or executive realms. Regardless, this point is not critical to our current work as we study the amicus networks and their interaction with the judicial system.

⁷ We selected the groups to interview based on their network position. That is, we wanted to get groups that scored both high and low on network measures to ensure that groups held various network positions.

³ Some interest coalition formation literature distinguishes types of interest groups, arguing that different types of interest groups are more or less likely to join coalitions (Clark and Wilson, 1961; Caldeira and Wright, 1990). This suggests that one should account for the type of interest group, such as whether it is a trade association, citizen group, or union, though Mahoney (2004) did not find this distinction to be statistically significant in her recent work. We are able to reexamine this question since we include Standard Industrial Classification (SIC) codes.

reputation. Caldeira and Wright (1988) argue that participation in *amicus curiae* is costly, while others emphasize the efficiency of filing briefs as a coalition (Hojnacki, 1997; Clark, 2004). *Amicus curiae* participation, whether or not it is considered a “low cost” activity, indicates the position of the interest group.⁸ Groups are unlikely to take it lightly when deciding whether to sign the brief, because it is a public expression of the opinion of the group and an indication of the network of groups that share some overlapping opinions. Indeed, Clark (2004) and Wasby (1995) argue that groups may join *amicus* briefs specifically to build and maintain relationships with similar groups.⁹

Whitford (2003) explicitly argues for the use of network analysis to analyze *amicus* networks. Our research also builds on the work of Koger and Victor (2009), LaPira et al. (2009) and Scott (2007) who similarly study interest group networks, but with alternative measures of those networks.¹⁰ LaPira et al. (2009) are one of the first to map interest groups. They use the Lobbying Disclosure Act (LDA) data to measure interest group networks as joined by issue areas, such that groups are linked if they work on the same general topic. They identify which policy areas are highly central to the overall network structure and show that central and peripheral policy domains are populated by different types of lobbyists: policy generalists versus specialists. A drawback of this work for our purposes is that interest groups are being mixed whether they are for or against an issue and whether or not there was coordinated action. One would expect that there are areas where the sides are not equally distributed in terms of resources and networking, and this is muddled in network measures based on the LDA.

Using campaign finance data to build interest group networks gets at direction better. Koger and Victor's (2009) innovative work focuses on the links between members of Congress and interest groups, where interest groups are considered to be in the same network if they gave a contribution to the same member of Congress. However, groups can be associated almost by accident as there is not likely to be coordination for almost all of the contributions. In addition, groups are crossing issue areas in these network measures. That is, groups are in a network because both gave a contribution to a particular member, but the first group may do so because of interest in *issue A* whereas another group may contribute because of interest in *issue B*. Finally, even though we may expect interest groups to primarily lobby their friends in Congress (Hall and Miller, 2008; Box-Steffensmeier and Dow, 1992; Box-Steffensmeier and Lin, 1997), two independent interest groups might contribute campaign donations to the same legislator on the same issue, but be contributing to move the member in opposing directions.¹¹ While the donation data provides more detail in terms of interest group networks, it still lacks the direction we desire. In

short, given that alliance behavior is the result of groups' strategic choices, assuming coordinated behavior based on these similarities is not the best measure.¹²

The names of the interest groups that sign *amicus* briefs are needed to map the network. We have collected that data from 1930 to the present.¹³ While there are valuable judicial data sets that have addressed *amicus* briefs, such as Gibson (1997) (1953–1993) and Collins (2008) (1946–1995), neither have all the names of *amicus* brief signatories. Gibson (1997) samples from the list of signatories when there are more than ten. Using that data would result in an incomplete network map and measures. In addition, the longer time span allows an analysis of network evolution. 1930 was chosen as the start date due to the rise of *amicus* filings (Krislov, 1963; McLauchlan, 2005). Specifically, McLauchlan states that “Despite the long history of *amicus* in English Courts, their use in the Supreme Court of the United States was rare until the 1930s when organized interests began to sponsor *amicus* briefs” (McLauchlan, 2005, p. 4).

We invoke both automated and manual coding in the collection and preparation of the various data sets. For the network lists, we rely on the Spaeth (1953) data set to cull a complete list of United States Supreme Court cases formally decided on the merits by the Court with a full or per curiam opinion since 1950, thereby excluding any case decided at the certiorari stage (see also Gibson, 1997).¹⁴ The relevant cases and *amicus* briefs were found on Lexis-Nexis from 2009 to 1979 and double-checked with the US Supreme Court Records and Briefs; all of the older cases are found with the US Supreme Court Records and Briefs. While most of the cases were found online, some cases necessitated coders using microfiche.¹⁵ Coders retrieve both the complete list of organization signatories and the direction of the *amicus* brief.

We broadly define an interest group as any organization that at any time has an interest in political outcomes. Following Gibson, we include all non-individual and non-state organizations in our data (Gibson, 1997). While individual lobbyists may exist among the individual signatories, the primary concern of this project is interest group networks; therefore we have less interest in individual signers.¹⁶ We have also collected data on the characteristics of the interest groups from 2000 to 2009.¹⁷ Using business and

¹² We plan to compare and contrast our measure to the two alternatives in the literature across the same time periods and policy areas.

¹³ Kawai and Iida (2011) examine whether having cross-cutting brokerage positions across different types of groups has an impact on the success of the *amicus* for patent cases.

¹⁴ While *amicus* briefs serve as a cue at the certiorari state, it is rare. Since it is rare, there is less coalitional activity. There are fewer briefs and less cosigners. In addition, we have found that the great majority of *amicus* briefs are usually filed at both stages. Our work follows Collins (2008) on this point.

¹⁵ The undergraduate coding was overlapped so that any evidence of intercoder unreliability would be apparent. We also had a coordinator and supervisor who randomly checked each spreadsheet. In addition, random samples of automated coding for cases without “et al.” abbreviations was compared to the hand coded cases.

¹⁶ The *amicus curiae* network and related variables provide a valuable data set in its own right, but will also be useful as an amendment to currently available interest group, judicial, and legislative data sets. By maintaining unique Court case identifiers, the interest group network data can be merged with the Spaeth (1953), Gibson (1997), and Collins (2008) data sets. By maintaining unique lobbyist group identifiers, we will also make the data ready for mergers with important datasets such as the Lobbying Disclosure Act (LDA) data, Open Secrets collections (2009) (1980–2010), and Baumgartner et al.'s (2009) Lobbying and Public Policy Project data set.

¹⁷ We are missing less than 3.5% of the interest group characteristics data. In order to be listed in the Gale Associations Unlimited database, an organization must be related to a national interest. Less than 2% of the organizations on the list created from the *amicus curiae* signatories appear to be regional or local. For example, Oregon Rural Action focuses on regional issues within the state of Oregon, so it is not listed in the Gale Associations Database. The website for the organization does not include much of the information required by our research nor did emails or phone

⁸ We thank a reviewer for pointing out that it may be that cosigning a brief may not be a costly activity, but a cheaper method of sharing overlapping interests.

⁹ At the federal level, we did not find evidence of groups creating smaller groups just for the purpose of submitting *amicus curiae* briefs in either the quantitative or interview data, as the larger group would risk losing credibility. Somewhat related, there are examples of groups, such as the NAACP, that have formed a legal defense fund to file briefs, which has to do with their 501c status and this appears to occur more at the state level.

¹⁰ Scott's (2007) work, which identifies interest group coalitions via archived websites and interviews, is particularly appealing because he tries to identify all players in a coalition. However, this is unrealistic for all networks, due to many coalitions not being reported in the press or recorded on the participating group's website (e.g., Mayer, 2007; Cummings, 2008). In addition, interviews are difficult to use due to the passage of time and the difficulty of collecting full network information across all possible issues. Most work on interest group coalitions use surveys about specific issues given a specific period of time, however, this makes generalizing to broader networks difficult. In contrast, our measure has the advantage of being more comprehensive across time and policy areas.

¹¹ This may occur the most for moderates on the issue or members cross pressured by ideology or constituency groups.

lobbyist directories, Gale (2010) and D and B (2010), we gather a host of related information on interest groups, including, but not limited to Standard Industrial Classification (SIC) code, year established, ownership, number of employees, total sales and plant size.

4. Network analysis

This paper focuses on three empirical analyses of amicus curiae networks. We begin by looking at the basic network and node properties of interest groups from 1930 to 2009. We then offer three theoretically ideal coalition strategies, and explore the extent to which the network and various interest groups resemble each of them. We conclude with the use of exponential random graph models (ERGM) to estimate the effects of interest group and network structural characteristics on the formation of the network from 2000 to 2009.

4.1. Network centrality

Who are the key opinion leaders and influentials among interest groups? Where does influence flow? Who are the “connectors” (those who connect the unconnected in the network) and the “mavens” (who are sought out for knowledge)? Ultimately, wherein this vast network lies the power? We argue that the network of amicus curiae cosigners provides insight into the dominant players and coalition strategies at work in the U.S. political system. To tease out these players and strategies, we begin by exploring the inference of some basic network statistics.

Fig. 1 displays the network mapping of all interest groups that have signed amicus briefs on Court per curiam or full opinions from 1930 to 2009. The nodes represent interest groups that are linked together by virtue of signing the same amicus briefs.¹⁸ While the linked groups have cosigned at least one amicus brief, the stand-alone groups have signed one or more amicus briefs without any cosigners during this period. Thus the figure illustrates that both a host of coalitions as well as various solitary actors on the periphery of the graph sent a brief to the Supreme Court. All of the interest group relationships are symmetric, or undirected, because they represent the act of cosigning an amicus curiae brief.¹⁹

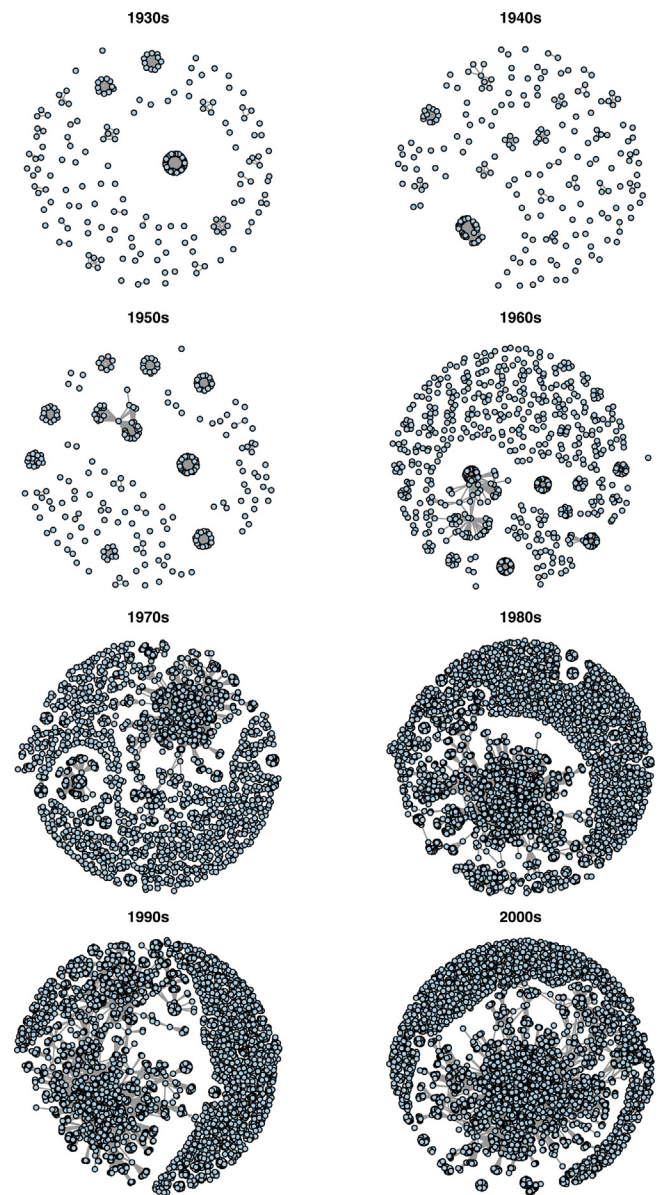


Fig. 1. Interest group networks, 1930–2009.

calls result in obtaining the information. The D & B Million Dollar Database only lists organizations or companies that gross over one million dollars in sales. Approximately 0.5% of our missing information is due to sales less than a million dollars. Finally the organization may no longer be active, so they do not have a web presence and are not found in the online databases. However, searching the older print versions did allow us to locate many more organizations. About 1% of the organizations cannot be found with web searches or in any of the databases, electronic or print, and therefore are missing.

¹⁸ The data can be built as a time-indexed bipartite network, but we are currently collapsing over time (by decade) and projecting onto interest groups for theoretical reasons, as discussed. There are alternative ways to analyze the data 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 (Hanneke and Xing, 2007; Desmarais and Cranmer, 2010). Another interesting approach is Opsahl's recent work (forthcoming), which offers new definitions and calculations for clustering coefficients in two-mode networks. The development of the options for these relatively new approaches is currently an active area of research. Examining these alternative approaches will lead to a better understanding of all facets of this large dataset, but it is beyond the scope of our current paper.

¹⁹ In this analysis, we have chosen to only link those interest groups that have signed the same brief. An alternative approach would be to link all interest groups that sign a brief in the same direction (i.e., for respondent or petitioner or neither). Or to consider positive and negative ties that are defined by being on opposite sides of a case. This would create a denser or more linked network of interest groups based on both issue area and ideological direction; however it would not signify any sort of coordinated action on the part of the signers. We do not yet analyze the additional network level that is created by all signatories who filed on the same case either. Coordinated action is central to our beliefs about interest group networks,

Table 1 provides some basic properties of the nodes across the last eight decades. Various centrality indices, particularly degree and betweenness, help characterize the extent to which any particular group plays a central role in the network (Freeman, 1979). Degree is simply the number of interest groups directly linked to any other single group in the network. Degree helps determine centrality in so far as interest groups with high degree can be thought of as being directly connected to other interest groups. High degree interest groups are well connected in that they are signatories on many amicus briefs. A high degree therefore signals key groups that bring together other groups on common issues.

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., 1998c). Despite the fact that one of the organizations is listed first as the filer of the amicus brief, to give more weight to such an organization would be inappropriate. Often times the reports are filed alphabetically or in some other manner that gives no indication as to a lead signatory (see also Gibson, 1997).

Table 1
Interest group node properties.

	Node	Mean	Std Dev	Max	Min
2000s	<i>Degree</i>	22.3	27.5	239.0	0.0
	<i>Betweenness</i>	4880.3	37670.3	1310162.0	0.0
1990s	<i>Degree</i>	35.0	53.4	404.0	0.0
	<i>Betweenness</i>	4596.8	40194.1	1338931	0.0
1980s	<i>Degree</i>	13.4	19.5	368.0	0.0
	<i>Betweenness</i>	1777.3	17810.9	901973.4	0.0
1970s	<i>Degree</i>	11.1	17.4	141.0	0.0
	<i>Betweenness</i>	574.7	4856.9	121877.8	0.0
1960s	<i>Degree</i>	8.7	13.8	61.0	0.0
	<i>Betweenness</i>	16.1	185.1	3825.7	0.0
1950s	<i>Degree</i>	8.6	8.6	30.0	0.0
	<i>Betweenness</i>	1.2	15.0	238.7	0.0
1940s	<i>Degree</i>	6.0	10.5	34.0	0.0
	<i>Betweenness</i>	0.5	1.6	14	0.0
1930s	<i>Degree</i>	7.0	11.1	31.0	0.0
	<i>Betweenness</i>	0.0	0.1	1.0	0.0

Looking at the first ten years of the 21st century, there are 5291 organizations that signed onto 3807 amicus briefs on 718 cases in this most recent subset of our data set (see the 2000s in Table 1). We see that several interest groups signed an amicus brief alone, which means the minimum degree is zero. On the other end of the spectrum, among the best linked interest groups, the National Wildlife Federation (NWF), was linked to 191 other groups and the American Civil Liberties Union (ACLU) to 239. Table 1 shows that on average, degree is 22.3, implying that over the ten year period any interest group amicus brief filer would have about 22 cosigners. Fig. 2 presents the top percentile of degree centrality interest groups in this period. Given the multiple case framework of the network, the links can be over several cases and thus repeat players are typically, but not always, those with a higher degree.

The degree generally decreases going back further in time, with the exception being the 1950s. The 1950s stand out since a host of newspaper organizations cosigned a brief arguing for the petitioner in the case of the Times-Picayune Publishing Co. v. United States, 345 U.S. 594 (1953). Our research suggests that such mass cosigning was unusual for its time in U.S. history. While the degree of cosigning has generally increased, with highs of 404 in the 1990s and 368 in the 1980s, even by today's standards such a united front in the form of a single cosigned brief is unusual. The analyses here therefore exclude the Times-Picayune Pub. Co. Vs. U.S. case of 1953.²⁰

Another way an interest group might play a central role is as a middleman between two other groups. Betweenness measures the number of times an interest group lies on the shortest path between several other groups. High betweenness interest groups are then directly along the stream of communication between other groups and thus have the ability to block the flow of information in the network. The average betweenness in the 2000s is 4880 in this network with a range from 0 to 1,310,162. Such a high average with a large range illustrates that several interest groups belong to large and intertwined networks, while others appear as a friend of the Court alone. The highest group in this measure is again the ACLU, followed closely by the National Association of Criminal Defense Lawyers (NACDL) at 1,177,660. This measure suggests that removing the NACDL or ACLU, for example, would have a disproportionately large

impact on the connections of other groups to each other. The high betweenness groups in this period revolve around various issues, including: civil rights, mental health, environment, education and technology, as shown in Fig. 3.

In the case of the over time trends, we see that connecting distinct cosigners picks up in the 1970s. The 1950s saw one group, the Japanese American Citizens League, cosign broadly on a host of briefs before the Supreme Court. Though it heavily boosted the maximum betweenness over the previous periods, it was not until two decades later that cosigning multiple briefs in a decade would become common for some of the major players. While prevalent earlier, the 1970s saw an explosion in betweenness for civil liberties, disability, and minority rights groups. Many of the groups that arise in the 1970s stay in the system and remain among the highest in betweenness throughout the subsequent decades.

4.2. Egocentric networks

While the average node centrality measures tell us a great deal about the structure of the network, we next unpack the highest centrality interest groups in the 21st century and briefly examine their respective egocentric networks. These are the key players in the network and may lend insight into the common networking practices of successful interest groups. Degree suggests that the NWF was among the most central of interest groups. Betweenness suggests that the NACDL was similarly among the most central. Though their positions in the network are illuminated by the differences in their degree and betweenness centrality scores, both the NWF and the NACDL are in the top percentile with both measures. In typical social science fashion, both measures of centrality are applicable and lend insight into how interest groups can successfully use their networks to accomplish their objectives.

Fig. 4 presents the egocentric networks of three central players: the NWF, the NACDL and the ACLU. It is readily apparent that these groups network with others that share issue areas as well as ideological positions. We have annotated the clusters in the graph based on their issues.²¹ As shown in Fig. 4, the NWF cosigned amicus briefs that link various regional wildlife organizations, conservation organizations and more general non-profit organizations, which may share interests and/or ideology. Thus contrary to networks built on the LDA issue areas or contributions alone, the amicus curiae

²⁰ Including this case changes the degree and betweenness values, such that mean degree is 69.2, the standard deviation is 76.7, the max is 165.0, and the min is 0.0. The betweenness is 0.8, 12.4, 249.7, and 0.0, respectively.

²¹ Graphs with fully labeled nodes are available in the [online appendix](#).

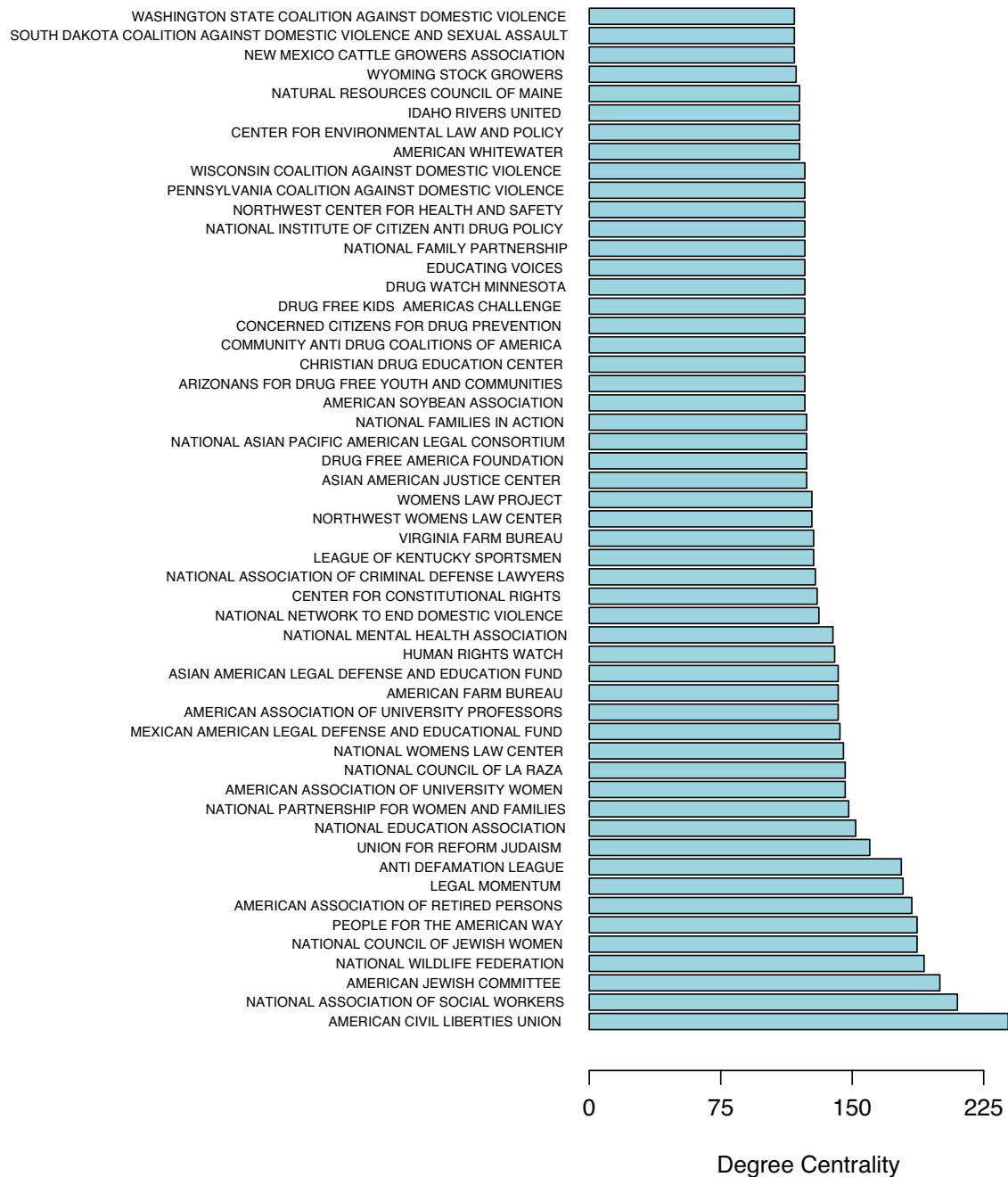


Fig. 2. Top percentile degree centrality, 2000s.

network illustrates links that are based on both issue areas and ideological direction.

Notably, the coalition strategies utilized by the NACDL and NWF are somewhat different. One aspect of why it is a central player is that despite various clusters in the network, the NWF cosigns widely. Other groups sign exclusively with a seemingly set network of like-minded organizations, illustrated by tight star-like clusters, but the NWF appears to have broad interests in cases before the Court and shares ideological positions with a few clusters. Thus the NWF serves as a hub to tightly linked networks of groups that share a common interest in the environment.

Contrarily, the egocentric networks of the NACDL suggests that power stems from their ability to indirectly link a host of seemingly unrelated organizations, which appear to only share a common left-leaning ideology. Its role as a central player is particularly

interesting because the seemingly broad issue interests in the network would not be linked to each other without the NACDL. Rather than linking tight clusters of groups the NACDL brings together more disparate groups. The network suggests that the NACDL is a key hub organization for various independent groups of a common ideological bent.

The American Civil Liberties Union (ACLU) shows up in the top position in both indicators of centrality (see Figs. 2 and 3). It exhibits characteristics of both high degree and high betweenness. It should come as no surprise to find the ACLU among those most connected interest groups before the Supreme Court. It cosigns with tightly linked clusters of religious, health law and women groups. The less obvious point is that it is also among the most central players in terms of betweenness. The ACLU, with its general scope and pervasive influence before the Court, links a host of interests that would

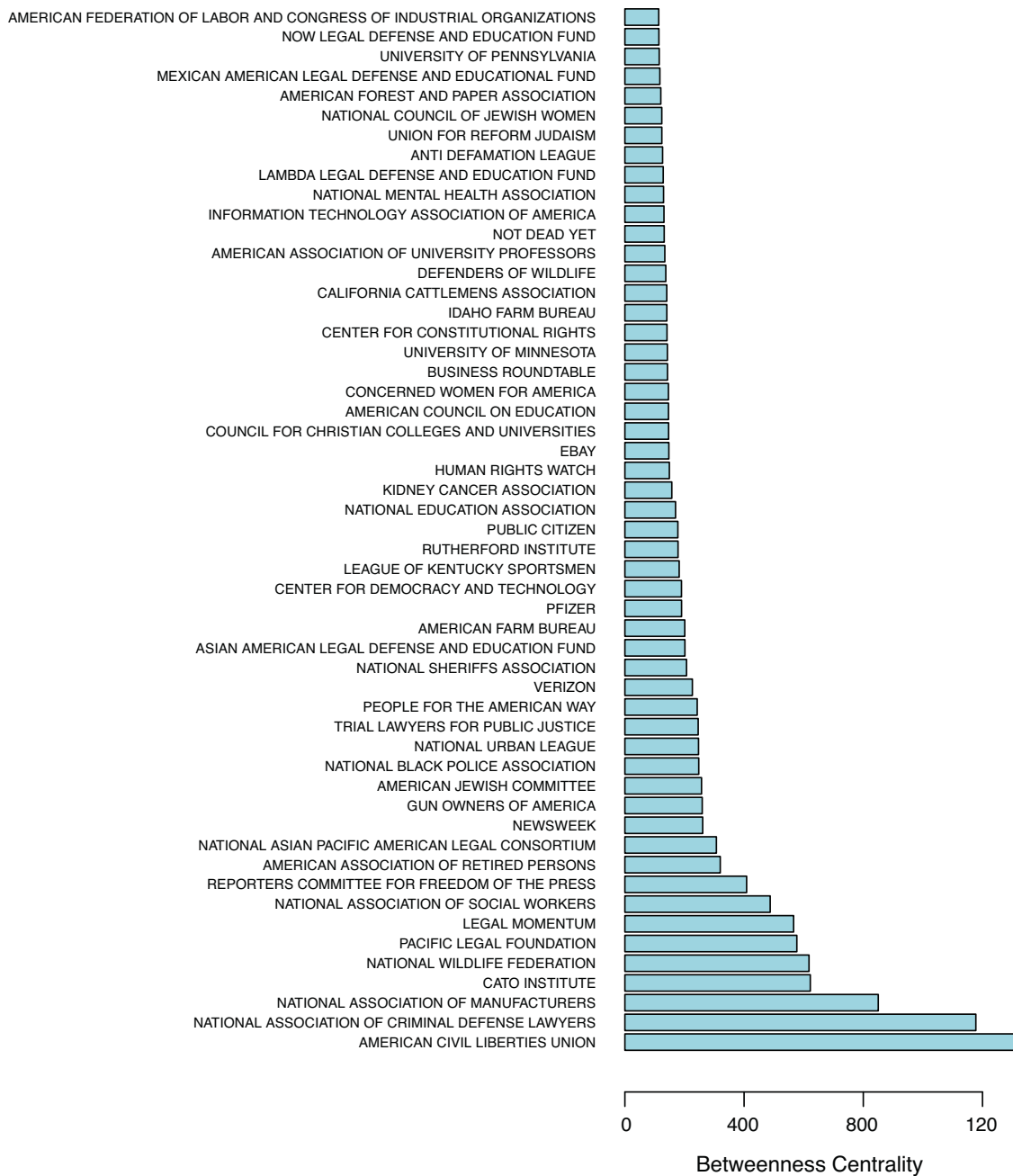


Fig. 3. Top percentile betweenness centrality, 2000s.

be unrelated otherwise, including regional ACLU groups and legal and educational groups. As such, it looks like a combination of features from the NWF and NACDL networks. Much like the NWF, the ACLU reaches out to tightly grouped factions, and much like the NACDL it acts as a central hub for diverse groups with less obvious commonalities.

4.3. Pure coalitions or mixed strategies?

The full interest group network escapes an easy characterization. In addition, the egocentric networks of the most central players show that different groups apply different coalition strategies. The distribution of centrality suggest that both circle and star networks exist simultaneously (see Barabási, 2002). Rather than one or the other, clusters of tightly linked organizations, linked circularly and individually, are networked to other clusters by hub

organizations, creating a sort of large scale star network. Looking at some of the key subnetworks above suggest a broad typology of interest group coalition strategy.

We contend that there is a reference set of ideal types that are useful when looking at interest group subnetworks. The ideal types are shown in the left column of Fig. 5. *Lone Wolves* are solitary organizations that do not work as part of a coalition, but rather pursue their ends alone. *Leaders* connect groups to themselves and function as hubs. These groups take a strong leadership and coordination role between groups that would be otherwise unconnected. Subnetworks formed around such a leader will score relatively low on the density and clique measures. However, these networks are highly centralized and efficient. Finally, *Teammates* are all equally connected in their subnetworks. Both density and transitivity measures are high, while centralization and efficiency are low.

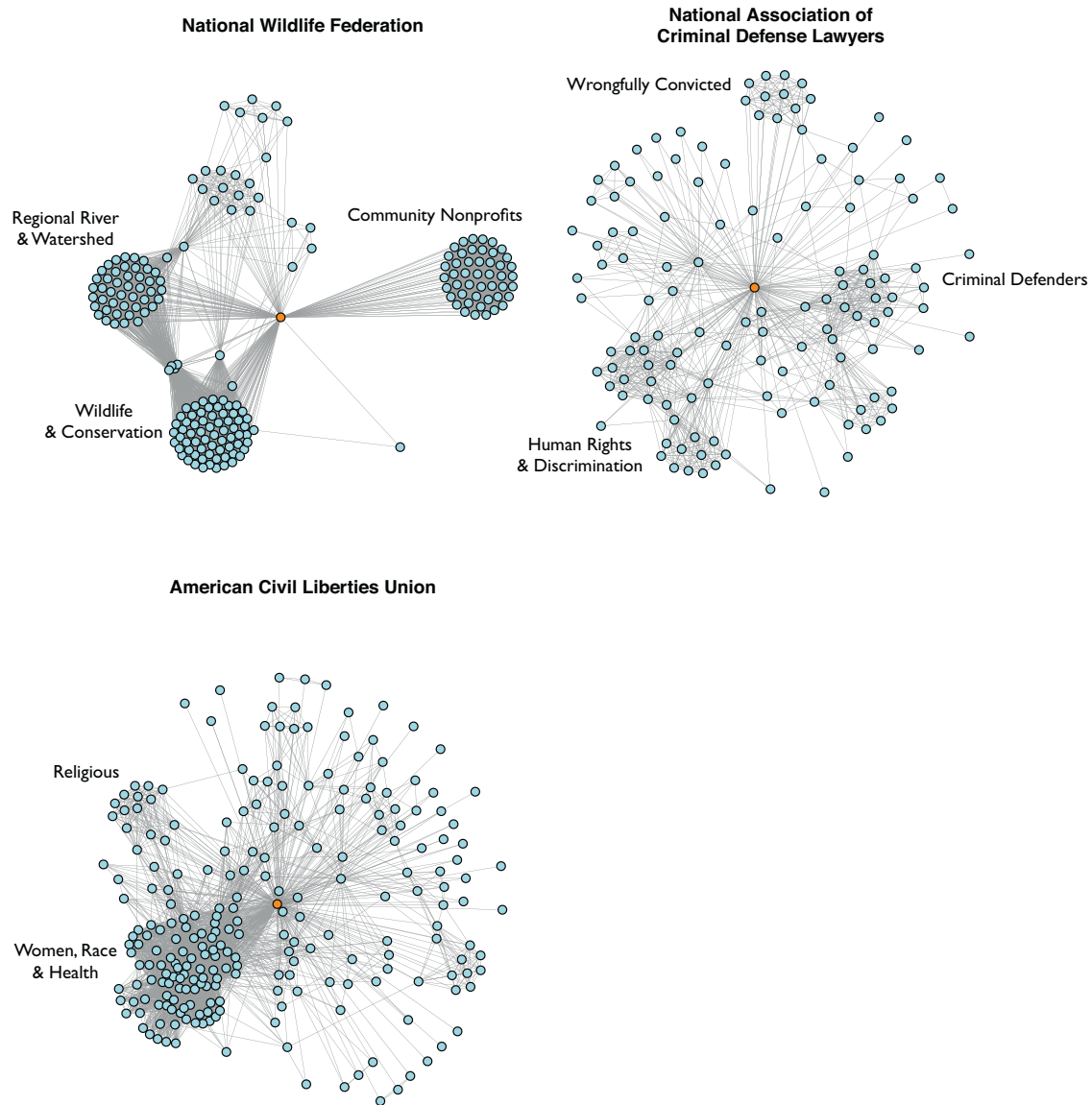


Fig. 4. Egocentric networks of central groups.

The right column of Fig. 5 shows actual groups from the 21st century network that resemble these ideal types. There are a number of Lone Wolves in the data. Specifically, 593 groups, or approximately 11% have no connection to another group between 2000 and 2009. The NACDL illustrates the Leader ideal type well. Table 2 shows that the density measure for this group is 0.101 and clique measure is 0.452, both of which are relatively low. The Vietnam Veterans of America is a classic example of a Teammate ideal type. The density and clique measures are both 1.000.

As a point of comparison, Table 2, row 1, provides some similar properties for the full 21st century network. The measures of density, clique and centralization help describe the network. 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. Density measures for each year from 2000 to 2009 range from 0.011 to 0.046, but the overall low 0.004 score for the entire window suggests that many of the interest groups are not connected to as many of the others as they could be. Interest groups do not coordinate with all stake holders. Thus instead of many weak ties, the interest group network appears comprised largely of factions.

Table 2
Interest group network properties, 2000s.

Graph structure	Density	Transitivity	Centralization
Full network	0.004	0.751	0.041
Pure strategy			
Leader: NACDL	0.101	0.452	0.913
Teammate: VVA	1.000	1.000	0.000
Mixed strategy			
Leader and teammate: ACLU	0.116	0.565	0.892
Multiple Teams: NWF	0.290	0.914	0.717

Graph structural properties calculated for the full network, and egocentric networks of the National Association of Criminal Defense Lawyers (NACDL), Vietnam Veterans of America (VVA), the American Civil Liberties Union (ACLU), and the National Wildlife Federation (NWF).

A measure of clique moves us to considerations of indirect relationships. It tells us the extent to which two interest groups that are indirectly linked by a third interest group, are also directly linked themselves.²² This is almost always the case in the interest group

²² Transitivity is a triadic, algebraic structural constraint. In its weak form, the transitive constraint corresponds to a situation where if *a* is a friend of *b* and *b* is a friend of *c*, then *a* is a friend of *c* (see Wasserman and Faust, 1994).

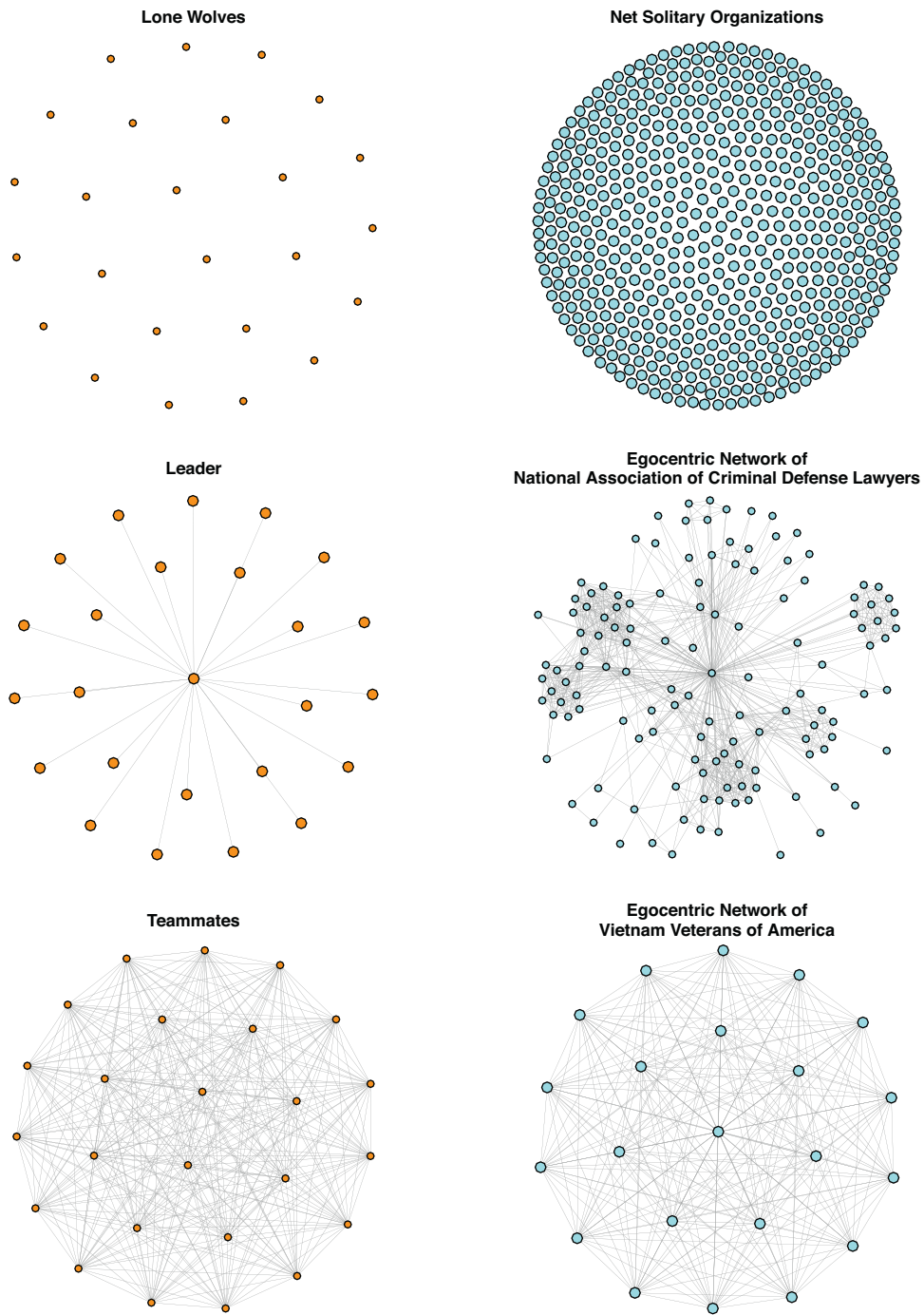


Fig. 5. Ideal and actual interest group coalition strategies. Ideal coalition structures are graphed in the left column. Examples of similar egocentric interest group network structures are graphed in the right column.

networks, which has a transitivity value of 0.846. It appears that in interest group networks being a *friend of a friend* also means *you are a friend*. Furthermore, for any single year in the 2000 to 2009 window, the transitivity score is higher than the that of the full period. Thus as opportunities for interest group coalitions increase, so too does the presence of indirect links between groups. In shorter periods, however, we note the greater potential for groups to enter that are part of interconnected relationships.

The general centralization score provides a sort of 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 .041. The centralization of a graph G for centrality measure $C(v)$ is defined by [Freeman \(1979\)](#) as:

$$C^*(G) = \sum_{i \in V(G)} | \max_{v \in V(G)} (C(v)) - C(i) |$$

Or, equivalently, the absolute deviation from the maximum of C on G .

As suggested in the egocentric networks in [Fig. 4](#), several sub-networks apply a mixed type coalition strategy. The ACLU and the

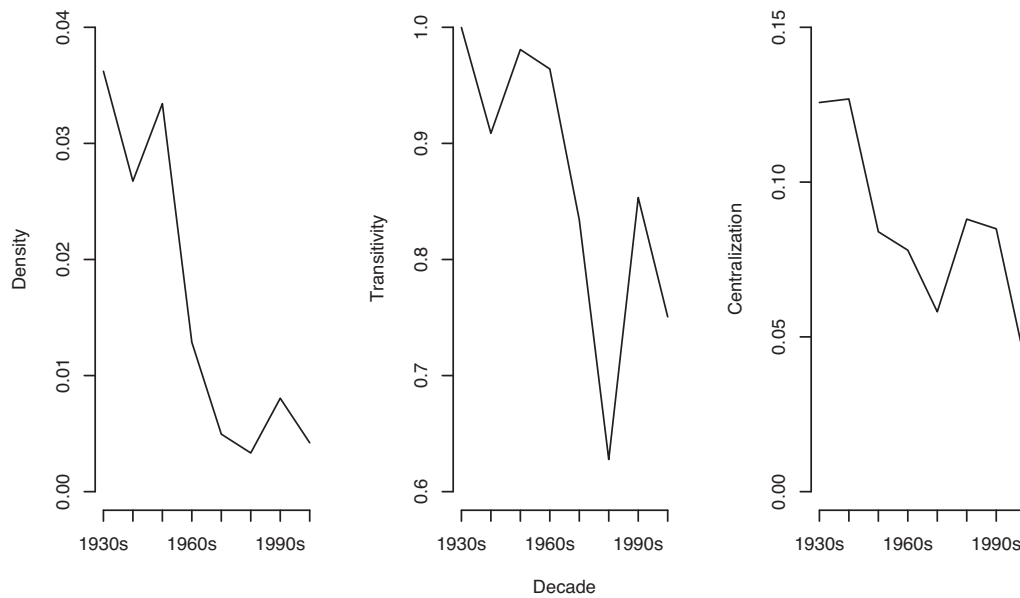


Fig. 6. Interest group network properties, 1930–2009.

NWF, for example, are sometimes part of a team, and other times take the role of a leader. Thus they do not fit easily into our three category typology. Instead they appear to pursue a mixed strategy that employs aspects of both ideal coalition strategies. Looking at the entire network, it appears that most groups pursue such a mixed coalition strategy, though not to the extent of these major players. We also compare the subnetworks based on the neighborhood properties in Table 2. The bottom rows report the information for the ACLU and NWF. Comparing across the four measures, we see that the ACLU plays a role closer to a Leader than a Teammate when compared to the NWF.

Our data also offers a perspective on the dynamics in interest group network properties. Fig. 6 displays the density, transitivity and centralization of each decade's network. Notably, each of the network properties show a downward trend. In all cases, the increase of organizations signing onto amicus briefs, and in particular the increase in the number of organizations on amicus briefs with few if any cosigners, drops the density, transitivity and centralization of the networks across time.²³

Of notable departures from the trend, the high density of the 1950s is indicative of the unusually strong connections in this period. Those that did sign, often signed with others in the network. In other words, the 1950s saw a period of increased coalition strategies relative to the number of attempts at persuasion. Accordingly, the 1950s were highest in terms of centralization as well. This was due exclusively to the Times-Picayune case. As such, we omitted

the case from the analyses and figures, which more clearly shows the general downward trend across the density and centralization measures.

While the trend in transitivity was also downward over the years, the 1980s were extremely so. More than in any decade before or after, though we might expect future decades to drop to similar levels, the 1980s showed a major departure from friends of a friend cosigning. Two groups that were connected with a third group were less likely to work with each other in the 1980s than in any period on record.

This look at network and subnetwork structures motivates questions of structural equivalence. To what degree are different interest groups exchangeable in these networks? And how are the positions of different groups in different cases similar? For example, an interest group may have a position in a network on a case involving patents that is quite similar to a group's in a case on free speech. This work allows for structural theories that generalize beyond issues, which we believe to be a contribution to the interest groups literature. We turn next to an examination of the factors that contribute to coalitions among interest groups.

5. Modeling interest group coalitions

Having described the general properties of the interest group network, we move to modeling it. We posit that the homophily principle should apply to interest group networks, or that similarities among interest groups lead to coalitions among them. We expect that network ties between interest groups will be largely homogenous, such that having generally similar business characteristics, issue areas and resources help determine coalition formation. Fig. 7, for example, displays the network mapping of all interest groups that have signed amicus briefs on Court per curiam or full opinions from 2000 to 2009, this time color-coded by industry area. If common industries lead groups to work together, as we might expect, we should see groupings in the network based on industry area. However, such grouping is hard to perceive in networks of this size. Even with the Fruchterman and Reingold algorithm applied here, which plots connected nodes closer to each other than to disconnected nodes, such visual tests are too subjective to be of much use in networks of this size. Instead we test with ERGMs whether industry area as well as other business

²³ The conclusion that all three of these features of the network decrease over time demands further examination. That is, the univariate analyses presented here do not account for the relationships among the measures. Take for instance, the possibility for a relationship between transitivity and density. Transitivity is often measured as the proportion of potential triangles that are closed. If the number of potential triangles remains constant over time and the transitivity, i.e., the tendency for triangles to close, decreases, fewer edges will exist in the network and the overall density will go down. However, univariate analysis of either density or transitivity does not reveal the dynamics of the general degree of connectivity in the network or the transitivity of the network, controlling for the other. To account for this, we also estimated ERGMs parametrized with measures of density, isolates and 2-star by decade to assess the dynamics of each property, controlling for the others. These results are archived with the data in an [online appendix](#). We find that for overall the results suggest a similar picture to that painted by the more naive univariate network statistics.

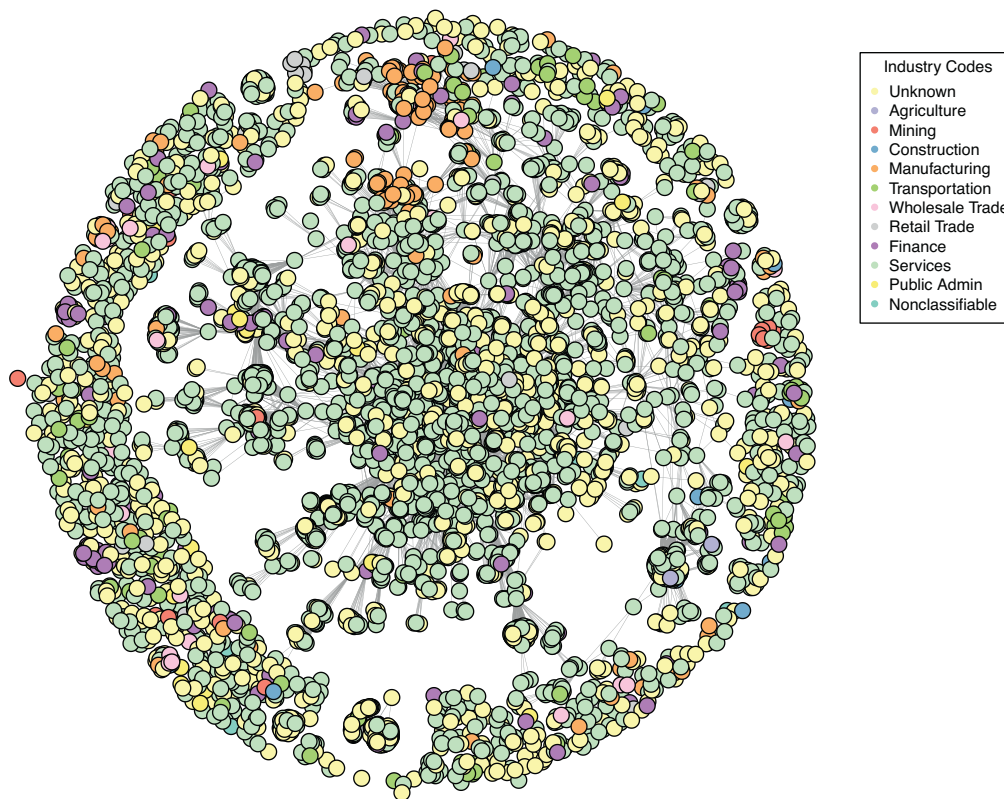


Fig. 7. Interest group network, 2000–2009.

characteristics help predict the kinds of coalition formations in the network. Thus we attempt to model the probability of observing this network of relationships conditional on graph-theoretic characteristics and interest group covariates.

5.1. Graph-theoretic characteristics

By using graph-theoretic characteristics in our model, we are modeling the structural effects of the network. Robins et al. (2007a, 4) points out that in the ideal case, “we might even hypothesize that the modeled structural effects could explain the emergence of the network.” Our model focuses on several commonly used graph-theoretic measures. Edges provide a statistic for a mere count of the number of edges in the network. Interpreting this statistic helps us assess if groups are connected and the density of the entire network. Given the strong presence of cliques, we also employ 2-star and 3-star explanatory variables. The k -star refers to the number of nodes in the network with exactly k adjacent edges with unconnected end points. A triangle parameter builds on the k -star configuration by closing the loop between connected individuals. Specifically, it is the number of 3-cycles in the network (Saul and Filkov, 2007). Finally, we also employ a control for the isolates in the network. The isolates measure captures an aspect of the network structure by assessing the number of nodes in the network without any connections.²⁴

²⁴ Cranmer and Desmarais (2011) point out that in contrast to traditional likelihood methods, ERGMs control for network structure without introducing endogeneity (see also Handcock et al., 2008; Snijders et al., 2006). The core structural parameters of a network are ties (link between two nodes), stars (centralization measures), and triangles (where three nodes are all linked) (Shumate and Palazzo, 2010). Additional structural parameters can be estimated by ERGMs, but most are combinations of these basic structures.

5.2. Interest group characteristics

We use a number of interest group characteristics commonly thought to affect coalitional behavior as explanatory variables, i.e., to explain the likelihood of links (or edges) in the network. Table 3 list some descriptive statistics for the covariates in the model.²⁵ The *number of employees* is a general measure of the size of the interest group. We also tap size through the *number of members*, an indicator that may be more reliable than employees for many of the public service associations. We believe that large groups are more likely to work with other large groups. Interest groups may want to display a united front to government on an issue of concern, and are likely to perceive organizations of similar size most necessary and, more importantly, most approachable in coalition building. Of course, the contrary argument is also quite attractive. 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 *longevity* of the group is added to the model in the form of year in which the organization was established or founded. Such an indicator of linkages might suggest that long standing, and perhaps wise, as testified to by their longevity, political groups are sought out.

²⁵ Because many organizations that work to influence the government do not register as lobbyists, using more focused “lobbying databases” is not possible. Instead, we culled the attribute data from business and association directories. In particular, we relied on the Associations Unlimited (Gale, 2010) and Million Dollar (D and B) databases for interest group characteristics. These databases contain up-to-date association and business information for thousands of firms, organizations and associations. Information that was missing from both the Associations Unlimited and Million Dollar 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.

Table 3
Interest group characteristics.

Covariates	Mean	Median	Std Dev	Min	Max
SIC	79	86	16	1	99
Year	1962	1975	41	1620	2009
Employees	7707	15	64143	0	2.76 ^a
Members	240946	2500	3.27 ^a	0	100 ^a
Budget	138 ^a	2.00 ^a	3480 ^a	0	94700 ^a
Sales	3710 ^a	1.30 ^a	24400 ^a	0	477000 ^a
Plant Size ^b	53646	5319	286010	0	10.00 ^a

Interest group characteristics refer to the average and range of the covariates for each interest group in the data set.

^a In millions.

^b In square feet.

The *industry* of the group may also help explain interest group linkages. This is essentially a measure of shared issue interests. We expect groups that share industrial demands to seek out mutually beneficial outcomes via cooperation. We measure *industry* by using the associated U.S. Standard Industrial Classification (SIC) system. We divide groups according to the SIC Division. Fig. 7 above uses the SIC covariate to color each of the groups in the full network. It is readily apparent, for example, that the bulk of interest groups were categorized as “service”, category values 70–89. This term broadly refers to service industries, including the 1986s, which are political, religious and member organizations.²⁶

In addition, different groups have different access to resources. We believe that many groups will seek out groups that are financially well endowed. To that end we control for both a group's *budget* and *annual sales*. Budgets indicate the potential influence of an organization. Large budgets signal the opportunity to muster resources, while small budgets suggest limitations in pursuing common goals. Likewise, sales provide some indicator of prior success and thus future expectations. We test whether interest groups work with groups that are likewise endowed or the opposite.²⁷

5.3. Explaining network formation

We use the interest group characteristics described above and ERGMs to examine how the networks form (Wasserman and Pattison, 1996). ERGMs explicitly model nonindependence among observations “by including parameters for structural features that capture hypothesized dependencies among ties” (Faust and Skvoretz 2002, p. 274). We expect assortative mixing (or homophily) of interest groups based on policy area, region, ideology, size, and other business characteristics.²⁸ Understanding why networks form, that is, estimating the effect of the characteristics of participants in a network on the likelihood of being in the network is insightful. In our case, we can estimate the impact of interest

²⁶ In future work, we intend to use a more refined level of the SIC code. We currently use the Division level of classification, but will move to the Major Group level and/or the Industry Group level to further examine the impact of industry on network composition. For example, the Division level divides groups into A to K where A is Agricultural Production, B is Mining, C is Construction, and so on. If one uses the Major Group level, each Division is broken down further, such that within the Agricultural division the 01 is Agricultural Production – Crops, 02 is Agricultural Production – Livestock and Animal Specialties, while 08 is Forestry and 09 is Fishing, Hunting, and Trapping (SIC Code List, N.d.). Moving to the Industry Group, 01 is further broken down to 011, which is Cash Grains, 013, which are field crops, 016, which is Vegetables and Melons, and so on. The refinement logic is that one wants the industries to be similar enough to assess whether industry helps explain interest group linkages (Grier and Croseclose, 1994; Grier et al., 1990).

²⁷ Hansford (2010) utilizes political variables, particularly case and brief characteristics, to tap political behavior (For additional insight into amicus networks, see Iida, 2010).

²⁸ Basic ERGMs have been extended to the analysis of longitudinally observed networks (Cranmer and Desmarais, 2011).

group characteristics on why the groups are in the networks we observe. The basic idea of ERGMs is that the propensity of a network structure is compared to the propensity that the structure would occur by chance alone.

ERGMs are described by Cranmer and Desmarais (2011) as “a statistical model that can be used to estimate the effects of covariates on the ties in a network while simultaneously estimating parameters that provide a precise and parsimonious description of the forms of dependence extant in relational data” (2009, 1). In this way, ERGMs can be thought of as akin to regression techniques that specifically account for the relational (nonindependent) nature of the data. Goodness-of-fit measures are available for ERGMs, which is another advantage of this approach compared to other network approaches.

The foundational model of Holland and Leinhardt (1981) is built on the idea that a statistical model can be generated by predicting the counts of types of ties, which are symmetric, null, and asymmetric. The log-linear model they develop is equivalent to a logit model of the dyads.

$$\text{logit}(X_{ij} = 1) = \alpha_i + \beta_j + \rho(X_{ji})$$

The subscripts imply a different parameter for every node i and j in the model, plus one for reciprocity. The many ERGM extensions are built off this foundational and intuitive equation.²⁹

We estimate the ERGM with Markov Chain Monte Carlo (MCMC), an important and rather recent innovation that allows for estimation on large, complex networks, arguably like that of interest groups (see Snijders et al., 2006).³⁰ To simplify, an ERGM uses network statistics and covariates to maximize the likelihood of observing the network. Appropriate fit of the ERGM implies that the collection of statistics do a better job of creating the network at hand than other possible networks. Unfortunately, for anything but the smallest of networks, the computational demands of the maximization are too great. MCMC provides an alternative by iteratively sampling networks from a distribution based on the model maximum likelihood parameters from the previous sample (Geyer and Thompson, 1992). The estimates are gathered when the sample iterations can no longer improve on the likelihood.

5.4. ERGM results

To demonstrate the respective power of the graph and covariates, we proceed in steps to model the network. The ERGM is first estimated with the key graph-theoretic characteristics of the network: edges, 2-star, 3-star, triangles, and isolates for our relatively

²⁹ Anderson et al. (1999) provide a useful primer.

³⁰ Even though a number of the graph-theoretic characteristics are collinear, in practice this does not cause a problem for estimation (Hunter, 2007; Robins et al., 2007).

large and complex, undirected interest group network (see Model I). Interest group characteristics that may play a role in the formation of the network are then added to the model (see Model II). The final step is to simplify by estimating a more restrictive model (which is determined by looking at the statistical significance of the variables) until the simplest model is estimated that does not decrease the fit of the model (Anderson et al., 1999) (see Model III). The interpretation of the model coefficients is similar to that of logit models. Thus 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.

The MCMC MLE parameter estimates for the ERGM are presented in Table 4. At first glance, it is clear that the graph-theoretic properties are extremely important, as expected. All of the parameters are statistically significant and quite powerful in terms of the information criterions.³¹ Focusing on Model III, The negative density parameter tells us that the edges, which link the groups in this undirected network, are not common and that when they do occur, they are part of higher order structures such as the stars and triangles. The 2-star parameter is also negative. Similarly, it tells us that interest groups ties between three groups are less likely unless part of a higher order structure, in our case triangles.

The 3-star parameter is positive, but very close to zero.³² The triangle parameter is positive and thus tells us that the interest group network structure clearly clusters in cliques. Our pattern of alternate signs on the 2-star versus triangle parameter is a common one. Robins et al. (2007) explain that this is interpreted as two countervailing forces. One that is a triangulated core-periphery structure and one against a degree-based core-periphery structure. Overall, we see that the global outcome is “not a single core of one internally densely connected set of nodes, but several (often connected) smaller regions of overlapping triangles” (Robins et al., 2007, 205). Simulations show that if there is a positive fixed value for the triangle parameter and the k -star parameters move from 0 to increasingly negative values, then the overall network moves from centralization to segmentation (Robins et al., 2007). The last graph-theoretic parameter is for the isolates. For our undirected 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.

In addition, several of the interest group covariates appear statistically significant and in the appropriate direction in the final model, Model III. Interest groups with large budgets are more likely to be linked to groups with small budgets, this is also true for interest groups with large and small sales. Thus, the wealthy and profitable organizations work with each other to accomplish their goals. In addition, the large employers work with other large employers more often than not, as do large membership organizations. Finally, interest groups that work in the same industry also influence the formation of the network. More established groups tend to form coalitions as well. Only size of the operating plant and number of employees are insignificant, suggesting they have no effect on network formation.³³

A minimum criteria for a model to fit well is parameter convergence and to be nondegenerate. For a model to be nondegenerate, it should not place all of the probability on a few networks that are unlike the observed network, such as a full or empty network. Beyond this, the information criterions, AIC and BIC, can be compared with the lower values showing an increase in the model fit. Looking again at Table 4, we see the preferred model is Model III in the last two columns, which contains both the graph-theoretic and interest group characteristics as covariates. 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 iid, they are lacking (Hunter and Handcock, 2006). To that end, we also tested goodness of fit with post-estimation graphical plots. The trace plots show that the models converge with a 1000 burnin and 10,000 iterations. The fit of the simulation results for dependence show that the model does a respectable job of reproducing this large and complex network.

6. Discussion

The paper and larger project aim to make both theoretical and empirical contributions to the study of political behavior and network analysis.³⁴ The illuminated network structures lend some insight into the central players and overall formation of the network from 2000 to 2009. Factions of interest groups are tied together by central players, who act as hubs, leaving a disparate collection of organizations that work alone. A mixed strategy between acting as an efficient leader or a team player is pursued by many of the groups, though there is ample evidence of interest groups employing pure leadership or pure teammate strategies as well.

The longitudinal analysis furthers our understanding of interest group formation in the United States. Over the last 80 years, interest groups have sought to make their preferences known before the Supreme Court in greater and greater numbers. And since the beginning of amicus filings in the 1930s, the average interest group degree and betweenness centrality in the network have increased. Both suggest that the interest groups of today are better connected on average than those in the past, with some interest groups increasingly connected to greater numbers of other groups and along the lines of communication to other groups.

The network of interest groups has also shown a negative pattern when it comes to over time change in network density, transitivity and centralization. The decrease in density suggests that while more interest groups have entered as signers on briefs in recent years, they have not all entered as cosigners. In fact, many have entered alone or as a part of small factions. Likewise the downward trending transitivity implies that the old days of teammate networks are being increasingly replaced with more leadership style networks. Finally, low and decreasing centralization means that the maximum centrality interest group is looking more like the average interest group, and thus a network that is less diverse in terms of general centrality.³⁵

It is important to remember, however, that despite these dynamics, the overall values of density, transitivity and

³¹ While the distribution of the ratio of the estimate to its standard error is not known, literature uses the approximate t -distribution (Robins et al., 2007; Snijders and Van Duijn, 2002). In addition, a one-sided test is appropriate for the triangle parameters, re : 1.65 times the standard error at the 5 percent level (Robins et al., 2007).

³² Note that a 1-star is simply the density or number of edges over $n(n-1)/2$ in a undirected network such as ours.

³³ The likelihood of the model and overall results are virtually untouched by removing the insignificant variables. They are left in the model for illustrative purposes.

³⁴ Additional work in the project examines the impact of interest group networks, including an analysis of how interest group network measures affect Supreme Court decision making. That is, there is an extensive literature on explaining the ideological direction of individual justices' votes and the decision to author an opinion (e.g., Rohde and Spaeth, 1976; Segal and spaeth, 1993; Segal and Spaeth, 2002; Sunstein et al., 2006). Interest groups are posited to have a major role. We argue that our interest group network measures offer an improvement on the operationalization of the posited influence, which is currently assessed with a count of the number of briefs filed.

³⁵ These results continue to hold when using ERGMs to assess the dynamics of each property, controlling for the others.

Table 4
ERGM of interest group coalitions, 2000–2009.

Term	Model I estimate	Std. error	Model II estimate	Std. error	Model III estimate	Std. error
Edges	−5.858	(0.044)			−5.488	(0.118)
Triangle	0.383	(0.011)			0.449	(0.035)
k-Star 2	−0.047	(0.001)			−0.052	(0.007)
k-Star 3	0.001	(0.000)			0.001	(0.000)
Isolates	2.504	(0.717)			2.833	(0.250)
Budget			−3.124	(0.006)	−0.595	(0.012)
Employees			−1.972	(0.007)	0.024	(0.020)
Sales			−1.857	(0.008)	−0.304	(0.028)
Founded			−1.747	(0.007)	0.051	(0.026)
SIC			−3.108	(0.006)	0.377	(0.016)
Members			−1.781	(0.006)	0.242	(0.011)
Plant size			−0.968	(0.008)	0.044	(0.032)
AIC	761858		2150640		757599	
BIC	761931		2150741		757773	

All covariates are coded categorically and result in a uniform homophily statistic when the respective attribute is shared by two edges.

centralization were consistently low, high, and low, respectively. In all, the interest group network is not dense nor centralized, but still quite transitive. The full interest group network appears to resemble a host of tightly grouped factions and leadership hub organizations employing mixed coalition strategies.

By applying an ERGM, we gain some understanding into underlying social processes that could (or could not) have generated the interest group network structure. This model moves us toward a more focused examination of the multitude of factors that have created the current network of interest groups. In short, the overall structure of the network revealed many, often connected regions of tight association rather than a single core of densely connected groups. The overall network is better characterized as segmented than centralized. The interest group covariates show that policy interest, organizational structure of the groups, and resources all matter in choosing partners. Graph-theoretic and shared interest group attributes both help to recreate and characterize this large, complex interest group network.

The state of our democracy depends on the ability of individuals and organizations to find representation for their respective values in the bodies of government. Organizations, however, do not simply attempt to influence government alone. Instead, as network and interest group theories suggest, organizations typically collaborate. Combining forces is a time-honored tradition in the pursuit of political ends, and yet there is much to still learn about the gamut of networks in our political system and how they operate.

While informative work has focused on understanding the network of interest groups across issue areas, we still have much to learn about purposive network formation. Our work helps provide additional information about interest group networks, which contributes to a fuller understanding of key political players and the behavior of those players, while also addressing the alternative theoretical perspectives on interest group coalition ideal types.

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Appendix A. Supplementary Materials

Supplementary Materials associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.socnet.2012.07.003>.

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