Contributions by Interest Groups to Lobbying Coalitions

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Abstract

Decisions by interest groups about when and how to work together inside coalitions are critical components of interest group strategies. This article argues that the composition of lobbying coalitions is a key factor that relates to these decisions. First, partisan diversity within a coalition may enhance contributions from groups if bipartisanship is seen as a positive signal of the coalition's likely success. Second, network embeddedness may enhance contributions from coalition members if concomitant relationships make it easier to collaborate. Using a Two-Mode Exponential Random Graph Model (ERGM) with structural zeros, the study draws upon interviews with congressional staff members, interest group representatives, and coalition representatives working on health policy in the United States. The results demonstrate a robust, positive association of partisan diversity with contributions by interest groups to lobbying coalitions. The results also reveal positive correspondence with network embeddedness, though these results are contingent on model specification.

Keywords

Partisanship, diversity, social networks, interest groups, lobbying coalitions

Note

Supplementary materials are available in an online appendix (at the end of this document). Replication files are available in the *JOP* Data Archive on Dataverse (https://dataverse.harvard.edu/dataverse/jop). Data collection in this project was conducted in accordance with Institutional Review Board requirements.

With thousands of interest groups clamering for the attention of policymakers, it is challenging for any single group, acting on its own, to exert influence over how public policy is made (Mahoney and Baumgartner 2015). Because of this challenge, group strategies give close attention to when and how they should work with other groups (Hojnacki 1997; Hula 1999). As a result, much of groups' work is done inside coalitions, which are agreements among two or more autonomous groups to collaborate in advocating for a common policy position. Hojnacki (1997) explains that groups decide whether to join coalitions by weighing the benefits – such as sharing resources and establishing a united front – against the costs – such as the loss of autonomy during collective advocacy and the public-relations risks of joining a controversial debate. Although some groups prefer to go it alone, most groups become members of several coalitions (Heaney and Lorenz 2013).

Despite the ubiquity of lobbying coalitions, their *internal* politics have received only limited attention from scholars. Hojnacki (1998) and Hula (1999) document considerable variation in contributions by groups to coalitions; some interest groups act as leaders, while others assume more specialized or peripheral roles. Hojnacki and Hula establish that which role a group plays depends on factors such as the degree to which the group cares about an issue and how its reputation among other groups would be affected by its participation. These studies identify the mechanisms through which the members of a lobbying coalition act in concert with one another. Just as there are collective action problems among groups in initially forming coalition, so too are there collective action problems within coalitions as they engage with the policy process.

We argue that making sense of coalition politics not only requires modeling why a group *joins* a coalition, but also why some groups actively *contribute to* and *lead* the coalition, while others are involved more passively. Therefore, this research investigates the conditions under which some groups become recognized as leaders of coalition, while others do not.

Understanding the conditions under which coalitions are able to collaborate is a vital piece of the puzzle of which interests are represented effectively in the policy process. However, prior studies provide an incomplete picture of coalitional collaboration. Specifically, their analysis focuses only on interest groups; they explain why *groups* vary their effort in coalitions, in general, without explaining why that effort might be related to the nature of the *coalition* in question. That is, they neglect to examine the *coalition level* of analysis and fail to explain why some coalitions may attract different amounts of participation than others. A more complete analysis ought to examine the interaction between individual groups and specific coalitions; it would model how a particular group distributes effort (equally or unequally) across the coalitions of which it is a member.

We argue that a key reason why interest groups vary in the degree to which they contribute effort to coalitions of which they are members is because distinct coalitions are composed of different sets of other groups; contributions correspond to who is on the coalition's team. For example, a group may devote more effort to Coalition *A* than to Coalition *B* because it is more compatible with the other groups in *A* than in *B*. Thus, understanding group contributions to coalitions requires theorizing about what makes groups compatible (or not) in a coalition setting.

This study focuses on two aspects of the *composition* of coalitions. First, *diversity* is the degree to which members are homogeneous or heterogeneous. There are numerous ways in which coalitions may be diverse, such as with respect to their members' organizational types, geographic origins, resources, or preferred tactics. We concentrate on *partisan* diversity because partisanship is one of the principal identifying features of political actors in the contemporary United States, which is deeply polarized by party (Green, Palmquist, and Schickler 2002; Sinclair 2006). We ask whether a coalition elicits greater contributions from its members when it is more homogeneous – that is, its members tend to be similar to one another in their partisan identification – or more diverse – that is, its members tend to be closely identified with different parties.

Network embeddedness is the second aspect of coalition composition that we consider.

Embeddedness is the extent to which members of a network are connected to one another by multiple, overlapping, ongoing relationships (Granovetter 1985). Does the coalition consist of interest groups that are tied to one another through a variety of relationships? For example, have interest groups in the coalition worked together in prior coalitions, do they share close contacts with some of the same policymakers, or do they rely on some of the same sources of funding? Or are the groups in the coalition relative strangers to one another? We ask whether a coalition elicits greater contributions from its members when they are more closely connected with one another.

This article begins by theorizing how coalition composition relates to contributions by member organizations. It develops hypotheses regarding the effects of partisan diversity and network embeddedness, as well as how these factors may interact with one another. Next, it describes an empirical research project to test these hypotheses based on interviews with representatives of interest groups and coalitions, as well as congressional staff members. To examine these data, it builds Two-Mode Exponential Random Graph Models (ERGMs) in order to conduct statistical analysis. Finally, it discusses the results, their limitations, and implications.

This article contributes to knowledge about interest groups, political coalitions, diversity, and social networks. For interest group politics, it provides a basis for understanding the mechanisms of collective action among groups *after* they have already committed to a cause, thus expanding upon the extant literature that concentrates on the initial commitment decision by groups. For the study of political coalitions, it offers a rare, systematic analysis of behavior inside of coalitions, accounting for how the composition of their members relates to the coalition as a whole. For the study of diversity, it adds a new kind of context to understand the relationship between diversity and cooperation. For social network analysis, it provides an example of two-mode data with extensive structural zeros, thus extending network analysis to examine variations in effort within relationships.

Coalition Composition and Member Contributions

The decision by an interest group to join a lobbying coalition is a decision to lend its name to the coalition's cause. By doing so, the interest group conveys to its allies in government, other advocacy groups, and the public that it is willing to put its reputation behind the coalition. Doing so may assist in achieving the coalition's goals, especially if the interest group is prominent or represents a niche constituency, such as a vital industry, ethnic minority, or ideological perspective.

While there is certainly a place for some members of a coalition to act in name only, if a coalition is to accomplish its goals, then some subset of its members must contribute effort to the coalition's work. This work may involve attending coalition meetings, lobbying policymakers, drafting letters, holding press conferences, or deploying other tactics. The extent to which a group contributes substantially to the collective action of the coalition likely depends on a variety of factors, such as whether the group is committed to the coalition's issues, whether it has surplus staff and resources, and the prospects for success by the coalition. These calculations may also depend on a group's commitments to other coalitions in its *coalition portfolio* (Heaney and Lorenz 2013); a group has to decide how much effort to allocate to each of the coalitions it has joined.

The willingness of a group to contribute effort to any particular coalition corresponds to the composition of the coalition. Do the members of the coalition make a good team? Interdisciplinary research on teams has long examined how a team's composition affects its performance (Bell 2007; Carter et al. 2015). Two key questions in this area are, first, what is the best mix of types for the members of a team (Mannix and Neal 2005)? In particular, is it better to have a team made up of similar or diverse members? Second, how do the relationships among members affect the way the team operates (Leenders, Contractor, and DeChurch 2016)? Does it make a difference if members are closely embedded with one another or are relative strangers? In the following three sections, we discuss these questions in the context of lobbying coalitions.

Partisan Diversity. Page (2007) explains that there are both potential advantages and disadvantages of diversity in teams. On the positive side, more diverse teams have the potential to bring more varied perspectives, interpretations, heuristics, and predictive models to bear on a problem. If these differences are relevant to the problem at hand, then diversity may increase the likelihood that the team is successful. On the negative side, diversity may make it more difficult for the members of a team to get along with one another. If the team's task is primarily *conjunctive* – that is, everyone's contribution is critical – then diversity may disrupt the team's work more than it helps.

The ability of members to work together and solve problems is as important in lobbying as it is in many other fields. The composition of a coalition may matter not only because of the work that the coalition actually does, but also because external audiences observe the formation of the coalition and attach political significance to who its members are. As Kollman (1998) argues, policymakers look to political mobilization for *signals* of the likely consequences of taking different positions on an issue. From a signaling perspective, the existence of a diverse coalition may be particularly powerful because it indicates that actors who usually have reasons to disagree with one another have found a way to resolve their differences (Phinney 2017). On the other hand, diversity in a coalition may provide a negative signal if the coalition brings together groups that some power holders would prefer not to see working together.

If the groups in a coalition are connected with different political parties, then they might be more likely to bring different perspectives to the coalition than if they are connected with the same political party. Moreover, if a coalition has united groups across partisan boundaries, this unity may signal that it has overcome differences that are typically associated with legislative polarization. Prior research suggests that groups that form networks across partisan boundaries have greater reputations for policy influence than groups that do not cross these boundaries (Heaney 2006). Thus, coalitions with greater partisan diversity may be a better investment for groups' effort than coalitions that are more homogeneous on this dimension. Based on these arguments, we state

Hypothesis 1a: *Members of a lobbying coalition are more likely to contribute effort to the coalition when groups in the coalition have greater partisan diversity than when coalition members have greater partisan homogeneity.*

Alternatively, partisan diversity may create problems for a coalition. Groups that are closely connected to different political parties may experience ideological disagreements or clashes of loyalty. Moreover, coalitions that cross partisan boundaries may be a negative signal to party leaders (Pearson 2015). Hence, groups that find themselves in a coalition with partisan diversity may worry that active participation in the coalition risks the wrath of party leaders. Thus, we state

Hypothesis 1b: *Members of a lobbying coalition are less likely to contribute effort to the coalition when groups in the coalition have greater partisan diversity than when coalition members have greater partisan homogeneity.*

Network Embeddedness. If members of a team are to work well together, it is important that they trust one another (Lin 2001). An important question for understanding teams, then, is what are the conditions under which their members are likely to trust one another? A significant strand of institutional theory holds that the structure of institutions is critical to establishing the conditions for trust (Alchian and Demsetz 1972; Miller 1992). For example, institutions may be able to enhance trust by monitoring contributions from team members. In contrast, Granovetter (1985, p. 4) argues that the institutional perspective is incomplete since "[t]he widespread preference for transacting with individuals of known reputation implies that few are actually content to rely on either generalized morality *or* institutional arrangements to guard against trouble." He argues that trust is fostered by closely-connected, recurrent relationships embedded in intricate social structures.

Prior research demonstrates that embeddedness affects the willingness of groups to share information with one another and join together in coalitions (Carpenter, Esterling, and Lazer 2004; Leifeld and Schneider 2012). Coalition formation is promoted by preexisting networks among groups, the visibility of central network positions, and endogenous processes of network formation

(Box-Steffensmeier and Christenson 2014; Simpson 2015). The success of groups in attaining policy influence depends in part on their ability to position themselves strategically within these networks (Box-Steffensmeier, Christenson, and Hitt 2013; Heaney 2006, 2014).

Emeddedness effects are likely to matter to groups' efforts inside coalitions. Since working in a coalition may require groups to share sensitive information with one another, they may be more inclined to work closely with those that are integrated into the same relationships than those with which they are more distantly connected. Moreover, working with closely embedded groups may have lower transaction costs than working with groups that are less closely embedded. Finally, embeddedness may create social obligations for future interactions – a "shadow of the future" (Axelrod 1984) – that may motivate groups to contribute to a coalition. Thus, groups may put more effort into coalitions the more closely that they are embedded within them. Thus, we state

Hypothesis 2a: *Members of a lobbying coalition are more likely to contribute to a coalition when they are more closely embedded with other groups in the coalition than when they are more socially distant from these groups.*

However, it is also possible for actors to become "overembedded" such that excessively closely connected networks serve to undermine the effectiveness of a team in working together (Burt 1992; Uzzi 1996). For example, reliance upon embedded relationships may discourage actors from building new relationships or seeking new information. In that case, social network ties may be unnecessary or harmful to the coalition's collaboration. Coalitional institutions may be sufficient to generate the trust needed for interest groups to work together effectively, thus reducing the importance of networks. Further, coalition members may become so closely connected that their social relationships interfere with the coalition's operation. Thus, we state

Hypothesis 2b: *Members of a lobbying coalition are less likely to contribute to a coalition when they are more closely embedded with groups in coalition than when they are more socially distant from these groups.*

Interactions between Diversity and Embeddedness. The preceding analysis assumes that partisan diversity and network embeddedness are unrelated aspects of a coalition. Yet, these two aspects could be closely related. The tendency of actors of the same type to be more likely than actors of different types to form network ties is the well-established principle of *homophily* (McPherson and Smith-Lovin 1987). Thus, it is reasonable to expect that coalitions with homogeneous members are likely to be more closely embedded than are coalitions with diverse members. This principle is especially likely to hold in our case because co-partisanship is a strong predictor of network formation in an era of partisan polarization (Heaney et al. 2012).

An important question for coalition politics is whether coalition participation is related to interactions between the partisan diversity and network embeddedness. Considering first the positive case, it is possible that diversity and embeddedness are complementary to one another. Such complementarity could be present if embeddedness helped to offset negative aspects of working with groups closely tied to members of the opposite party. In such a situation, the hesitancy to contribute to a bipartisan coalition may be ameliorated when coalition members are closely embedded; they trust each other despite partisan differences. Thus, we state

Hypothesis 3a: *Partisan diversity and network embeddedness interact to promote group contributions to a coalition.*

Considering second the negative case, it is possible that diversity and embeddedness undercut one another. Partisan tensions could be exacerbated when groups that have fundamental disagreements with one another also find themselves connected through common networks. Thus, partisan diversity and network embeddedness may trade off with one another. In such a situation, coalition managers may choose between the strategy of assembling a coalition that is diverse and a coalition that is closely interconnected. Otherwise, probable inter-member conflicts may dampen group contributions to the coalition. Thus, we state

Hypothesis 3b: *Partisan diversity and network embeddedness interact to undercut group contributions to a coalition.*

Research Design

A study that examines the effects of membership composition on contributions to coalitions must have several features. First, it must observe the same organizations acting within different coalitions so that an organization's contributions to a particular coalition can be distinguished from its contributions to coalitions in general. Second, it must observe multiple organizations acting within the same coalition to determine why some organizations contribute to the coalition and others do not. Third, it must observe a variety of coalitions so that the effects of the coalition's political-organizational features can be identified. Fourth, it must observe organizations within a coherent political domain within which organizations are closely connected. Fifth, it must observe organizations within a broad enough area of politics that organizations vary with respect to their contributions, partisan diversity, network embeddedness, and other salient features. A sample constructed within these parameters would allow a test of the hypotheses in this article.

In order to satisfy these criteria, a sample of interest groups and coalitions was selected from a single, prominent policy domain: health policy. Health involves a wide range of issues, such as government-financed health care, pharmaceutical regulation, medical education, health insurance, public health, reproductive rights, and medical research. Because of their broad impact on society, health policy debates draw involvement from interest groups outside the field of health – such as business associations, labor unions, veterans' service organizations, and citizens' advocacy groups – as well as groups focused on health – such as doctors, nurses, pharmacists, hospitals, pharmaceutical companies, medical device manufacturers, and insurance companies. Health policy contains many different types of politics; for example, the politics of providing veterans' health benefits are not very similar to the politics of reproductive health services. At the same time, the issue area is narrow enough that many groups and coalitions in this field are interconnected.

We derived a sample of the most prominent health policy interest groups active at the national level in the United States in 2003 by using multiple criteria, as is required by the boundary-specification principles of Laumann, Marsden, and Prensky (1989). First, the federal lobbying reports of interest groups were examined if they indicated that the group lobbied on health care, Medicare and Medicaid, or medical research issues from 1997 to 2002 (U.S. Senate, Office of Public Records 2003). Groups from this list were ranked based on their reported federal lobbying expenditures. Second, groups were ranked based on the number of times that they testified at health-policy-related hearings on Capitol Hill from 1997 to 2002 (LexisNexis 2003). Any group that ranked among the top 50 groups on either of the first two lists, or among the top 100 groups on both lists, was included in the study. Third, groups with a long history of involvement in health policy debates were included (based on data from Laumann and Knoke 1987). Fourth, a preliminary list of groups, which was compiled based on the first three sources, was circulated to a panel of experts from academia and the policy world to solicit additional recommendations. Any group recommended by at least two experts was included in the study. This procedure led to the identification of 171 groups as the "most active" groups in the health policy domain.[1]

After identifying the sample of interest groups, data were collected by executing three waves of interviews. The first wave was conducted with 95 congressional staff members working on health policy (49 Republicans and 46 Democrats, a proportionate split based on control of Congress at the time). These interviews yielded information on the reputations of groups for partisanship. Each staff member was shown the list of groups and asked to rate the frequency (regular, occasional, no contact) and reliability (reliable, sometimes reliable, not reliable) of their contacts. The second wave was conducted by inviting representatives of each of the 171 groups to participate in a personal interview. Interviews were conducted with representatives of 168 groups, which yielded data on coalition memberships. These data were supplemented with data on lobbying resources,

[1] The complete list of all interest groups included in the study is in Online Appendix 1.

organizational structure, and organizational age. Coalition memberships of the 3 groups that did not participate in an interview were derived from information provided by other respondents.

The third wave of interviews was constructed from information obtained in the second wave, which allowed us to establish which interest groups were members of which coalitions. We asked our second wave of respondents to list their coalition memberships for us. We then obtained membership lists (official when possible, unofficial when necessary) for each coalition named by the respondents to ensure a more reliable record of coalition memberships than is possible based on respondent recall alone. We used the rule that any coalition that counted among its members at least 5 of the 171 most prominent groups was selected for the third wave, yielding a total of 80 coalitions.[2] For example, the Health Benefits Coalition for Affordable Choice and Quality met these criteria. The goal of this coalition was to promote broader health coverage and higher quality care with more marketplace competition – thus marrying Democratic and Republican policy goals. It unified groups such as the Business Roundtable, the Healthcare Leadership Council, the United States Chamber of Commerce, and the Blue Cross Blue Shield Association. Representatives of each of the 80 coalitions were contacted in 2004 and invited to participate in an anonymous, personal interview. Of these, representatives of 74 coalitions agreed to participate in the study.

During the third wave of interviews, each respondent was shown a list of all the members of her or his coalition. We determined the degree of contribution by interest groups to the coalition based on whether they were identified as one of the leaders of the coalition. Respondents were asked: "Please look at the list of members of the coalition. Which organizations would you identify as the leaders of the coalition? Leadership need not necessarily be indicated by a formal position, but may also be suggested by the informal contribution that the organization makes to the work of the coalition." Responses to this question constitute the dependent variable for the study.

[2] The complete list of all coalitions included in the study is provided in Online Appendix 2.

While some scholars describe a "leader" as a single, elected person who directs a hierarchical organization, the use of the concept of leadership in the context of coalitions – which are voluntary groupings of autonomous organizations – is more akin to what is known as "distributed" or "endogenous" leadership (Ahlquist and Levi 2011, pp. 13-14; Spillane 2006). From this perspective, leadership is indicated more by the tasks an actor performs than by its formal position. Leaders are those whose behavior is a guide to others and enables them to achieve their goals. In this sense, elected leaders may fail to exert leadership, while unelected actors may be critical to leading a group. Direct participants in coalition politics generally use concepts of distributed leadership to describe how coalitions work (see Leavitt and McKeown 2013, p. 67). Along these lines, the coordinator of a coalition advocating for children's interests explained in an anonymous interview in 2015 that "a leader helps to drive the coalition's discussion and decision making. They are very active in the coalition". This perspective recognizes that a coalition may have more than one interest group as its leader, depending on how much of a contribution each group makes to it. When an interest group seeks to advance a cause, there is no issue that is so small that it would not benefit from another group acting in a leadership role. Leaders may play this part without controlling or monitoring others, but rather by providing an example that others follow.

Of course, interest groups may also contribute to coalitions in numerous ways that do not necessarily exemplify leadership, such as allowing their names to appear on the coalition letterhead, attending meetings, paying dues, sharing staff resources, providing limited technical advice, or circulating information. Hula (1999) refers to groups that play these roles as "specialists" and "tag alongs". As coalitions and their internal decision modes are diverse, we deliberately chose to adopt an open question that acknowledges different kinds of leadership provision, yet allows a comparison across coalitions using the standardized interview.

Network Analysis of Two-Mode Data

The data collected for this study allow for the analysis of recognized leadership contributions (our measure of effort) by 171 interest groups in 74 lobbying coalitions. On average, each group in the sample joined 6.25 of the coalitions in the study, ranging from a minimum of 0 to a maximum of 22. On average, each coalition had 14.46 groups from the sample, ranging from a minimum of 5 (by design) to a maximum of 39.

Recognition of leadership contributions was less widely distributed than was membership. Each group was recognized as a leader in an average of 1.53 coalitions, ranging from a minimum of 0 to a maximum of 11. Each coalition had an average of 3.66 recognized leaders, ranging from a minimum of 0 to a maximum of 13. Thus, groups vary in the degree to which they are recognized for supplying leadership contributions to the coalitions of which they are members, while coalitions differ in the leadership contributions that they recognize receiving.

We conceptualize interest groups and coalitions as two-mode networks, or bipartite graphs, with groups and coalitions as separate classes of nodes. In a bipartite graph, edges exist between the two node classes but not within either class of nodes. We model the presence or absence of recognized leadership by groups in coalitions (i.e., the "ties" in the study) as the dependent variable. However, as these leadership dyads are potentially dependent on each other, we employ inferential network analysis to model the observations as a joint multivariate system rather than as independent observations. A formal description of this data structure is given in Online Appendix 3.

An illustration of the data structure is provided in Figure 1A, which is a sample of four coalitions drawn from the data. These coalitions are the Consortium for Citizens with Disabilities (CCD), the Coalition to Fight Sexually Transmitted Diseases (the Coalition to Fight STDs), the Ad Hoc Group for Medical Research Funding (the Ad Hoc Group), and the Health Benefits Coalition for Affordable Choice and Quality (the Health Benefits Coalition). In this graph, groups are represented by white circles, coalitions by gray squares; membership ties are represented by thin lines, and leadership ties by thick lines. Selected groups are labeled with letters for the purpose of illustration. Structural zeros are indicated by the absence of lines between circles and squares.

INSERT FIGURE 1 HERE

Three of the four coalitions in Figure 1A share groups with one another. It is apparent from the graph that CCD and the Ad Hoc Group share three members (**A**, **B**, and **C**), CCD and the Coalition to Fight STDs share one member (**A**), and the Ad Hoc Group and the Coalition to Fight STDs share five members (including **A**, **D**, and **E**). There is exactly one group that is a member of all three of these coalitions (**A**). On the other hand, the Health Benefits Coalition does not share any members with the other three coalitions. There are notable variations among the coalitions in the likelihood that interest groups are recognized as making leadership contributions. In the Health Benefits Coalition, 8 of the 12 members (66 percent) are recognized as making leadership contributions. The rate of leadership recognition is 42 percent for CCD, 32 percent for the Ad Hoc Group, and 5 percent in the Coalition to Fight STDs.

The recognition of leadership in this example is associated with high levels of *Partisan Diversity* and *Network Embeddedness*. In particular, the Health Benefits Coalition has the highest levels of recognized leadership, diversity, and embeddedness of the four coalitions. This coalition was able to bring together both moderate and highly partisan business associations that had a track record of working together on numerous issues. Under these conditions, a relatively high share of its members were recognized for their leadership roles.

Figure 1A is translated into matrix form for selected groups in Figure 1B. Groups are represented as the first mode and constitute the rows of the network matrix. Coalitions are represented as the second mode and constitute the columns of the network matrix. A value of 1 in a cell (a "tie") indicates that a group is a member of the coalition and is recognized as making a leadership contribution to the coalition. A value of 0 in a cell indicates that a group is a member of the coalition, but is not recognized as making a leadership contribution to the coalition. A value of X in a cell indicates that a group is neither a member of the coalition nor is recognized as contributing leadership. The Xs represent the "structural zeros" of the network: they are instances where a positive value of 1 is not possible within the framework under which the data were collected. Statistical analysis of such a network would reveal why a group is recognized as contributing leadership to a coalition, conditional on its being a coalition member.

Use of the exponential random graph model (ERGM) enables us to account for specified network dependencies in the data (Cranmer 2017). In an ERGM framework, we can model a network by describing how the network is composed of endogenous local structures and how its structure is additionally co-determined by exogenous covariates, such as nodal attributes, that increase or decrease the tie probability of a connected dyad. This model captures both the dependencies between observations as well as covariate effects. Two interpretations of ERGMs are: (1) a global interpretation where the probability of an observed network over the networks one could have observed is considered; and, (2) a local interpretation where the same probability governs whether any particular edge in the network is realized. In an ERGM, the probability of an observed network topology over the networks one could have observed is modeled as

$$P(N, \boldsymbol{\theta}) = \frac{\exp\{\boldsymbol{\theta}' \boldsymbol{h}(N)\}}{\sum_{N^* \in \mathcal{N}} \exp\{\boldsymbol{\theta}' \boldsymbol{h}(N^*)\}}$$

where N is a matrix representing the observed network, $\boldsymbol{\theta}$ are the coefficients that need to be computed, $\boldsymbol{h}(N)$ is a vector of statistics to be included in the model (including the endogenous dependencies and exogenous covariates), and N^* refers to a particular permutation of the topology of the network from the set of all possible permutations of the topology, denoted as $\mathcal{N}$ (Cranmer et al. 2017). The denominator is a normalizing constant that scales the probability between 0 and 1.

ERGMs are typically estimated by Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMC MLE) because the denominator contains a sample space that is too large to be evaluated using exhaustive optimization algorithms.

Three non-standard constraints to this default ERGM definition are necessary in the context of the present analysis. First, we analyze a two-mode network, which does not have edges within node classes. Therefore, all group-group dyads and all coalition-coalition dyads are constrained to be zero in any $N^* \in \mathcal{N}$ (so-called structural zeros). This constraint means that we must adjust the size of the sample space to contain only network matrices in which no positive entries are present in these within-mode dyads. Second, $N^* \in \mathcal{N}$ must never contain any edges that are not contained in the membership graph. Hence, we must also add structural zeros where a group is not a member of a coalition to prohibit leadership ties to be predicted where membership does not exist. Third, some specifications of the model require that we fix some values of the dependent variable so that they are determined a priori, rather than being estimated within the model. In particular, we specify in Models 2 and 4 below that a group must be assumed to make a leadership contribution to the coalition if it was a founding member of the coalition and is still observed to contribute leadership. In this case, we have set this group-coalition dyad as a "structural one".

These deviations from the standard probability density function in ERGMs are required for an appropriate scaling of the probability. Without these corrections, the probability of the observed graph would be underestimated relative to what could have been observed. At the estimation stage, constraints are introduced by adding a dyadic covariate to $\boldsymbol{h}(N)$ that contains a positive value in these entries (and 0 elsewhere) and by constraining the coefficient corresponding to this covariate in $\boldsymbol{\theta}$ to be negative infinity (for structural zeros) or positive infinity (for structural ones).

Estimation of the statistical models is carried out using the ergm package (Hunter et al. 2008) from the statnet suite of packages (Handcock et al. 2008) for the R computing environment.

Model goodness of fit is assessed using the xergm package (Leifeld, Cranmer, and Desmarais 2017).

Empirical Models

We report four ERGMs in the article, with additional models in Online Appendix 4. Model 1 represents a straightforward test of Hypotheses 1 and 2. The dependent variable is whether an interest group is recognized for making a leadership contribution in a coalition, conditional on it being a member of the coalition. Hypotheses 1a and 1b are tested using *Partisan Diversity*, which is measured with the standard deviation of the partisan ratings of interest groups in a coalition. A group's partisan rating was determined by subtracting the number of Democratic congressional staff members who rated it as "regular" and "reliable" from the number of Republican congressional staff members who gave it the same ratings. Thus, the partisan rating indicates the Republican lean of the group. *Partisan Diversity* is the standard deviation of these ratings within a coalition.

Hypotheses 2a and 2b are tested using *Network Embeddedness*, which is measured with the number of other coalition memberships that an interest group shares with the other groups in the coalition. Membership lists were derived from organizational members listed on the coalition's website, policy letters it sent to members of Congress, and/or a list provided by the coalition's representative during the interview. Embeddedness was calculated for each group-coalition dyad by adding the number of shared memberships that each group had in common with every group in the coalition and standardizing by the maximum number this count could possibly achieve in a given coalition. The standardization ensures that different coalition sizes are taken into account because the potential for co-memberships among members is otherwise greater in larger coalitions. This measure indicates the extent to which a group is allied with coalition partners through coalitions other than the one presently under analysis.

We include a series of control variables in Model 1, the first three of which account for the potential effects of partisanship on the coalition. *Interest Group Partisanship* is based on the partisan rating of the group by congressional staff, with Republican-leaning groups indicated by positive scores and Democratic-leaning groups indicated by negative scores. This variable checks for whether Democratic- or Republican-leaning groups are more likely to contribute to coalitions. *Coalition Partisanship* is the average of *Interest Group Partisanship* of all members of a coalition. It examines whether coalitions that lean Republican are more or less likely to recognize their members as leaders than are coalitions that lean Democratic. *Interest Group-Coalition Partisan Differential* is the absolute value of the difference between *Interest Group Partisanship* and *Coalition Partisanship* in a group-coalition dyad. It evaluates whether a group is more or less likely to contribute to a coalition if it is close to or distant from the coalition's average partisanship.

We include five control variables that represent key group characteristics. *Number of Coalition Memberships* indicates how extended the interest group is in alliances across the policy domain. *Interest Group Age* (in years) accounts for the possibility that more established groups may differ from newer groups in their involvement in coalitions. *Citizens' Advocacy Group* takes the value of 1 if the group advocates for a citizens' issue, as opposed to advocating for a trade association, professional society, or other organizational interests. It allows for the possibility that citizens' groups may participate in coalitions differently than do other kinds of groups. *Lobbying Expenditures* is the dollar value of the group's reported lobbying spending in 2003 under the Lobbying Disclosure Act. *Interest Group Crosses Issue Boundaries* takes the value of 1 if the group's policy agenda comes from outside health, 0 otherwise. For example, while the National Association of Manufacturers is certainly concerned about health policy, its primary focus is outside health, giving it a 1 on this variable.

We include eight control variables that represent key coalition characteristics. *Coalition Size* is the number of groups in the sample that are members of the coalition. It allows for the possibility that larger coalitions have fewer recognized leaders, possibly because they experience greater collective action problems as they get larger and/or because there are economies of scale in leading coalitions, reducing the need for more leaders as the coalition gets larger. *Coalition Age* (in years) enables us to evaluate if older coalitions differ in the recognition of their members as leaders from younger coalitions. *Coalition has Dues* takes the value of 1 if the coalition collects dues from its members, 0 otherwise, thus factoring in the coalition's access to monetary resources. *Coalition Faces Legislative Threat* takes the value of 1 if the coalition is responding to a legislative *threat*, as opposed to being part of an effort to achieve policy *gains*. *Coalition Focuses on Authorizing Legislation* takes the value of 1 if it focuses on the authoring legislation, as opposed to appropriations or disseminating policy information, which take the value of 0. *Coalition has Steering Committee* takes the value of 1 if the coalition has a steering committee or other formalized leadership structure, 0 otherwise. *Coalition is Visible* takes the value of 1 if it had a web page or publicly available membership list, 0 otherwise. *Coalition Issue is Controversial* takes the value 1 if the coalition's issue was part of a highly contentious policy debate during the 108th Congress (2003-2004), as indicated by a review of all articles on health-related topics during those years in *Roll Call*, *The Hill*, and *CQ Weekly*. These issues included abortion, prescription drugs, medical tort reform, funding long-term care, health savings accounts, association health plans, health insurance for mental illness, stem cell research, sex, and sexually-transmitted diseases. Examples of less controversial issues, which take the value of 0, included funding for the Agency for Health Research and Quality (AHRQ), treatment for colorectal cancer, greater emphasis on preventive health, and Medicare reimbursements.

We include two control variables to account for the endogenous structure of the networks that capture additional dependencies between observations, other than the endogenous variation captured by the main variables of interest. *Interest Group Mode Two-Star*s accounts for clustered activity of groups that results from recognition of leadership contributions in multiple coalitions. This variable models dependence when the same group appears in the data set several times as a member of multiple coalitions. Online Appendix 3 contains a formal definition and fuller explanation of the two-star model term. *Edges* accounts for the number of ties in the network. It is analogous to the constant in a generalized linear regression.

Model 2 contains the same variables as Model 1, thus allowing for tests for Hypotheses 1 and 2. It also includes a restriction that accounts for the fact that some groups determine their leadership role prior to joining the coalition. In particular, the entrepreneurs that found a coalition exert their critical leadership contributions prior to the coalition coming into existence. We separate these contributions from contributions that emerge after the coalition comes into existence. Hence, Model 2 treats all cases in which a group was one of the founders of a coalition and contributed leadership to the coalition as structural ones, thus adding 136 structural ones (of which 102 were leadership ties out of a total of 271 leadership ties). This corresponds to an average of about 2 founding members per coalition. Thus, for Model 2, the dependent variable is that a group is recognized for making a leadership contribution in a coalition, conditional on it being *a member but not a founder of the coalition*. Leadership by founders is fixed by the model.

Model 3 follows Model 1 and adds tests of Hypotheses 3a and 3b. It does so by including *Diversity* × *Embeddedness*, measured by multiplying *Partisan Diversity* by *Network Embeddedness*. Likewise, Model 4 follows Model 2 and adds *Diversity* × *Embeddedness* to test H3a and H3b.

Results

Table 1 presents coefficients, standard errors, and significance levels for Models 1 through 4. In all four models, we find positive, statistically significant coefficients on *Partisan Diversity*, thus supporting H1a over H1b. These findings indicate that coalitions whose members have more partisan heterogeneity tend to have more recognized leadership contributions than do coalitions with more partisan homogeneity. From an interest group perspective, a group is more likely to be recognized for leadership contributions if the coalition in which it is a member has high partisan diversity. In any group-coalition dyad, the effect size of 0.26 in Model 1 indicates that a one-point increase in diversity increases the odds of recognized leadership provision by about 30 percent. Partisan leaning is measured on a scale from -16 to +17. The standard deviations, which constitute the *Partisan Diversity* variable, vary across coalitions from a minimum of 1.34 to a maximum of 9.78 (mean=4.29). A one-point increase in this standard deviation of partisan leaning leads to 30 percent higher odds of being recognized for providing leadership.

INSERT TABLE 1 HERE

These results speak directly to the types of strategic decisions that coalition members make on a regular basis. For example, the Director of Government Relations for a prominent medical specialty society expressed a willingness to embrace partisanship. He emphasized that "when it comes to coalitions, you have to make a choice of when you will be partisan. Partisanship can translate into influence without question, as long as you are partisan with the right party." Others preferred to avoid partisanship, if possible. A vice president of a disease research advocacy group warned that "coalitions can become fairly political. They may become affiliated with one political party. But we try to shy away from coalitions with a political bent." Still others adopted an explicit strategy of bipartisanship. The Executive Vice President of a business trade association asserted that "we try to avoid coalitions that are too closely associated with any one political party. Instead, we prefer to be bipartisan. Although the Republicans are in control now, if you are in it for the long term, you recognize that there are cycles over time."

All four models have positive, statistically significant coefficients on *Network Embeddedness*, thus supporting H2a over H2b. In Model 1, the coefficient is 17.97. Since we standardize embeddedness by the maximal number of co-memberships all coalition members could potentially have, the variable has rather small values between 0 and 0.099, with a mean value of 0.036 and a standard deviation of 0.020. An increase of 0.01 in network embeddedness, for example, is associated with a 20 percent increase in the odds of leadership provision. Increasing embeddedness by one standard deviation is associated with a 50 percent increase in the odds of a contribution. These findings are consistent with the remarks of many respondents in the study, who stressed the benefits of being embedded within coalitions. For example, the Executive Director of one of the older organizations in the study reflected that "Coalitions are how other organizations get a clear picture of our capabilities. They are great for reputation building."

Models 3 and 4 include *Diversity* × *Embeddedness* in order to test H3a and H3b. The coefficients on this interaction term are not statistically significant in either model, thus providing no support for either hypothesis. The lack of a significant interaction means that there is insufficient evidence to conclude that diversity and embeddedness are interdependent. Thus, we cannot conclude that the effects of *Partisan Diversity* or *Network Embeddedness* either amplify or undercut one another in ways that affect our conclusions with respect to Hypotheses 1 and 2.[3]

Among the control variables, *Coalition Partisanship* has a positive, statistically significant effect in Model 1 only. A group's *Number of Coalition Memberships* is negative and significant in Models 1 and 3, but not Models 2 and 4. *Coalition Size* has a negative, significant effect in Models 1 and 3, but not in Models 2 and 4. *Coalition Age* is positive and significant in Models 2 and 4, but not in Models 1 and 3. *Coalition has Dues* is positive and significant in Model 2, but not in the other models. *Coalition Issue is Controversial* is negative and significant in Models 1 and 3, but not in Models 2 and 4.

Among the endogenous variables, the coefficient on *Interest Group Mode Two-Stars* is positive and significant in all four models, which reveals positive network dependence, resulting from the fact that certain groups are more likely to be recognized as making leadership contributions to coalitions than are other groups. For example, the American Medical Association, AARP, and U.S. Chamber of Commerce are more widely recognized for their leadership contributions to coalitions

[3] To examine potential interaction effects more closely, we present predicted probabilities and marginal effects plots in Appendix 5 for Models 3 and 4. These graphs reveal some dampening of diversity effects when embeddedness is high, as well as some dampening embeddedness effects when diversity is high, consistent with H3b. However, these effects are not statistically significant.

than are the American Osteopathic Association, the National Hemophilia Foundation, and the United Mine Workers of America. Also, the *Edges* variable, which accounts for the effects of network density, is negative and significant in all models. This variable is analogous to the constant in a standard regression model and, thus, should not be given a substantive interpretation.

We evaluate the goodness of fit of Model 1 by simulating 1,000 new networks from the model and comparing these simulations to the observed leadership network. First, we compare distributions of several relevant network statistics: non-edge-wise shared partners, geodesic (i.e., shortest path) distance between members of a dyad, degree centrality, and *k*-stars at varying levels of *k*.[4] If the simulated distributions (represented by boxplots in Figure 2) approximately match the observed network (represented by a black lines in the boxplots), then the model captures the network properties of the observed leadership graph well and does not suffer from omitted-variable bias with regard to endogenous dependencies (Hunter, Goodreau, and Handcock 2012). With the exception of coalition mode *k*-stars, the models fit well in terms of network properties.

INSERT FIGURE 2 HERE

The Online Appendix contains more information about model fit (for Models 2 through 18) and diagnostics, including precision-recall curves that indicate within-sample classification performance in terms of the fraction of ties successfully predicted by the model versus the type II error with which such a prediction is made (Online Appendix 7) and the MCMC trace plots as indicators of convergence (Online Appendix 8).

In terms of the generalizability of our results, an important consideration is how typical health coalitions are of coalitions on other issues. We believe that because the health policy field is both large (in terms of the number of active groups) and broad (in terms of the diversity of issues it addresses), that health coalitions – on average – are not deviant from coalitions in other policy

[4] A *k*-star is a configuration of *k* nodes that each has one connection to a central node.

domains. Indeed, a recent study by Crosson and Heaney (2014) documents this comparability. They interviewed lobbyists working for 124 randomly-selected groups from any area of public policy. They asked the respondents to list the coalitions that they had worked with the past year. They then followed up with a second round of interviews with leaders of 84 coalitions randomly selected from this set. They found that 34 of these coalitions (40 percent) dealt in some way with health. No statistically significant differences were detected between coalitions on health and those on other policy areas with respect to factors such as coalition size, number of leaders, perceived cooperativeness, perceived effectiveness, and founding year, based on a similar data collection strategy. Given these results, we think that it is reasonable to view behavior inside health policy coalitions as representative of behavior inside coalitions focused on other policy domains.

Robustness Analysis

We sought to determine whether the conclusions drawn from our analysis in Models 1-4 are sensitive to our decisions about measurement and specification. To do so, we estimated a series of models (see Online Appendix 4) that made different choices on key issues. Focusing only on the variables used to test Hypotheses 1 through 3, we reached the following conclusions. First, the positive, significant effect of *Partisan Diversity* is robust to alternative specifications. This result holds up in every model we estimate. Thus, we have a very high degree of confidence in Hypothesis 1a. Second, the coefficient on *Diversity* × *Embeddedness* is insignificant in every model in which we included this variable. Thus, we find no support for either H3a or H3b. Third, the effects of *Network Embeddedness* are sensitive to model specification: while they are robust against a number of additional controls and alternative specifications, the positive, significant effect of this variable is conditional on the inclusion of *Number of Coalition Memberships* in the model. Thus, while there is much support for the positive effect of *Network Embeddedness* (i.e., H2a), this finding depends on the covariates with which it is examined. In the remainder of this section, we demonstrate how we reached these conclusions by describing the estimation of Models 5-18.

Model 5 is a variation on Model 2. It includes the same covariates, but uses a different restriction for founders of the coalition. Instead of fixing these groups as structural *ones* in the model, they are fixed as structural *zeros*. This variation examines how the way that we model prior leadership affects our conclusions. We find that it does not affect conclusions about our hypotheses.

Model 6 is a variation on Models 1 and 2. It includes the same covariates, but places no restrictions on the analysis in terms of structural zeros or ones. This variation examines how the way we set up the network analysis affects our conclusions. This difference in the specification does not affect conclusions about our hypotheses. Yet, it is also important to note that the standard errors in this model are unrealistically small because they include many observations that could not possibly take the value of 1. For example, a pro-life group could never act as a leader of a pro-choice coalition, yet this possibility is allowed in Model 6 (but not in any other model).

Models 7 and 8 are variations on Models 1 and 3. The difference is that Models 7 and 8 use an alternative measure of *Network Embeddedness* that gives greater weight to weak ties among members of a coalition than they are given in Models 1 and 3. Similarly, Models 9 and 10 use an alternative measure of *Network Embeddedness* that relies on intra-coalition communication rather than coalition co-membership. We did not use this measure in the main models because of a likely endogenous relationship between the presence of leadership a coalition and the likelihood that coalition members are in communication. Models 11 and 12 use alternative measures of *Network Embeddedness* based on the partisan nature of ties. Model 11 draws only upon within-party ties, and Model 1 uses only cross-party ties, to construct embeddedness. These models are estimated to account for the fact that there is not a unique way to measure embeddedness. The use of these alternative measures does not lead to different conclusions about our hypotheses.[5] Thus, our analysis is robust to multiple, alternative measures of embeddedness (defined in Online Appendix 9).

Models 13 and 14 are stripped-down versions of Model 1. Model 13 includes only *Partisan Diversity*, *Network Emeddedness, Interest Group Mode Two-Star*s, and *Edges*. These models were estimated to ascertain if the estimated effects are artifacts of which control variables are included in the equation. In this minimal model, *Partisan Diversity* has a coefficient that is positive and significant. However, the coefficient on *Network Embeddedness* falls short of the threshold for significance. Model 14 is a variation on Model 13 with the addition of *Number of Coalition Memberships*. In this model, the coefficients on *Partisan Diversity* and *Network Embeddedness* are both positive and significant. Comparison of Models 13 and 14 reveals that the significance of *Network Embeddedness* is conditional on including *Number of Coalition Memberships* in the specification. We suspect that this condition may hold because groups that are in a greater number of coalitions may be affected less by their embeddedness in any one coalition than are groups with memberships in fewer coalitions.

Number of Coalition Memberships is the only variable in the dataset that moderates Network Embeddedness. Model 15 is a variation on Model 1 that considers other measures of diversity within a coalition in addition to *Partisan Diversity*. This variation ascertains if *partisan* diversity is crucial or if other kinds of diversity may have similar effects on coalitions. It looks at diversity in group age, lobbying expenditures, citizens' advocacy groups, and groups from outside health policy. These alternative measures of diversity do not enter Model 15 with statistically significant coefficients, thus suggesting the distinctive importance of diversity is based on partisanship. Further, these specifications do not affect conclusions about our hypotheses. As the effect size and significance for *Partisan Diversity* is nearly identical in Models 1 and 15, none of the other diversity measures seem

[5] We examined predicted probabilities and marginal effects plots (see Online Appendix 5) for Model 10, which includes an interaction term, and did not find that interactive effects challenged our conclusions.

to moderate or mediate the effect of partisan diversity on leadership contributions.

Models 16 and 17 are variations on Model 1 that consider the possibility that *Partisan Diversity* interacts with *Coalition is Visible* (in Model 16) and *Coalition Issue is Controversial* (in Model 17). These variations evaluate if the relevance of diversity is increased when coalitions receive greater attention from the public. The results reveal a significant, positive interaction effect with controversy, but not with visibility. However, neither model yields conclusions that differ from Model 1, thus allaying concerns that the impact of diversity may be a function of the visibility or controversy surrounding the coalition.[6]

Model 18 is a variation of Model 1 that uses *Coalition Mode Two-Stars* in addition to *Interest Group Mode Two-Stars*. This alternative specification examines the effect of controlling for network dependence in the *second* mode, rather than only in the *first*. This model considers whether common recognition of leadership contributions by several coalition members induces nonindependence of observations. To estimate this specification, we drop *Number of Coalition Memberships* and *Coalition Size* from the model, due to multicollinearity. The results reveal no significant network dependence in the coalition mode and do not alter the conclusions with respect to our other hypotheses.

Goodness-of-fit plots for all models discussed in this section are included in Online Appendix 6. Code to estimate all models and robustness checks is provided in Online Appendix 10.

Limitations

Three limitations in our study require discussion. First, we measure the recognized leadership contributions of all groups within a coalition using a single informant for each coalition, usually a coalition coordinator. Doing so requires the assumption that the informants are not systematically biased in favor or against particular groups in their coalitions. While we think that this

[6] We examined predicted probabilities and marginal effects plots (see Appendix 5) for Models 16 and 17, which include interaction terms, and did not find that interactive effects challenged our conclusions.

assumption is reasonable, fully evaluating the fixed effects of possible bias would require us to estimate statistical models containing 73 dummy variables (for each of N-1 coalitions). We attempted to do so, but such a model does not converge in the ERGM, generalized linear model, or linear mixed-effects model framework. Hence, future research should evaluate how possible respondent biases might influence estimates about the effects of coalition composition. An alternative approach would be to turn to multiple informants per coalition, though such a strategy would greatly increase the resources required to study he same number of coalitions.

Second, the heterogeneity of a coalition with high partisan diversity may make the different contributions made by multiple groups more visible or salient. In other words, the partisan diversity effect on recognition of contributions may be at least partly about perception – rather than substantive contributions of time and effort – which we do not directly observe. A way around this limitation would be to observe group contributions to coalitions directly (rather than relying on informants). However, this approach would dramatically reduce the number of coalitions that could be observed with the same level of resources.

Third, we measure contributions by groups dichotomously. Either groups are recognized for contributing leadership or they are not. Future research might fruitfully examine effort in a more continuous fashion. This approach would allow the comparison of leadership to other types of contributions, such as financial or staff contributions.

Conclusion

This study yields new insights about how interest group collaboration is related to the composition of lobbying contributions, as indicated by partisan diversity and network embeddedness of their members. The results strongly support the hypothesis that partisan diversity is positively associated with greater recognition of leadership by members of lobbying coalitions. Coalitions that cross the partisan divide tend to operate differently than coalitions cloistered within one party. This finding reveals that partisan polarization not only corresponds to the decision-making of *legislators*, but also behavior of *ancillary political actors* (see also Heaney and Rojas 2015).

At the same time, interest group participation in coalitions is positively associated with how connected the members of coalitions are through other coalitions, reinforcing the idea that working together on a number of topics increases the willingness of groups to embrace leadership among their peers. Observing the effects of network embeddedness, however, is associated with the number of coalition memberships that an interest group has. This contingency may hold because groups with more coalition memberships are less likely to serve as a leader of any one of them. That is, embeddedness matters more for groups that are more selective about which coalitions they join.

In evaluating the importance of these findings, it is necessary to consider the scope of conditions under which they are likely to hold. Our analysis of coalitions outside of the health policy domain suggests that these patterns are likely to apply to lobbying coalitions in other policy domains. To what extent are they likely to apply with regard to other types of policymaking venues (such as states or executive agencies) and earlier or later periods in Congress? We anticipate that our findings about network embeddedness apply broadly across political institutions and periods of time, as the embeddedness finding has already been demonstrated widely across the social sciences. We expect, however, that the effects of partisan diversity are likely to be more contingent on the institutional context. Executive agencies, for example, vary in the degree to which they are responsive to electoral pressures. We anticipate that agencies that are more responsive to electoral pressures are more likely to attract coalitions with partisan diversity. However, we expect that agencies that are less responsive to electoral pressures are less likely to have a bias either in favor of or opposed to partisan diversity in the coalitions that lobby them.

We imagine that the effects of partisan diversity would correspond closely with the degree of partisan polarization in the political system, both at the state and national levels. The high partisan polarization of the present period makes it perhaps an ideal time to observe effects from forging coalitions across partisan boundaries. For example, the recent passage of the 21st Century Cures Act benefitted from lobbying coalitions that spanned the two parties (Lorenz 2017). Thus, as partisan polarization has increased in the decade since the data for this article were collected, the benefits of diverse partisan coalitions appear to remain in place. During less polarized times, such effects would likely be less evident. That is, there are likely greater benefits to transcending partisanship when it is a major factor that divides the political system than when it is not. Alternatively, if the political system is divided by another factor, such as a region, then research might fruitfully search for the benefits of coalition heterogeneity by region (or other factors). Thus, it would be potentially productive to consider the effects of different types of coalition heterogeneity over time and space.

Coalitions are a vital aspect of interest group strategy but are relatively neglected by interest group scholars. This research demonstrates that prior studies of coalitions, which focused exclusively on the interest group level of analysis, were insufficient to understand the nature of interest group contributions to lobbying coalitions. Additionally, it is essential to incorporate analysis of coalitions themselves, especially their membership composition in terms of partisan diversity and network embeddedness. This analysis, which views coalitions as relational teams, demonstrates the crucial role of advocacy networks in linking interest groups and coalitions to one another.

Acknowledgements

The authors are grateful for helpful feedback from Frank Baumgartner, Jeff Berry, Jesse Crosson, Don Green, Jen Hadden, Mark Hansen, Marie Hojnacki, Greg Huber, Kevin Hula, Lorien Jasny, Geoff Lorenz, John Padgett, Jen Victor, and the anonymous reviewers. The second author carried out parts of this work at the Swiss Federal Institute of Aquatic Science and Technology (Eawag), the University of Bern, Institute of Political Science, and at the University of Konstanz.

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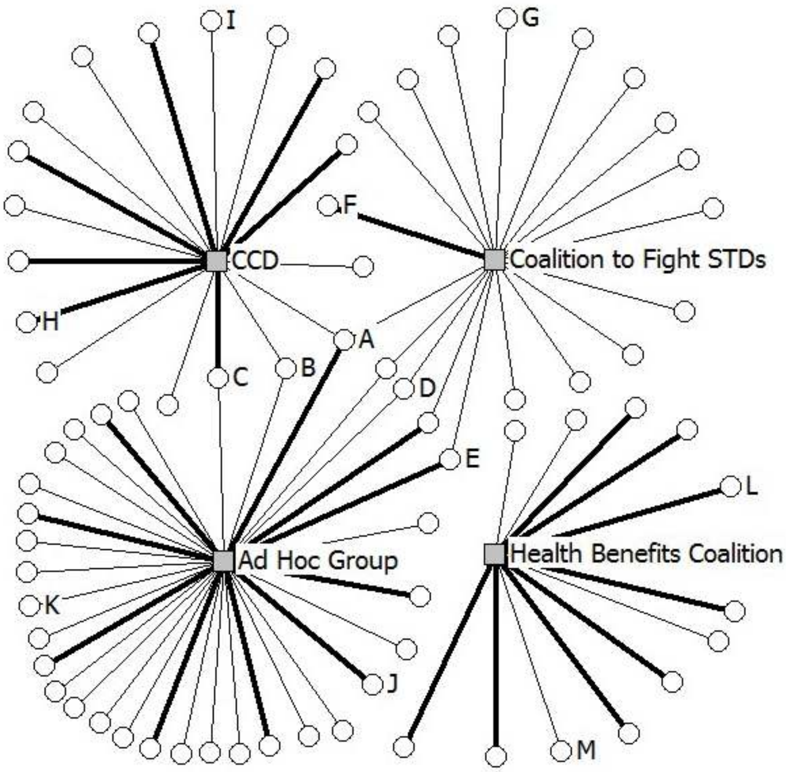
Table 1. Factors Associated with Recognition of Leadership Contributions to Coalitions
(Two-Mode Exponential Random Graph Models with Structural Zeros and Ones)

	Hypotheses	Mode	Model 1	Model 2	Model 3	Model 4
Focal Variables						
Partisan Diversity	H1a, H1b	Coalition	0.26 (0.06)***	0.34 (0.08)***	0.42 (0.12)***	0.44 (0.14)**
Network Embeddedness	H2a, H2b	Interest Group	17.70 (5.52)**	17.82(6.65)**	36.67 (12.77)**	31.04 (15.64)*
Diversity × Embeddedness	H3a, H3b	Both			-4.49 (2.73)	-3.08 (3.33)
Partisanship						
Interest Group Partisanship	Control	Interest Group	0.02 (0.02)	0.03 (0.02)	0.02 (0.02)	0.03 (0.02)
Coalition Partisanship	Control	Coalition	0.06 (0.03)*	0.05 (0.04)	0.06 (0.03)	0.05 (0.04)
Interest Group-Coalition Partisan Differential	Control	Both	-0.01 (0.03)	0.01 (0.03)	-0.02 (0.03)	0.01 (0.03)
Interest Group Characteristics						
Number of Coalition Memberships	Control	Interest Group	-0.07 (0.03)**	-0.06 (0.03)	-0.07 (0.03)**	-0.06 (0.03)
Interest Group Age	Control	Interest Group	0.36 (0.20)	-0.08 (0.25)	0.35 (0.20)	-0.09 (0.25)
Citizens Advocacy Group	Control	Interest Group	0.30 (0.16)	0.28 (0.19)	0.31 (0.16)	0.29 (0.19)
Lobbying Expenditures	Control	Interest Group	0.00 (0.01)	-0.01 (0.01)	0.01 (0.01)	-0.01 (0.01)
Interest Group Crosses Issue Boundary	Control	Interest Group	-0.17 (0.21)	-0.15 (0.25)	-0.16 (0.21)	-0.14 (0.25)
Coalition Characteristics						
Coalition Size	Control	Coalition	-0.03 (0.01)***	-0.02 (0.01)	-0.03 (0.01)***	-0.02 (0.01)
Coalition Age	Control	Coalition	0.72 (0.65)	1.54 (0.73)*	0.72 (0.65)	1.53 (0.73)*
Coalition has Dues	Control	Coalition	-0.11 (0.18)	-0.43 (0.22)*	-0.09 (0.18)	-0.42 (0.22)
Coalition Faces Legislative Threat	Control	Coalition	0.01 (0.25)	-0.34 (0.33)	0.03 (0.26)	-0.31 (0.33)
Coalition Focuses on Authorizing Legislation	Control	Coalition	0.11 (0.19)	0.16 (0.22)	0.12 (0.19)	0.17 (0.22)
Coalition has Steering Committee	Control	Coalition	0.22 (0.16)	0.09 (0.19)	0.18 (0.16)	0.06 (0.19)
Coalition is Visible	Control	Coalition	0.48 (0.31)	0.66 (0.38)	0.47 (0.31)	0.66 (0.39)
Coalition Issue is Controversial	Control	Coalition	-0.44 (0.20)*	-0.19 (0.23)	-0.49 (0.20)*	0.22 (0.23)
Network Characteristics						
Interest Group Mode Two-Stars	Endogenous	Both	0.13 (0.04)**	0.15 (0.05)**	0.13 (0.04)**	0.15 (0.05)**
Edges	Endogenous	Both	-2.73 (0.55)***	-3.80 (0.67)***	-3.39 (0.69)***	-4.26 (0.84)***
Constraints			Structural zeros for nonmembers	Struc. 0s for nonmembers; Structural ones for founders	Structural zeros for nonmembers	Struc. 0s for nonmembers; Structural ones for founders

Note: ***$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$. All tests are two-tailed.

Figure 1. Illustrations of Two-Mode Network with Structural Zeros

A. Graphical Illustration

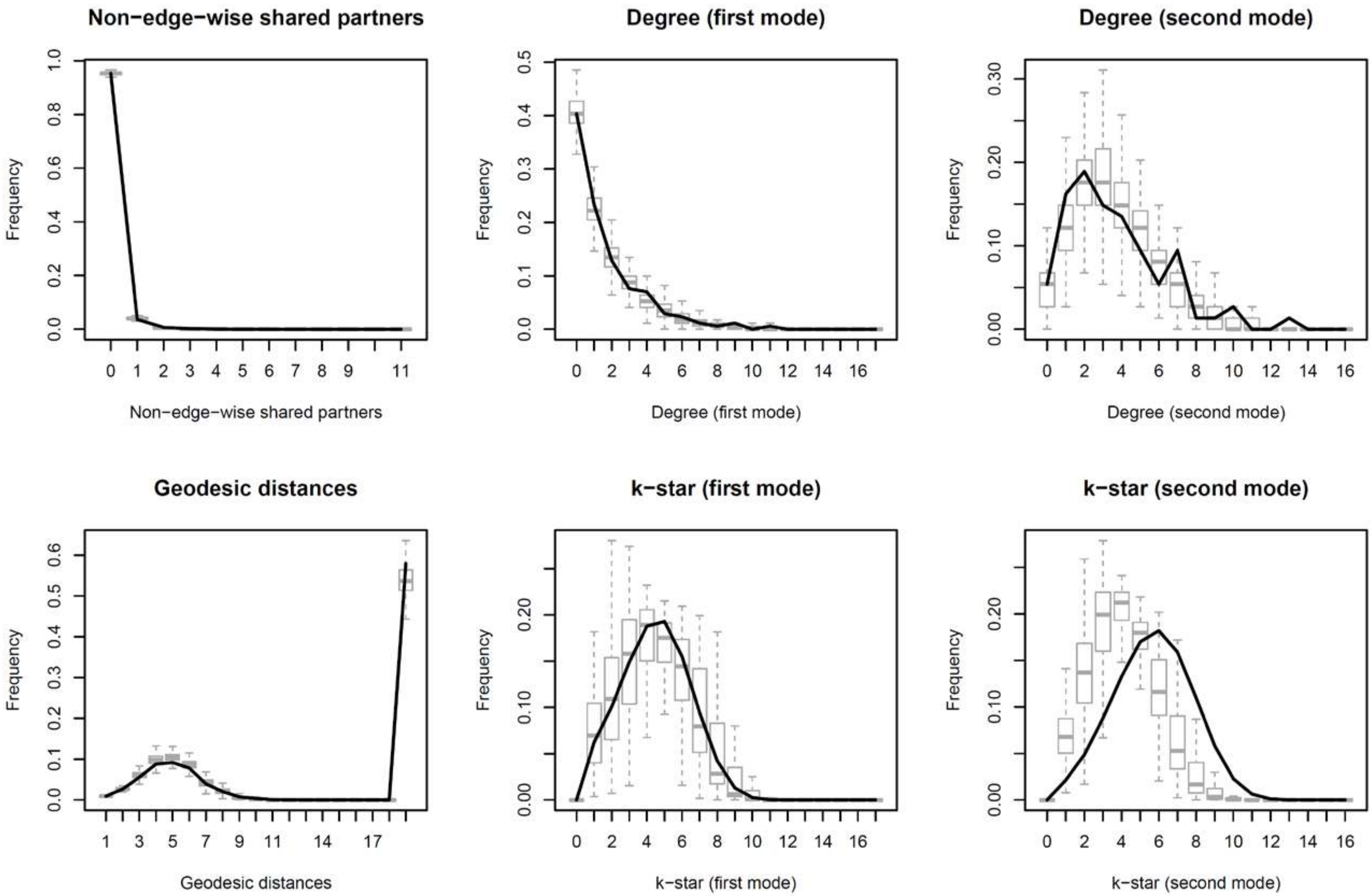


B. Matrix Illustration (for Selected Interest Groups with Labels)

	Coalition			
Interest Group	**Consortium for Citizens with Disabilities**	**Coalition to Fight Sexually Transmitted Diseases**	**Ad Hoc Group for Medical Research Funding**	**Health Benefits Coalition for Affordable Choice and Quality**
A	0	0	1	X
B	0	X	0	X
C	1	X	0	X
D	X	0	0	X
E	X	0	1	X
F	X	1	X	X
G	X	0	X	X
H	1	X	X	X
I	0	X	X	X
J	X	X	1	X
K	X	X	0	X
L	X	X	X	1
M	X	X	X	0

Note: 1 indicates that an interest group is a coalition member *and* is recognized as contributing leadership.
0 indicates than an interest group is a coalition member, but is not recognized as contributing leadership.
X indicates that an interest group is neither a coalition member nor is recognized as contributing leadership.
X represents the “structural zeros”.

Figure 2. Endogenous Goodness-of-Fit Assessment for Model 1



Online Appendix for Michael T. Heaney and Philip Leifled, "Contributions by Interest Groups to Lobbying Coalitions," *Journal of Politics*, 2018.

List of Items

Online Appendix 1. List of Interest Groups Included in the Research

60 Plus Association
AARP
Advanced Medical Technology Association
AFL-CIO
AIDS Action Council
Alliance for Retired Americans
Alzheimer's Association
American Academy of Child and Adolescent Psychiatry
American Academy of Dermatology
American Academy of Family Physicians
American Academy of Orthopaedic Surgeons
American Academy of Otolaryngology – Head and Neck Surgery
American Academy of Pediatrics
American Academy of Physician Assistants
American Association for Dental Research
American Association of Colleges of Nursing
American Association of Colleges of Pharmacy
American Association of Health Plans
American Association of Homes and Services for the Aging
American Association of Nurse Anesthetists
American Bar Association
American Benefits Council
American Cancer Society
American Chiropractic Association
American College of Cardiology
American College of Emergency Physicians
American College of Obstetricians and Gynecologists
American College of Physicians
American College of Preventive Medicine
American College of Surgeons
American Council of Life Insurers
American Dental Association
American Dental Education Association
American Diabetes Association
American Dietetic Association
American Farm Bureau Federation
American Federation for Medical Research
American Federation of Government Employees
American Federation of State, County, and Municipal Employees
American Gastroenterological Association
American Health Care Association
American Health Planning Association
American Health Quality Association
American Heart Association

American Hospital Association
American Insurance Association
American Legion
American Lung Association
American Medical Association
American Nurses Association
American Osteopathic Association
American Pharmacists Association
American Physical Therapy Association
American Psychiatric Association
American Psychological Association
American Public Health Association
American Social Health Association
American Society for Clinical Pathology
American Society for Microbiology
American Society of Anesthesiologists
American Society of Association Executives
American Society of Hematology
American Speech-Language-Hearing Association
Americans for Tax Reform
Arthritis Foundation
Association for the Advancement of Psychology
Association of American Medical Colleges
Association of Minority Health Professions Schools
Association of National Advertisers
Association of Schools of Public Health
Association of State and Territorial Health Officials
Association of Teachers of Preventive Medicine
Association of Trial Lawyers of America
Autism Society of America
Biotechnology Industry Organization
Blue Cross and Blue Shield Association
Business Roundtable
Candlelighters Childhood Cancer Foundation
Children's Defense Fund
Christian Coalition of America
Citizens for Public Action on High Blood Pressure and Cholesterol
Coalition for Health Funding
College of American Pathologists
Common Cause
Concord Coalition
Consumer Federation of America
Cooley's Anemia Foundation
Council for Government Reform
Crohn's and Colitis Foundation of America
Cystic Fibrosis Foundation
Disabled American Veterans
Endocrine Society

Environmental Defense
Epilepsy Foundation
Families USA
Federation of American Hospitals
Federation of American Societies for Experimental Biology
Generic Pharmaceutical Association
Greater New York Hospital Association
Grocery Manufacturers of America
Health Insurance Association of America
Healthcare Distribution Management Association
Healthcare Leadership Council
Human Rights Campaign
Independent Insurance Agents and Brokers of America
International Brotherhood of Teamsters
International Council of Cruise Lines
Joint Commission on Accreditation of Healthcare Organizations
Joint Council of Allergy, Asthma, and Immunology
Juvenile Diabetes Research Foundation International
March of Dimes Birth Defects Foundation
Medical Device Manufacturers Association
Medical Library Association
NARAL Pro-Choice America
National Alliance for Hispanic Health
National Alliance for the Mentally Ill
National Alliance of Breast Cancer Organizations
National Association for Home Care
National Association for the Advancement of Colored People
National Association of Chain Drug Stores
National Association of Children's Hospitals
National Association of Community Health Centers
National Association of Counties
National Association of County and City Health Officials
National Association of Independent Insurers
National Association of Insurance Commissioners
National Association of Manufacturers
National Association of Social Workers
National Association of State Alcohol and Drug Abuse Directors
National Breast Cancer Coalition
National Citizens' Coalition for Nursing Home Reform
National Committee to Preserve Social Security and Medicare
National Conference of State Legislatures
National Council for Community Behavioral Healthcare
National Council of La Raza
National Farmer's Union
National Federation of Independent Business
National Governors Association
National Hemophilia Foundation
National Kidney Foundation

National League for Nursing
National Mental Health Association
National Partnership for Women and Families
National Rehabilitation Association
National Restaurant Association
National Retail Federation
National Right to Life Committee
National Rural Electric Cooperative Association
National Society of Professional Engineers
National Union of Hospital and Health Care Employees / Local 1199
National Urban League
National Women's Health Network
Paralyzed Veterans of America
Parkinson's Action Network
Pharmaceutical Research and Manufacturers of America
Planned Parenthood Federation of America
Public Citizen
Renal Physicians Association
Seniors Coalition
Service Employees International Union
Society for Investigative Dermatology
The Arc of the United States
United Auto Workers
United Cerebral Palsy Associations
United Mine Workers of America
United States Chamber of Commerce
United States Conference of Catholic Bishops
United States Conference of Mayors
Veterans of Foreign Wars
Vietnam Veterans of America
Washington Business Group on Health

Online Appendix 2. List of Coalitions Included in the Research

Ad Hoc Group for Medical Research Funding
Alliance of Specialty Medicine
Alliance to Improve Medicare
AMA Large Group on "Part B" Issues (Coalition for Payment)
American Tort Reform Association (ATRA)
Americans for Long Term Care Security
Anti-Reimportation Coalition (a fabricated name) *
Antitrust Coalition for Consumer Choice in Health Care
Archer MSA Coalition
Association Health Plan Coalition
Campaign for Quality Care
Campaign for Tobacco Free Kids
CDC Coalition (Centers for Disease Control and Prevention)
Children's Environmental Health Network (CHEN)
Children's Health Group
Citizens for Better Medicare
Citizens for Long-Term Care Coalition
Coalition for Affordable Health Coverage
Coalition for Fair Medicare Payment
Coalition for Fairness in Mental Illness Coverage (Mental Health Parity Coalition)
Coalition for Genetic Fairness
Coalition for Health Funding
Coalition for the Advancement of Medical Research (CAMR)
Coalition on Human Needs
Coalition to Fight Sexually Transmitted Diseases
Confidentiality Coalition
Consortium for Children with Disabilities
Consortium for Citizens with Disabilities (CCD)
Cover the Uninsured Week Coalition
Employers' Coalition on Medicare
Families USA Medicaid Action Coalition
Family Planning Coalition
FamilyCare Act Coalition
Federation of Associations of the Schools of the Health Professions (FASHP)
FMAP Coalition (Federal Medicaid Matching Rate)
Friends of AHRQ (Agency for Health Research and Quality)
Friends of HRSA (Health Resources and Services Administration)
Friends of Indian Health
Friends of NICHD Coalition (National Institute of Child Health and Human Development)
Friends of VA Medical Care and Health Research (FOVA)
Genetic Alliance
Genome Action Coalition
GINE Coalition
Health Benefits Coalition for Affordable Choice and Quality
Health Coalition on Liability and Access (HCLA)
Health Professions and Nursing Education Coalition (HPBEC)

Health Professions Network
Independence Through Enhancement of Medicare and Medicaid Coalition (ITEM)
Independent Budget
Leadership Council on Aging Organizations
Limited English Proficiency Coalition
Long Term Care Campaign
Mental Health Liaison Group
National Alliance for Nutrition and Activity (NANA)
National Coalition on Health Care
National Coalition to Support Sexuality Education
National Colorectal Cancer Roundtable
National Council on Folic Acid
National Council on Patient Information and Education
National Health Council
National Immunization Council
National Medical Liability Reform Coalition
National Organizations Responding to AIDS Coalition (NORA)
National Partnership's Patients Bill of Rights Coalition
NIAMS Coalition (National Institute of Arthritis and Musculoskeletal & Skin Diseases)
One Voice Against Cancer (OVAC)
Opponents of a Medicare Home Health Copayment (a fabricated name) *
Opponents of Association Health Plans (a fabricated name) *
Partnership for Clear Health Communication
Partnership for Prevention
Patient Access Coalition
Patient Access to Responsible Care Alliance (PARCA)
Pro-Choice Coalition (The Small Lobby)
Research to Prevention
Research!America
Rx Benefits Coalition
Rx Health Value
Smallpox Compensation Coalition
Task force on the NGA Medicaid Task Force
Women's Health Research Coalition

Note: * In three cases, we created the coalition's name because the participants chose not to assign a formal name to the coalition. Acronyms are listed only if the coalition participants referred to the coalition by the acronym. If the official coalition name contains an acronym, the meaning of the acronym is in parentheses. If the coalition also uses an alternative name, that name is listed in parentheses.

Online Appendix 3. Explanation of Two-Mode Data Structure

The data structure is nested in the following way. In the membership graph $\mathrm{G} = (\mathrm{U}, \mathrm{V}, \mathrm{E})$, a group u is connected to a coalition v by an edge $\mathrm{e} = (\mathrm{u}, \mathrm{v})$ if it is a member of this coalition. In the recognized leadership graph, group u is connected to coalition v by edge $\mathrm{e}' = (\mathrm{u}, \mathrm{v})$ if it is recognized as a leader in the coalition. Therefore, recognized leadership is a proper edge-induced subgraph $\mathrm{G}[\mathrm{E}']$ of the membership graph with edge set $\mathrm{E}' \subset \mathrm{E}$.

There are $|U| \cdot |V| = 12{,}654$ observations (or possible edges) in the membership network, $|E| = 1{,}070$ observations (or possible edges) in the nested recognized leadership network (this is also the number of realized edges in the membership network), and $|E'| = 271$ realized edges in the recognized leadership network. These observations yield a density of $\frac{|E|}{|U| \cdot |V|} = 0.085$ in the membership network and $\frac{|E'|}{|E|} = 0.253$ in the nested recognized leadership subgraph.

The goal of the analysis is to model $G[E']$ (rather than G). Two non-standard constraints to the default ERGM definition are necessary. First, we analyze a two-mode network, which does not allow edges within node classes: $\forall\, e' \in E' : (u, u') \notin E', (v, v') \notin E'$. Therefore, N and N^* have dimensions $(|U| + |V|) \times (|U| + |V|)$, but all block-diagonal dyads $N_{u \in U, u' \in U}$ as well as $N_{v \in V, v' \in V}$ are constrained to be zero in any $N^* \in \mathcal{N}$ (so-called structural zeros). This constraint means that we must adjust the size of the sample space to contain only network matrices in which no positive block-diagonal entries are present. Second, since recognized leadership is an edge-induced subgraph of membership, $N^* \in \mathcal{N}$ must never contain any edges which are not contained in the membership graph G. Hence, we define the set of possible network topologies as $\mathcal{N} \setminus \bar{\mathcal{G}}$ (rather than $\mathcal{N}$) where $\bar{\mathcal{G}}$ is the set of matrices representing all edge-induced subgraphs of the complement graph $\bar{G}$ of G. At the estimation stage, this is solved by adding a matrix representing $\bar{G}$, the complement graph of the membership network, as an edge covariate to $\boldsymbol{h}(N)$, and by constraining the coefficient corresponding to this covariate in $\boldsymbol{\theta}$ to be negative infinity.

We include two-star terms in the ERGMs in order to control for clustered activity by interest groups and coalitions. *Interest Group Mode Two-Stars* account for the dependencies that result when an individual interest group has a propensity to be systematically recognized for contributing leadership to multiple coalitions or when its leadership contributions tend to be systematically ignored by others. *Coalition Model Two-Stars* account for the dependencies that result when a coalition has the propensity to systematically represent either more or fewer of its members as leaders. The inclusion of two-star terms in the models account for endogenous dependencies by controlling for either the tendency of an interest group's activities to be linked across coalitions or the tendencies of a coalition to have a common effect on whether its members are recognized as contributing leadership to the coalition. That is, it models the non-independence of observations in network data that is not captured by the main hypotheses.

Two-star statistics can be expressed as the count

$$h_{\text{twostar}} = \sum_{i<k} \sum_{j} N_{ij} N_{kj}$$

where $N_{ij} = 1$ if node j has an incoming tie from node i and 0 otherwise. This subgraph product counts the number of local graph configurations where a node has two incoming ties. The two-star statistic is included for groups (with $j \in U$ and $i, k \in V$) and, in Model 18, once for coalitions (with $j \in V$ and $i, k \in U$).

In this Equation, i and k are different nodes of the same node set, or mode. In order not to count cases where i=k and in order not to count two-star structures involving the same nodes in that mode twice, the first sum is over nodes i<k, which means all nodes assuming the value k and all nodes assuming the value i, where the index of node i is neither the same as k nor larger than k. This effectively rules out trivial cases where the two connected nodes are identical (and thus do not measure clustering), and it avoids counting configurations <i,k> and <k,i> twice.

Online Appendix 4. Factors Associated with Recognition of Leadership Contributions to Coalitions

Models 5-8

	Model 5	**Model 6**	**Model 7**	**Model 8**
Focal Variables				
Partisan Diversity	0.36 (0.08)***	0.88 (0.05)***	0.27 (0.07)***	0.49 (0.19)*
Network Embeddedness	37.63 (6.77)***	43.08 (5.48)***		
Network Embeddedness (Weak Ties Measure)			1.59 (0.43)***	2.90 (1.15)*
Diversity × Embeddedness (Weak Ties Measure)				-0.29 (0.23)
Partisanship				
Interest Group Partisanship	0.03 (0.02)	0.04 (0.02)*	0.02 (0.02)	0.02 (0.02)
Coalition Partisanship	0.12 (0.04)***	0.12 (0.03)***	0.07 (0.03)*	0.06 (0.03)*
Interest Group-Coalition Partisan Differential	-0.02 (0.03)	-0.06 (0.03)*	-0.01 (0.03)	-0.01 (0.03)
Interest Group Characteristics				
Number of Coalition Memberships	-0.12 (0.03)***	-0.09 (0.03)***	-0.05 (0.02)*	-0.06 (0.02)**
Interest Group Age	0.67 (0.20)**	0.55 (0.22)*	0.33 (0.19)	0.32 (0.19)
Citizens Advocacy Group	0.43 (0.17)*	0.44 (0.18)*	0.25 (0.16)	0.25 (0.16)
Lobbying Expenditures	0.02 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
Interest Group Crosses Issue Boundary	0.01 (0.22)	-0.62 (0.22)**	-0.06 (0.20)	-0.07 (0.20)
Coalition Characteristics				
Coalition Size	-0.04 (0.01)***	-0.01 (0.01)	-0.03 (0.01)***	-0.03 (0.01)***
Coalition Age	0.57 (0.70)	1.69 (0.63)**	0.57 (0.65)	0.48 (0.63)
Coalition has Dues	0.20 (0.20)	-0.21 (0.19)	-0.10 (0.18)	-0.07 (0.18)
Coalition Faces Legislative Threat	0.04 (0.28)	-0.03 (0.27)	-0.03 (0.25)	-0.02 (0.25)
Coalition Focuses on Authorizing Legislation	0.22 (0.20)	0.16 (0.19)	0.12 (0.19)	0.13 (0.19)
Coalition has Steering Committee	0.39 (0.17)*	0.25 (0.17)	0.20 (0.16)	0.18 (0.16)
Coalition is Visible	0.52 (0.33)	0.99 (0.33)**	0.53 (0.31)	0.53 (0.31)
Coalition Issue is Controversial	-0.44 (0.22)*	-0.75 (0.21)***	-0.44 (0.20)*	-0.47 (0.20)*
Network Characteristics				
Interest Group Mode Two-Stars	0.16 (0.04)***	0.06 (0.05)	0.14 (0.04)***	0.14 (0.04)***
Edges	-3.57 (0.61)***	-6.95 (0.49)***	-3.54 (0.64)***	-4.53 (1.04)***
Constraints	Structural zeros for nonmembers and founders.	None	Structural zeros for nonmembers	Structural zeros for nonmembers

Note: ***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05. All tests are two-tailed.

Models 9-12

	Model 9	Model 10	Model 11	Model 12
Focal Variables				
Partisan Diversity	0.24 (0.07)***	0.39 (0.16)*	0.26 (0.06)***	0.27 (0.06)***
Network Embeddedness (Communication Measure)	2.54 (0.41)***	3.53 (1.08)**		
Diversity × Embeddedness (Communication Measure)		-0.23 (0.23)		
Network Embeddedness (Same Party Ties)			12.03 (4.18)**	
Network Embeddedness (Cross Party Ties)				15.68 (5.22)**
Partisanship				
Interest Group Partisanship	0.02 (0.02)	0.02 (0.02)	0.03 (0.02)	0.01 (0.02)
Coalition Partisanship	0.05 (0.03)	0.05 (0.03)	0.06 (0.03)	0.07 (0.03)*
Interest Group-Coalition Partisan Differential	-0.03 (0.03)	-0.03 (0.03)	-0.02 (0.03)	-0.00 (0.03)
Interest Group Characteristics				
Number of Coalition Memberships	-0.04 (0.02)	-0.04 (0.02)	-0.06 (0.02)*	-0.06 (0.02)**
Interest Group Age	0.29 (0.21)	0.27 (0.21)	0.31 (0.19)	0.35 (0.19)
Citizens Advocacy Group	0.34 (0.17)*	0.35 (0.18)*	0.29 (0.16)	0.30 (0.16)
Lobbying Expenditures	-0.01 (0.01)	-0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
Interest Group Crosses Issue Boundary	-0.06 (0.21)	-0.06 (0.22)	-0.14 (0.20)	-0.16 (0.21)
Coalition Characteristics				
Coalition Size	-0.02 (0.01)*	-0.02 (0.01)*	-0.03 (0.01)***	-0.03 (0.01)***
Coalition Age	0.77 (0.66)	0.75 (0.66)	0.71 (0.64)	0.66 (0.66)
Coalition has Dues	-0.27 (0.19)	-0.25 (0.18)	-0.08 (0.18)	-0.09 (0.18)
Coalition Faces Legislative Threat	0.12 (0.25)	0.10 (0.25)	0.05 (0.25)	0.00 (0.25)
Coalition Focuses on Authorizing Legislation	-0.17 (0.20)	-0.19 (0.20)	0.10 (0.19)	0.10 (0.19)
Coalition has Steering Committee	0.09 (0.16)	0.08 (0.16)	0.23 (0.16)	0.22 (0.16)
Coalition is Visible	0.73 (0.32)*	0.74 (0.30)*	0.44 (0.31)	0.48 (0.31)
Coalition Issue is Controversial	-0.37 (0.20)	-0.40 (0.20)*	-0.41 (0.20)*	-0.45 (0.20)*
Network Characteristics				
Interest Group Mode Two-Stars	0.09 (0.05)*	0.10 (0.04)*	0.013 (0.04)**	0.13 (0.04)**
Edges	-3.71 (0.60)***	-4.30 (0.84)	-2.56 (0.55)***	-2.74 (0.55)***
Constraints	Structural zeros for nonmembers	Structural zeros for nonmembers	Structural zeros for nonmembers	Structural zeros for nonmembers

Note: ***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05. All tests are two-tailed.

Models 13-16

	Model 13	Model 14	Model 15	Model 16
Focal Variables				
Partisan Diversity	0.11 (0.05)*	0.10 (0.05)*	0.30 (0.07)***	0.40 (0.19)*
Diversity of Age			-0.01 (0.01)	
Diversity of Lobbying Expenditures			-0.02 (0.02)	
Diversity of Citizens Advocacy Groups			0.80 (0.70)	
Diversity of Crossing Issue Boundaries			-0.22 (0.57)	
Network Embeddedness	7.15 (4.23)	18.51 (4.97)***	18.59 (5.50)***	17.82 (5.56)**
Partisanship				
Interest Group Partisanship			0.02 (0.02)	0.02 (0.02)
Coalition Partisanship			0.11 (0.04)**	0.07 (0.03)*
Interest Group-Coalition Partisan Differential			-0.01 (0.03)	-0.01 (0.03)
Interest Group Characteristics				
Number of Coalition Memberships		-0.09 (0.02)***	-0.07 (0.03)**	-0.07 (0.03)**
Interest Group Age			0.38 (0.20)	0.37 (0.20)
Citizens Advocacy Group			0.26 (0.16)	0.30 (0.16)
Lobbying Expenditures			0.01 (0.01)	0.00 (0.01)
Interest Group Crosses Issue Boundary			-0.17 (0.21)	0.18 (0.21)
Coalition Characteristics				
Coalition Size			-0.03 (0.01)**	0.03 (0.01)***
Coalition Age			0.32 (0.71)	0.70 (0.66)
Coalition has Dues			-0.06 (0.18)	-0.12 (0.18)
Coalition Faces Legislative Threat			0.05 (0.26)	-0.06 (0.26)
Coalition Focuses on Authorizing Legislation			0.14 (0.21)	0.10 (0.19)
Coalition has Steering Committee			0.21 (0.16)	0.24 (0.16)
Coalition is Visible			0.52 (0.31)	1.26 (1.06)
Diversity × Visibility				-0.16 (0.20)
Coalition Issue is Controversial			-0.46 (0.20)*	-0.41 (0.20)*
Network Characteristics				
Interest Group Mode Two-Stars	0.08 (0.03)**	0.17 (0.03)***	0.13 (0.04)**	0.13 (0.04)**
Edges	-2.06 (0.26)***	-1.69 (0.26)***	-2.68 (0.71)***	-3.44 (1.09)**
Constraints	Structural zeros for nonmembers	Structural zeros for nonmembers	Structural zeros for nonmembers	Structural zeros for nonmembers

Note: $^{***}p \leq 0.001$, $^{**}p \leq 0.01$, $^{*}p \leq 0.05$. All tests are two-tailed.

Models 17-18

	Model 17	**Model 18**
Focal Variables		
Partisan Diversity	0.19 (0.07)**	0.28 (0.06)***
Network Embeddedness	19.28 (5.57)***	12.82 (4.62)**
Partisanship		
Interest Group Partisanship	0.02 (0.02)	0.03 (0.02)
Coalition Partisanship	0.06 (0.03)*	0.09 (0.03)**
Interest Group-Coalition Partisan Differential	-0.01 (0.03)	-0.00 (0.03)
Interest Group Characteristics		
Number of Coalition Memberships	-0.08 (0.03)**	
Interest Group Age	0.36 (0.20)	0.24 (0.21)
Citizens Advocacy Group	0.31 (0.16)	0.40 (0.18)*
Lobbying Expenditures	0.01 (0.01)	0.00 (0.01)
Interest Group Crosses Issue Boundary	-0.21 (0.21)	0.01 (0.21)
Coalition Characteristics		
Coalition Size	-0.03 (0.01)***	
Coalition Age	0.68 (0.66)	0.19 (0.64)
Coalition has Dues	-0.14 (0.18)	-0.03 (0.17)
Coalition Faces Legislative Threat	0.06 (0.25)	-0.00 (0.24)
Coalition Focuses on Authorizing Legislation	0.12 (0.19)	0.31 (0.17)
Coalition has Steering Committee	0.17 (0.16)	0.14 (0.15)
Coalition is Visible	0.47 (0.31)	0.59 (0.29)*
Coalition Issue is Controversial	-1.98 (0.73)**	-0.41 (0.19)*
Diversity × Controversy	0.32 (0.14)*	
Network Characteristics		
Interest Group Mode Two-Stars	0.13 (0.04)**	0.04 (0.05)
Coalition Model Two-Stars		-0.00 (0.03)
Edges	-2.41 (0.56)***	-3.89 (0.49)***
Constraints	Structural zeros for nonmembers	Structural zeros for nonmembers

Note: ***$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$. All tests are two-tailed.

Online Appendix 5. Marginal Effects Plots and Predicted Probabilities for Models with Interaction Terms

The following diagrams visualize the interaction effects in Models 3, 4, 10, 16, and 17. For each of these models, we first present predicted tie probabilities between an interest group and a coalition conditional on the interaction between two variables. We then proceed by showing marginal effects plots of the change of the effect of the first variable on leadership contribution conditional on the level of the second variable and vice-versa.

In Models 3, 4, and 10, both main variables are continuous. The predicted probability plots for these models therefore show the effect of partisan diversity conditional on the four quartiles of the potentially moderating variable in four separate facets of the respective plot. The line is the mean probability, and the shaded area represents the 95 percent confidence interval. If all four lines have a similar slope, or their confidence intervals are large enough to allow for this possibility, the moderating variable does not play a significant role in moderating the effect of the main variable, as represented by a non-significant interaction effect in the regression table. The slope of the line represents the strength of the association between the main variable and the probability of a tie (i.e., the magnitude of the coefficient for the main variable in the regression model, converted to the probability scale), and the effect is significant in the regression model if the confidence region in the plot does not allow for a horizontal line.

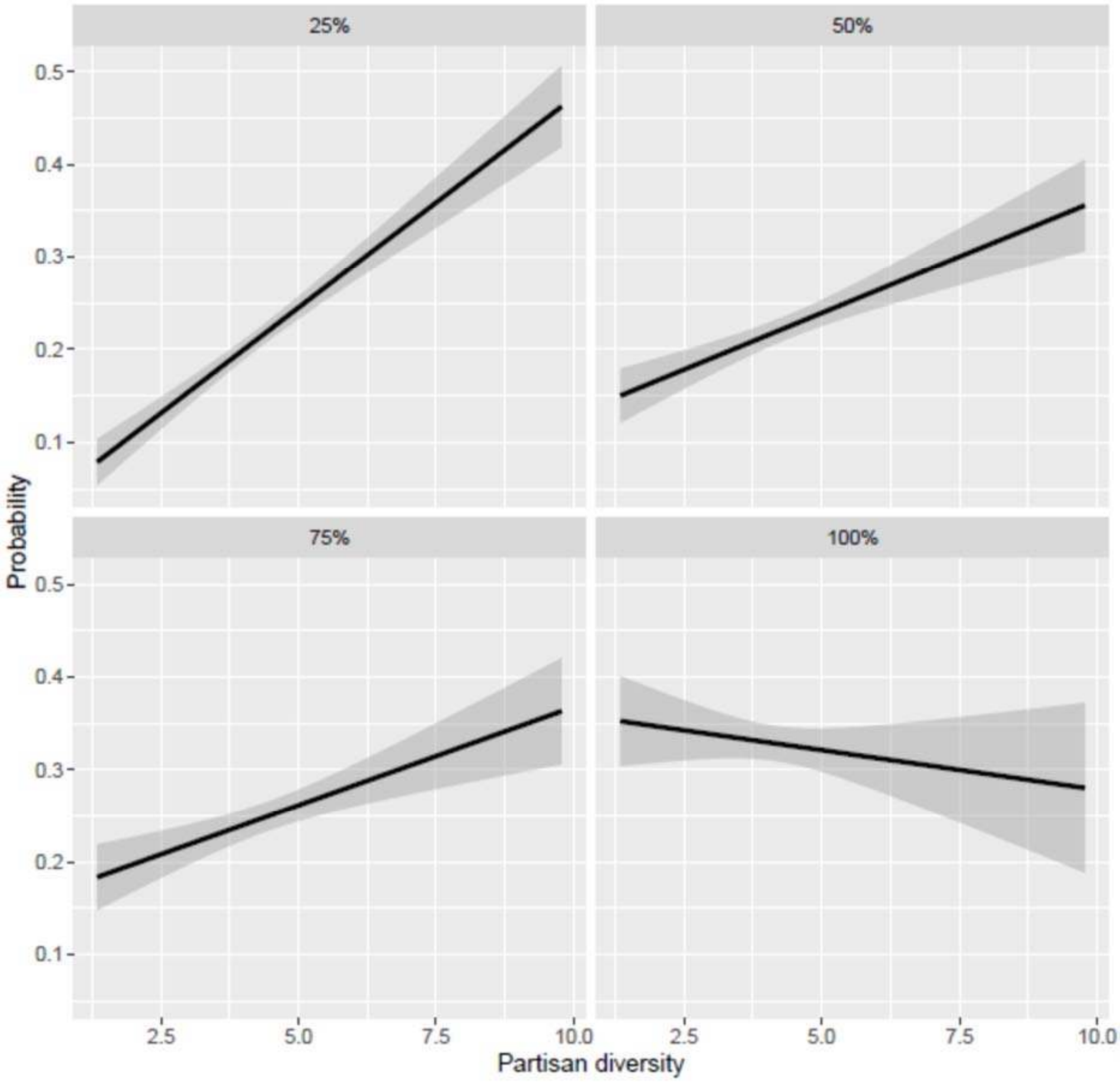
For each model, two predicted probability plots are generated: one with partisan diversity as the focal variable and the respective network embeddedness measure as the potential moderator, and one with the network embeddedness measure as the focal variable and partisan diversity as the potential moderator.

The marginal effects plots for Models 3, 4, and 10 show a continuous line that represents the coefficient of the partisan diversity (or network embeddedness) effect on the log odds scale (as in the model in the regression tables) on the y axis at different levels of the moderating variable (i.e., the respective network embeddedness or partisan diversity measure) on the x axis. The slope of the line denotes the magnitude of the interaction effect, and the 95 percent confidence region indicates the significance of the interaction. If the confidence region allows for a horizontal line, the interaction effect is insignificant. If the line is above zero at all levels of the moderating variable, this indicates a positive main effect of the focal variable.

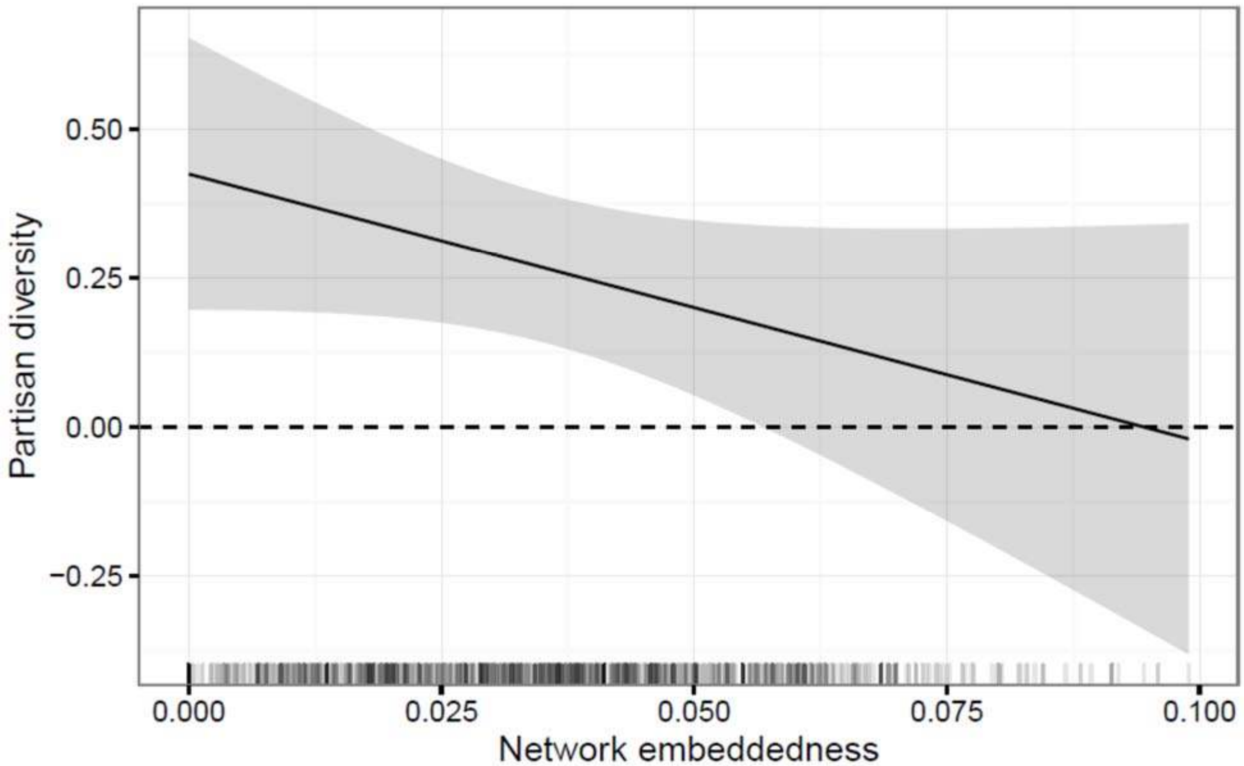
In Models 16 and 17, the moderating variables (visibility and controversy of a coalition, respectively) are binary. Therefore the predicted probability plots do not use facets for levels of the moderating variables, but plot two lines in the same diagram, one for dyads in which the moderating variable is 0 and one for dyads in which the moderating variable is 1. For all other aspects of these plots, the interpretation is the same as in the continuous case; the slope of the line still represents the main effect on tie probability conditional on the moderating variable. The marginal effects plots show two dots with error bars, which represent the coefficient at both levels of the moderating variable as well as the uncertainty around that point estimate. An interaction effect is significant if one of the two error bars does not include the other point estimate. The interaction effect is positive if the second point estimate is larger than the first one. The main effect of partisan diversity at one of the two levels is significant if the error bar at the respective level does not include 0.

Model 3 contains the interaction between our two main variables of interest: partisan diversity and network embeddedness. The first two diagrams show that increasing levels of network embeddedness lead to a higher tie probability (i.e., probability of leadership contributions) irrespective of the level of partisan diversity – except for the highest levels of partisan diversity – and that increasing levels of partisan diversity conversely lead to a higher tie probability irrespective of the level of network embeddedness – except for the highest levels of network embeddedness. However, the confidence interval in the upper quartile of the moderating variable is wide enough at the extreme points of the distribution that a line with the same slope as before is still a reasonable possibility. Therefore the interaction between partisan diversity and network embeddedness is not significant. The third diagram shows a downward slope of the marginal effect of partisan diversity with increasing network embeddedness, but the confidence interval would allow for a horizontal line, which confirms that the interaction effect is negative but insignificant, as in the regression table. Moreover, the line crosses zero at a high level of network embeddedness, which suggests that the partisan diversity effect is only significantly above zero in all but the most extreme coalitions with regard to network embeddedness. However, uncertainty at these extreme levels is large as there are few observations with such high network embeddedness scores, as indicated by the distribution at the bottom of the diagram. The fourth diagram shows the reverse direction of the interaction, with the same substantive conclusions.

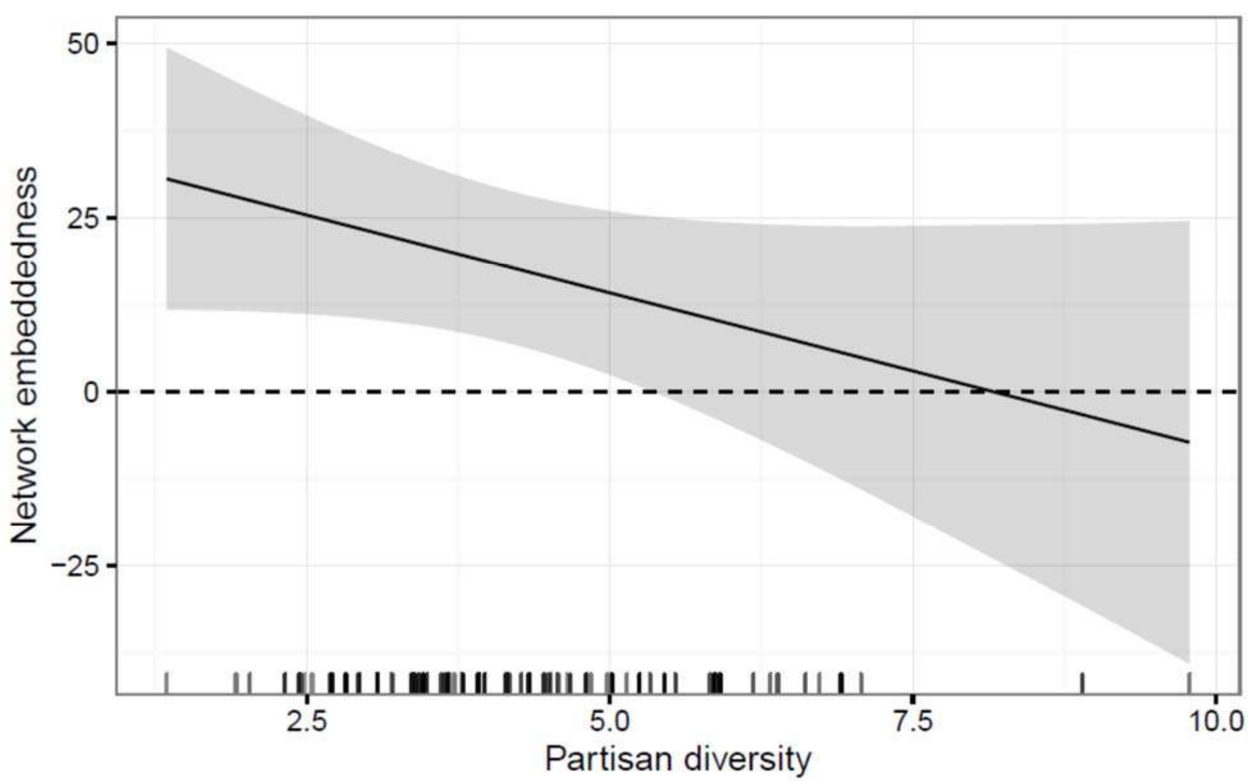
Model 3: Partisan Diversity Effect Conditional on Network Embeddedness



Model 3: Marginal Effect of Partisan Diversity with Increasing Network Embeddedness

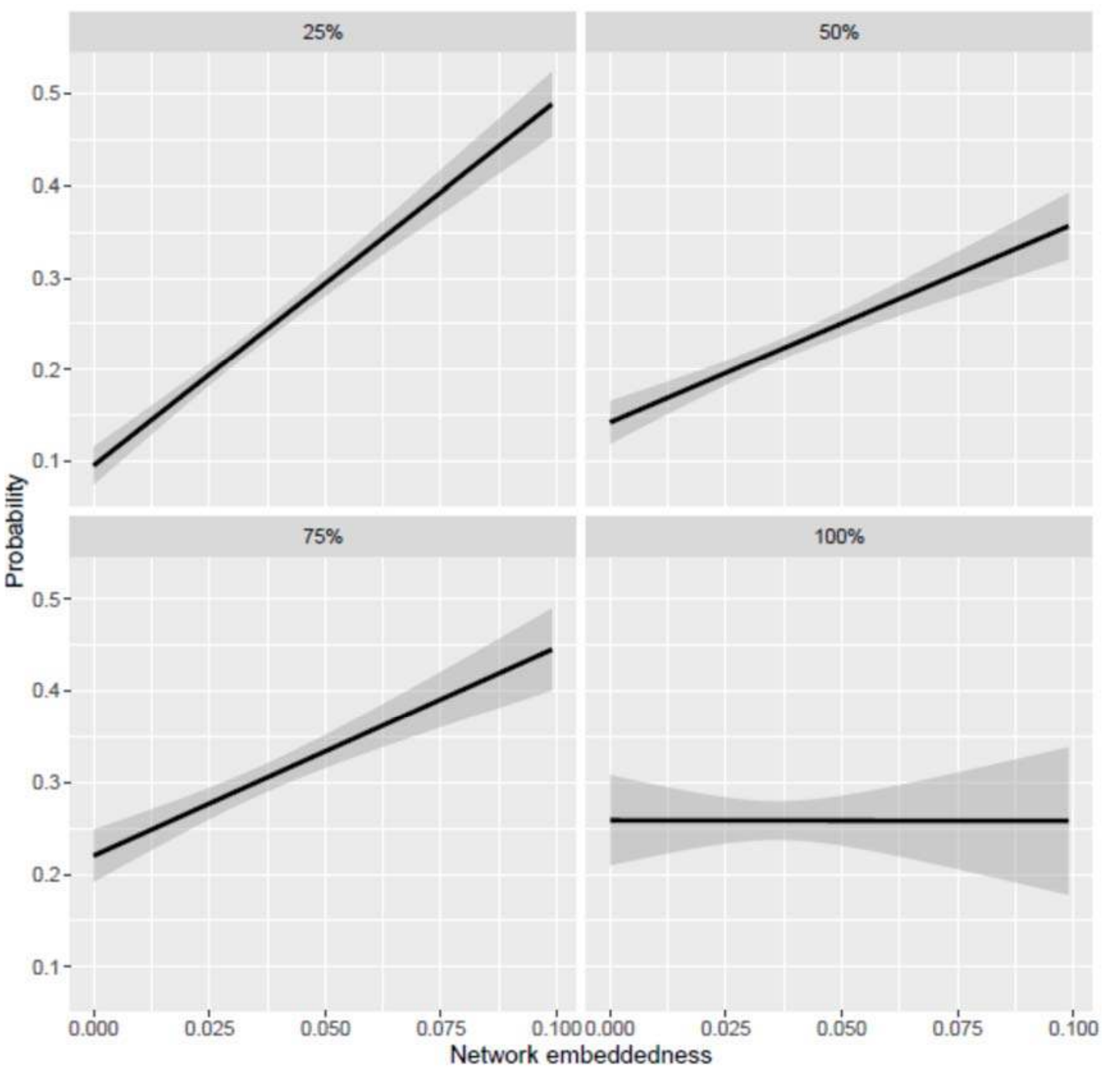


Model 3: Marginal Effect of Network Embeddedness with Increasing Partisan Diversity

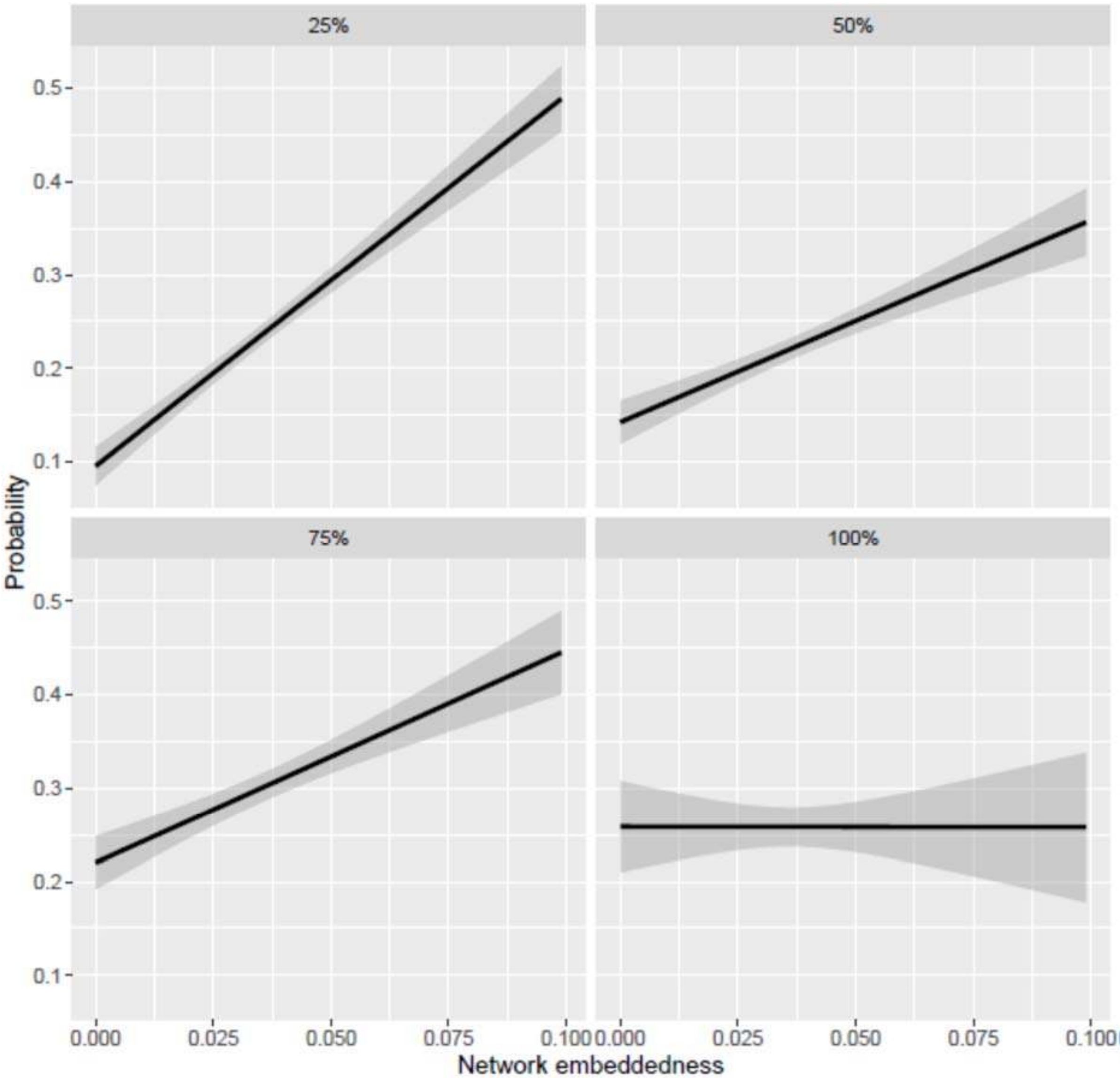


Model 4 features the same interaction effect but with additional structural ones for the founders of a coalition. With this model setup, the same conclusions can be drawn as in the previous model, with one minor exception: In the marginal effects plots, the partisan diversity effect never crosses the zero line, which means that the model never predicts partisan diversity to be associated with an absence of leadership contributions, at any level of network embeddedness (and vice-versa). However, at extremely high values of the moderating variable, the confidence interval still includes zero, i.e., we can be more certain about the positive effect of partisan diversity at low and moderate values of network embeddedness.

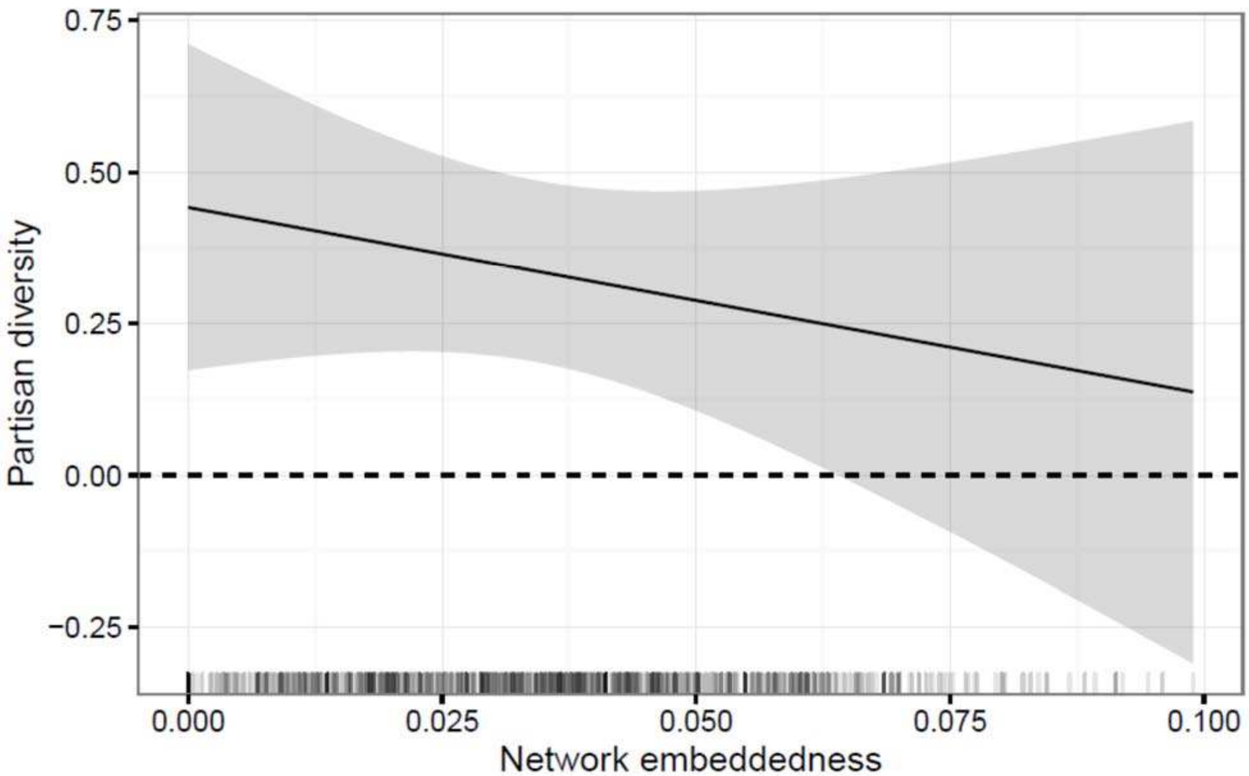
Model 4: Network Embeddedness Effect Conditional on Partisan Diversity



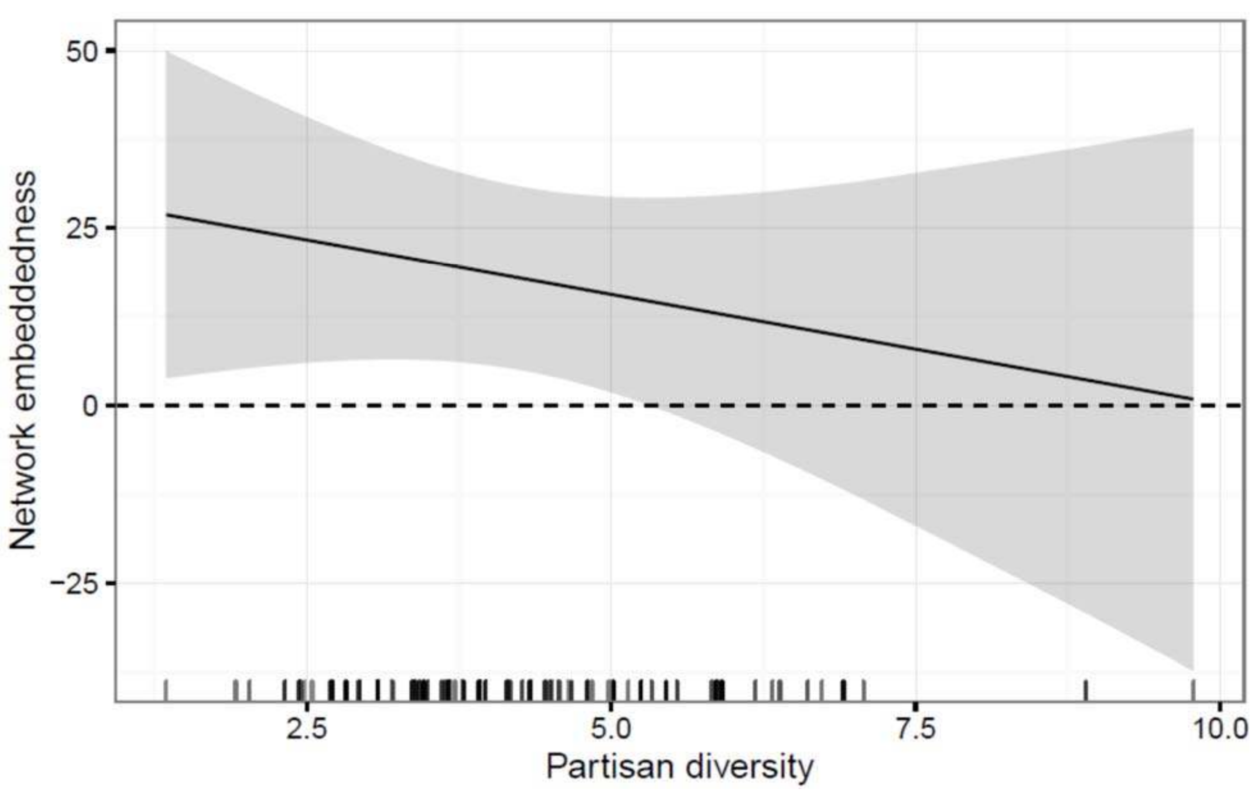
Model 4: Partisan Diversity Effect Conditional on Network Effectiveness



Model 4: Marginal Effect of Partisan Diversity with Increasing Network Embeddedness

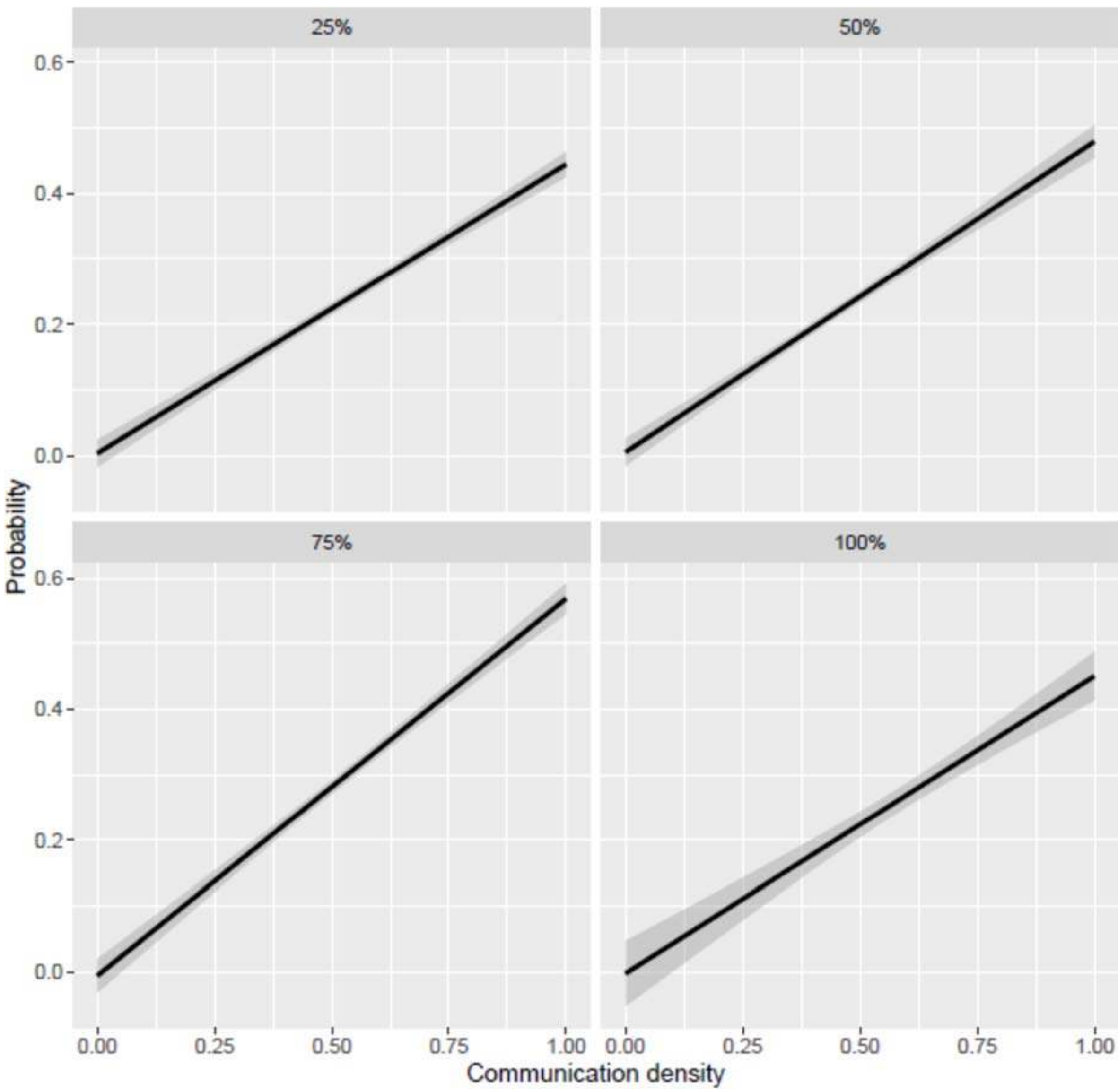


Model 4: Marginal Effect of Network Embeddedness with Increasing Partisan Diversity

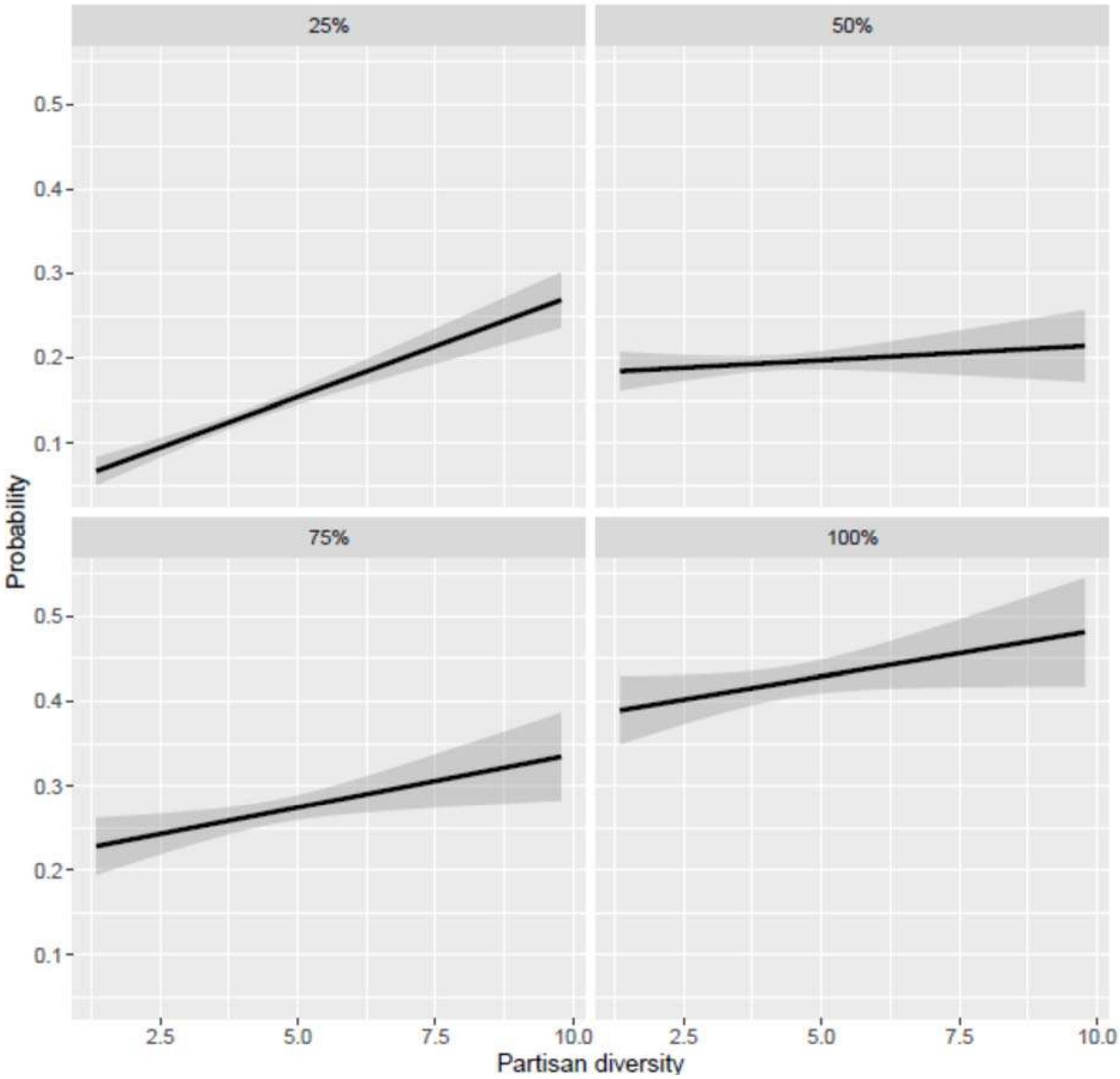


Model 10 uses communication density as an alternative measure of network embeddedness. The findings match those in Model 4.

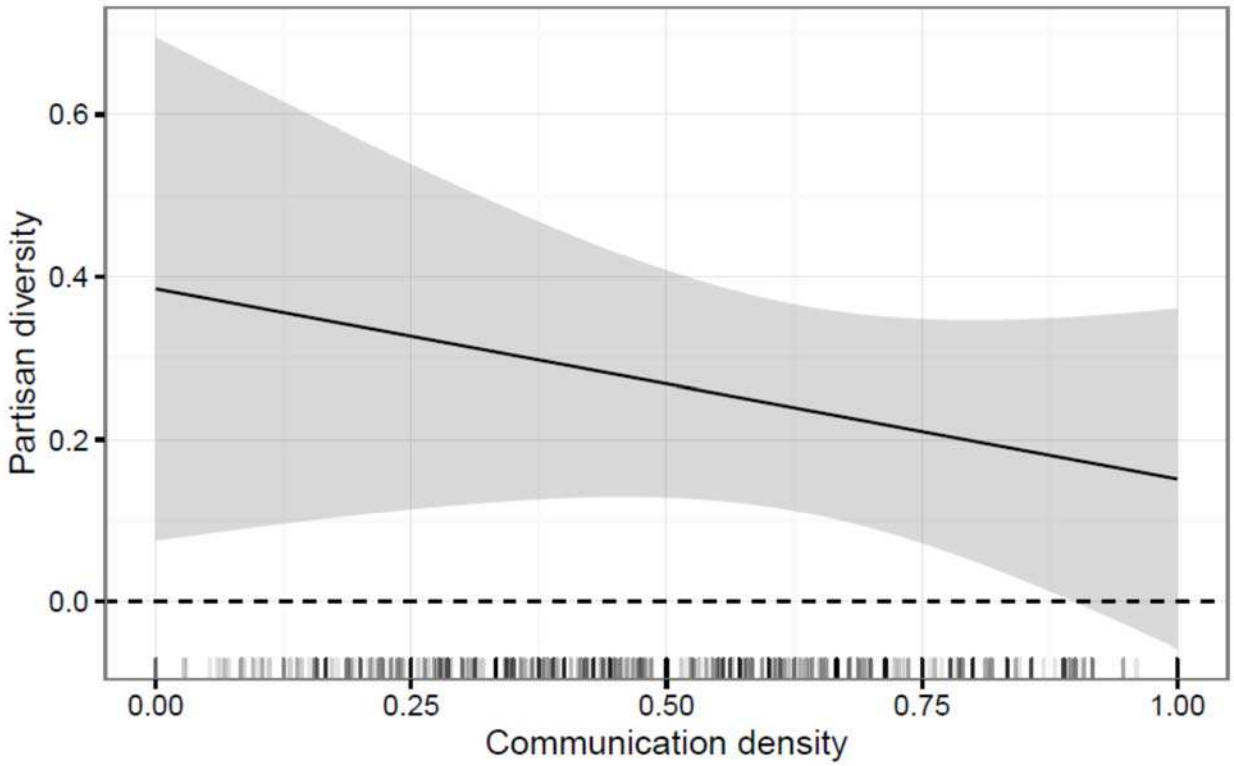
Model 10: Communication Density Effect Conditional on Partisan Diversity



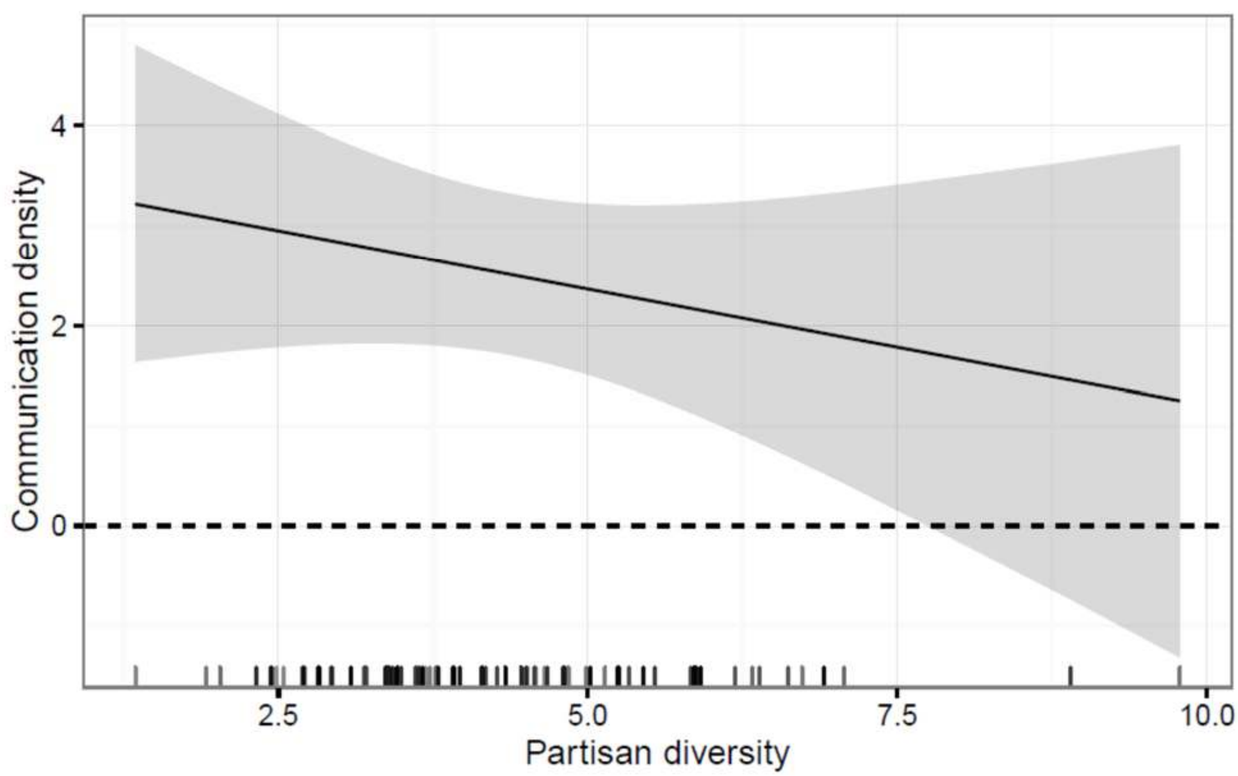
Model 10: Partisan Diversity Effect Conditional on Communication Density



Model 10: Marginal Effect of Partisan Diversity with Increasing Commuication Density

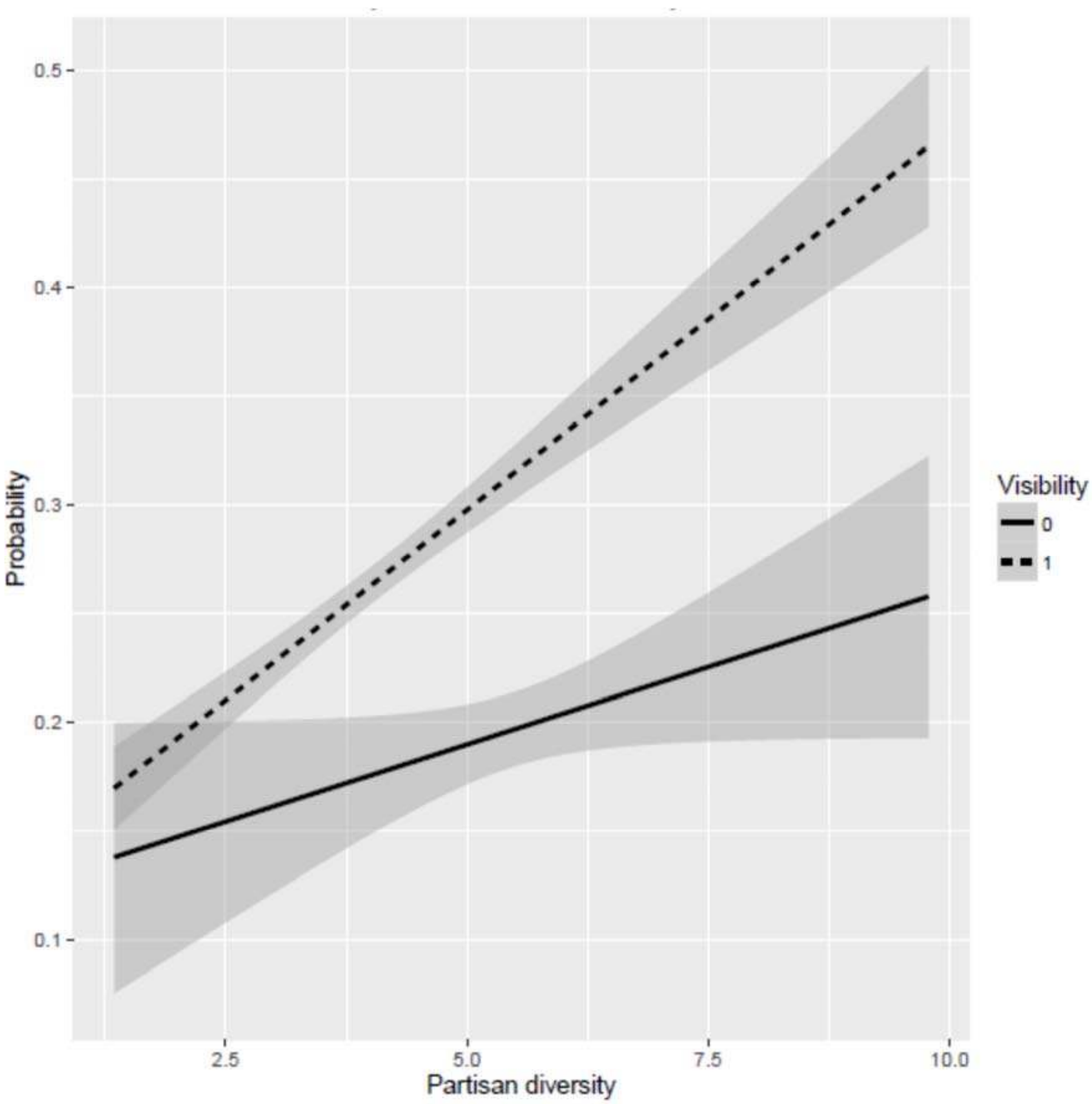


Model 10: Marginal Effect of Communication Density with Increasing Partisan Diversity

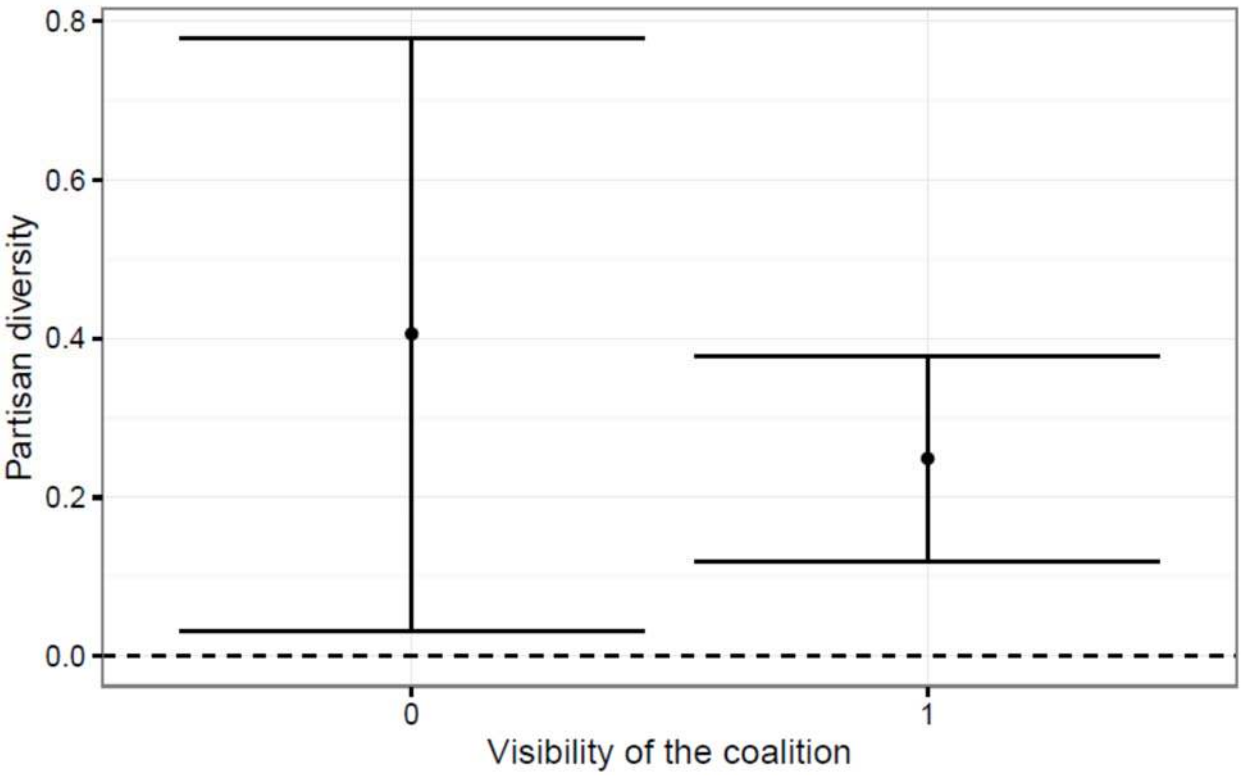


Model 16 shows the effect of partisan diversity on leadership contributions conditional on whether the coalition is highly visible or not. The partisan diversity line for visible coalitions is associated with a higher probability than the line for not highly visible coalitions at all levels of partisan diversity, which means there is a positive main effect of visibility. However, the slopes of the two lines cannot be distinguished when the confidence regions are used to assess uncertainty. Therefore, the interaction effect is insignificant. The confidence interval for high-visibility coalitions at low levels of partisan diversity is narrow enough that it never contains the low-visibility line. That is, at all levels of partisan diversity, the main effect is significant, even though the uncertainty is slightly higher in the low-visibility region. The marginal effects plot further illustrates how the point estimate of partisan diversity is slightly lower for highly visible groups, but the large confidence bar for non-highly visible coalitions is so large that the two point estimates cannot be distinguished with certainty, which is why the interaction effect is insignificant. However, in both groups, the errors bars do not include zero, indicating that partisan diversity is significant across the visibility covariate.

Model 16: Partisan Diversity Conditional on Visibility of the Coalition

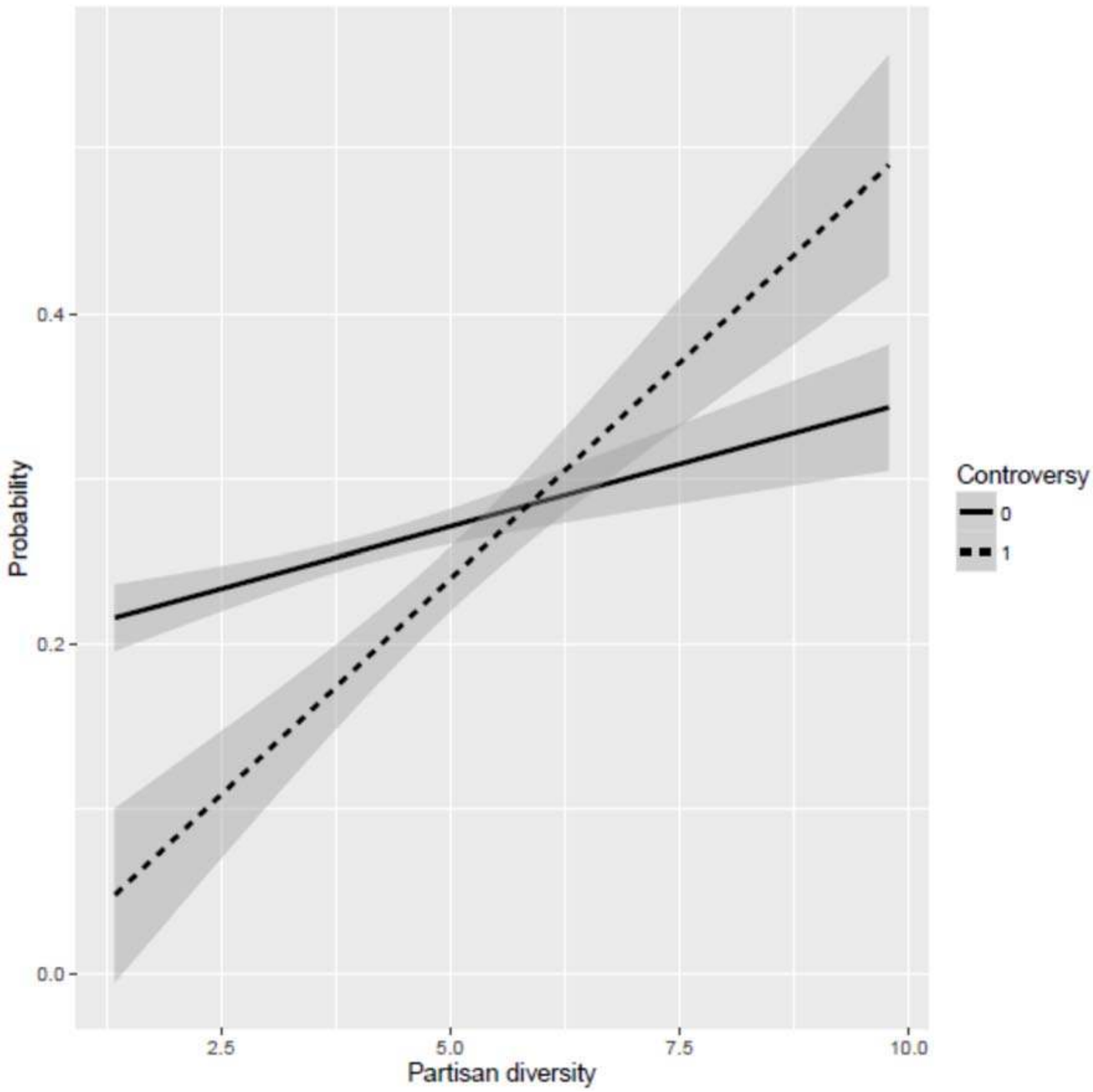


Model 16: Marginal Effects of Partisan Diversity at Alternative States of Coalition Visibility

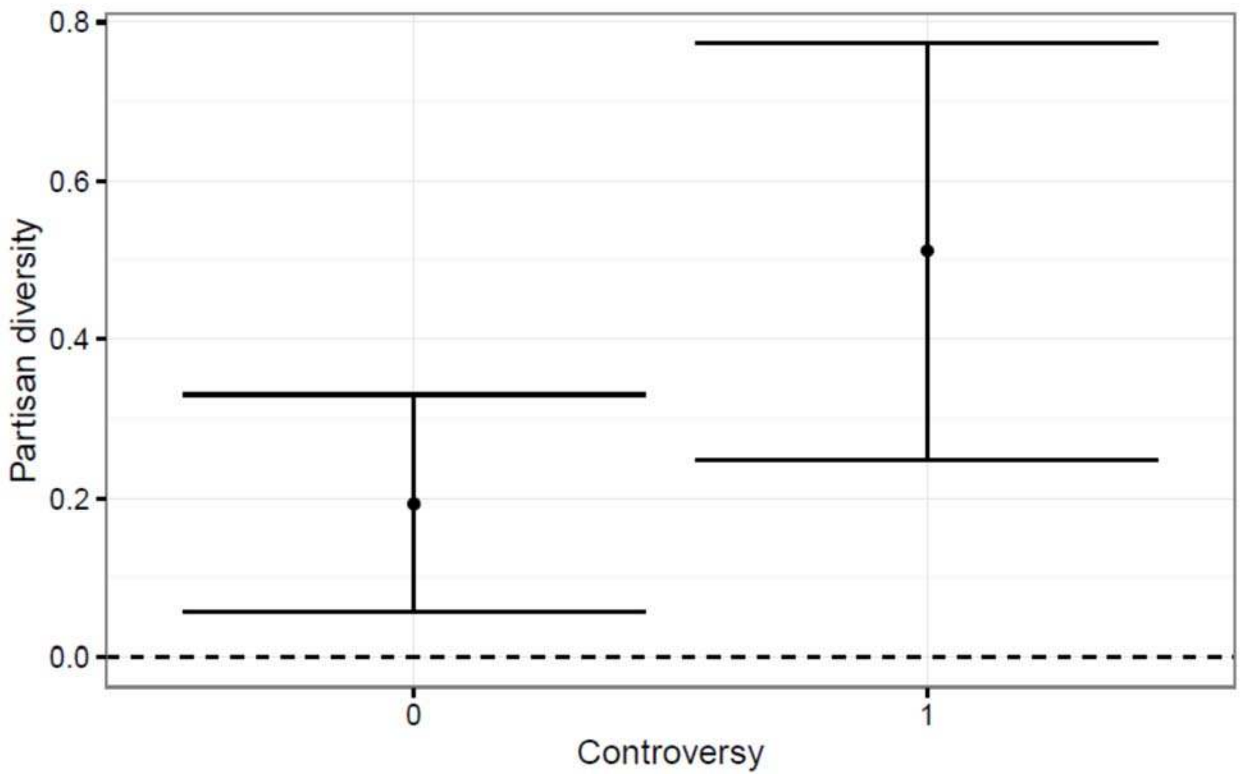


In Model 17, partisan diversity is evaluated conditional on whether the coalition deals with controversial issues or not. In the predicted probabilities plot, the slope of the two lines can be distinguished. The slope of the association between partisan diversity and predicted tie probability is steeper for controversial coalitions, which means that the interaction effect is positive and significant. In both groups, partisan diversity has a significantly positive slope, meaning that partisan diversity is significant across groups of controversy. At medium levels of partisan diversity, the probability is the same for controversial and non-controversial issues. At low levels of partisan diversity, the probability of leadership contributions is higher for uncontroversial issues, and at high levels of partisan diversity, the probability of such constributions is higher for controversial issues. The marginal effects plot further illustrates how both levels of controversy are associated with a significantly positive (i.e., above zero) partisan diversity effect and how each of the two confidence bars does not include the other respective point estimate, meaning that the interaction effect is positively significant.

Model 17: Partisan Diversity Conditional on Controversialness of the Coalition

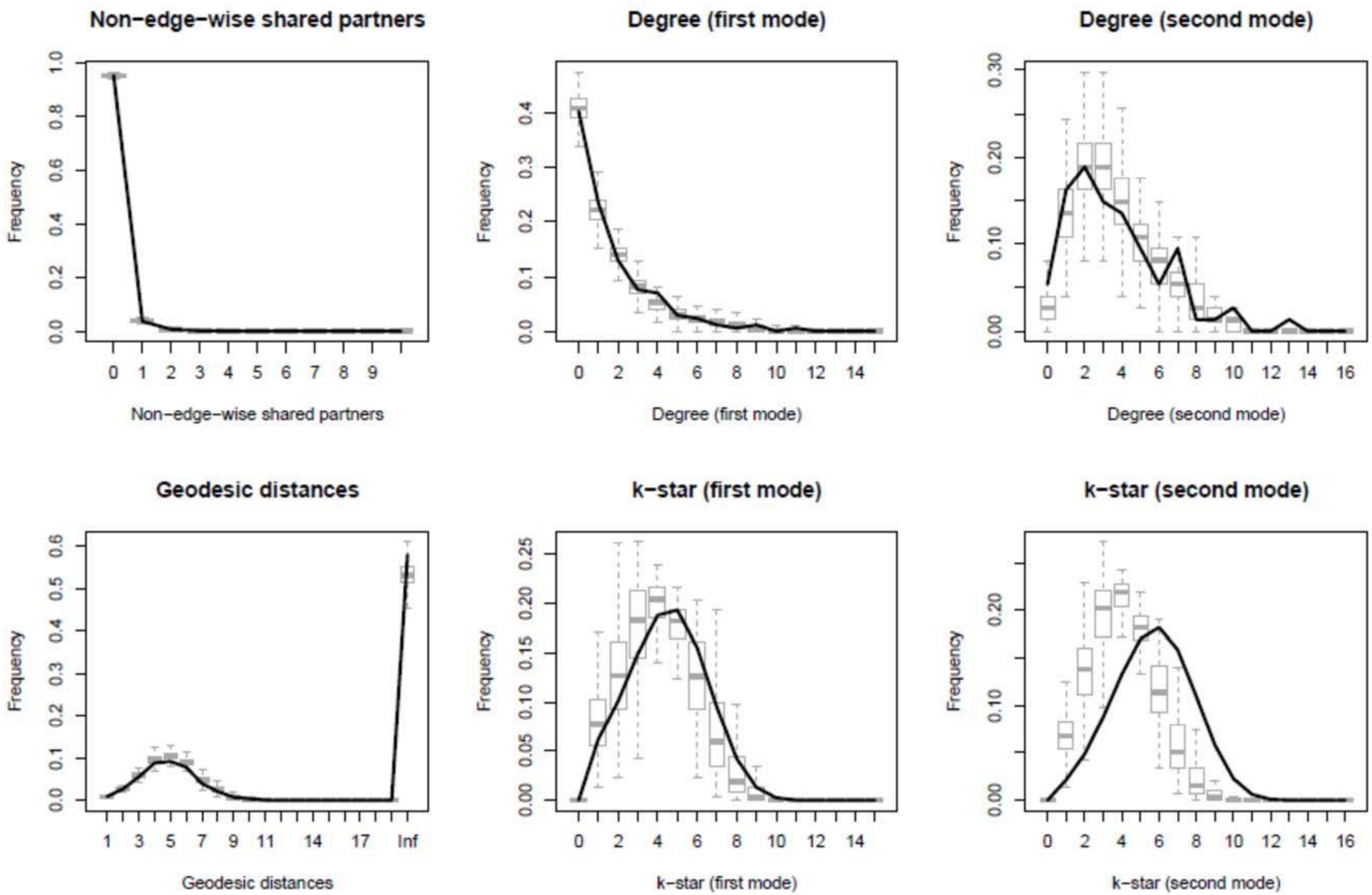


Model 17: Marginal Effects of Partisan Diversity at Alternative States of Controversy

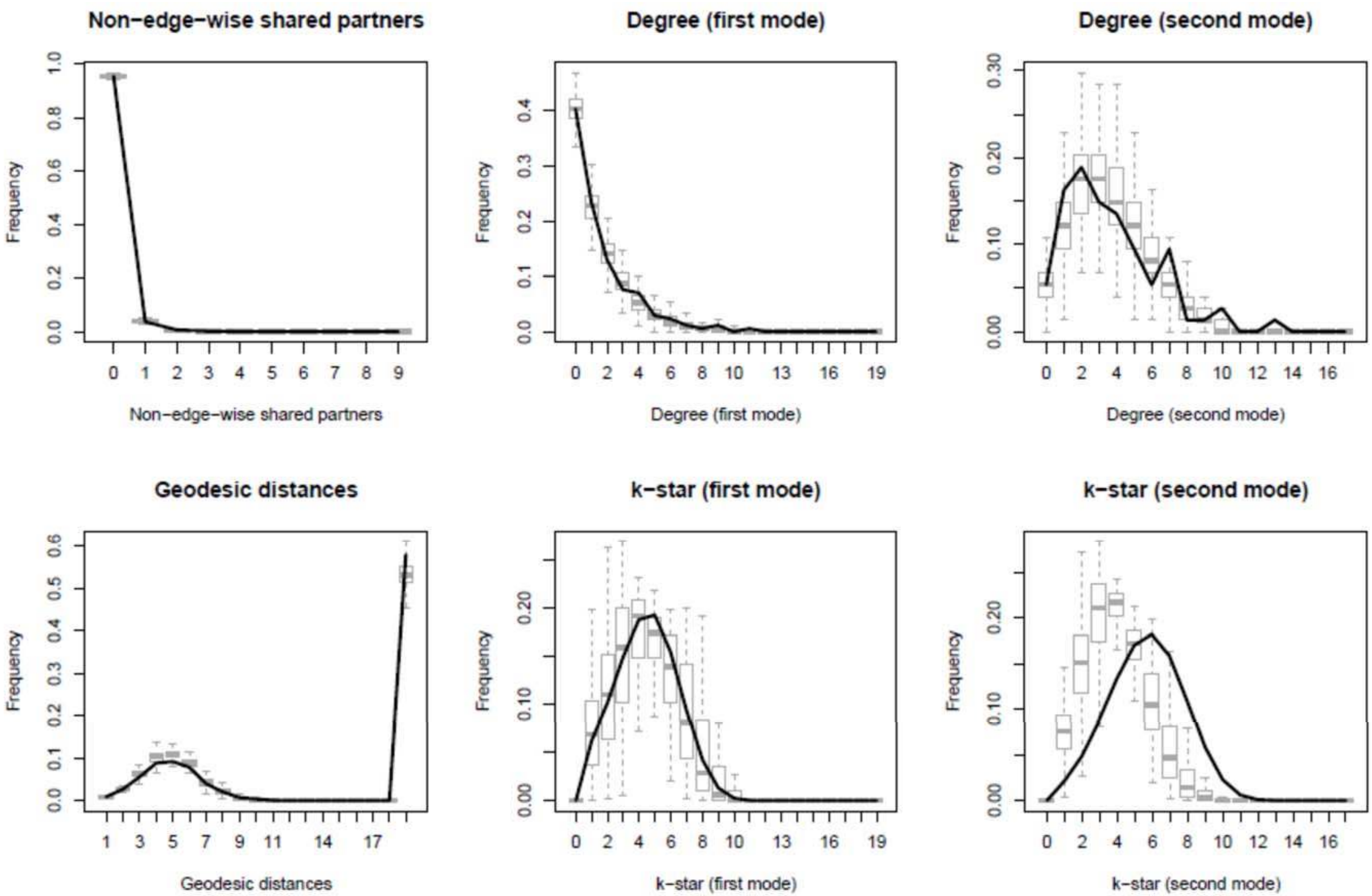


Online Appendix 6. Endogenous Goodness-of-Fit Assessment for Models 2-18

Model 2

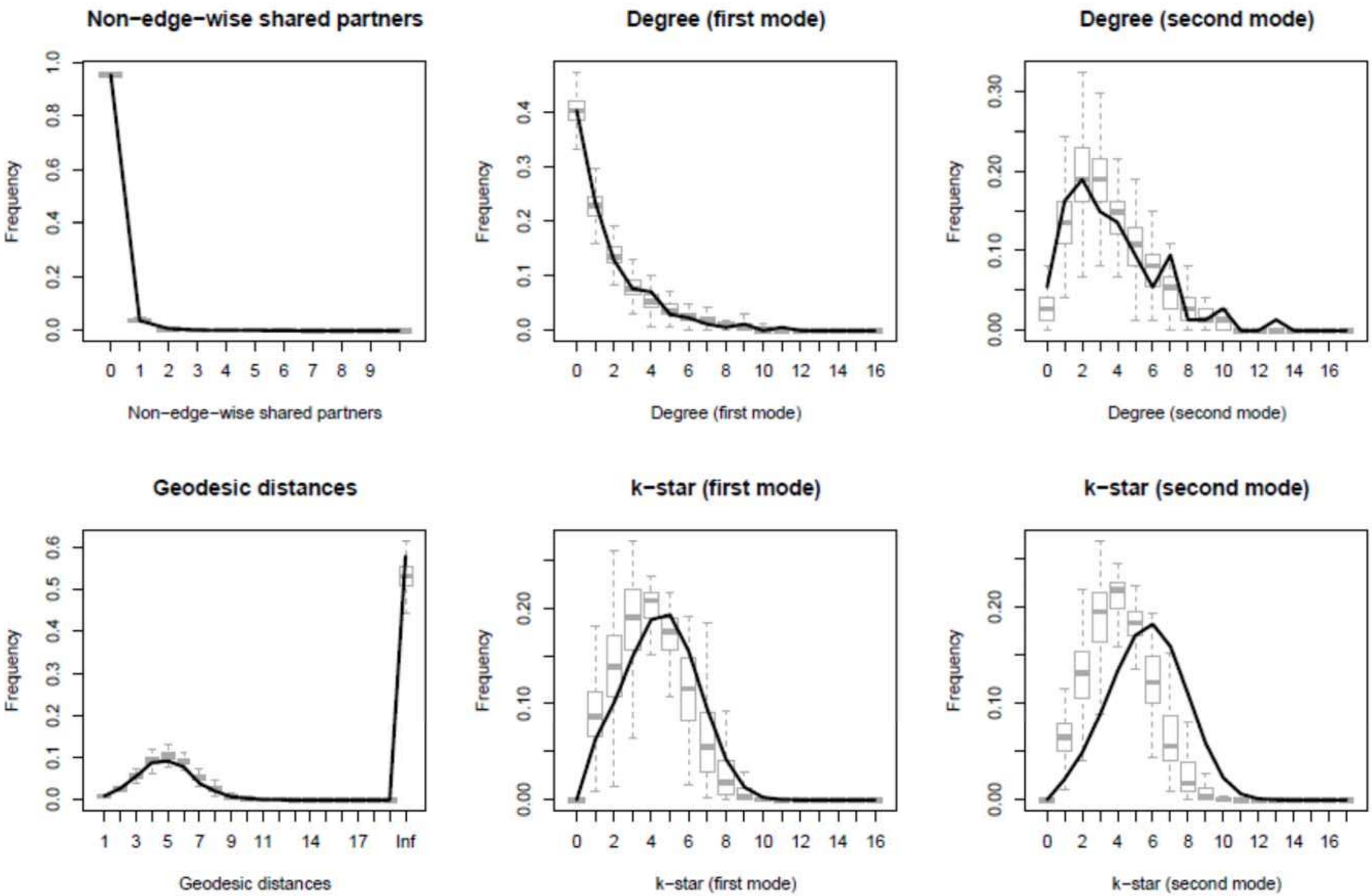


Model 3

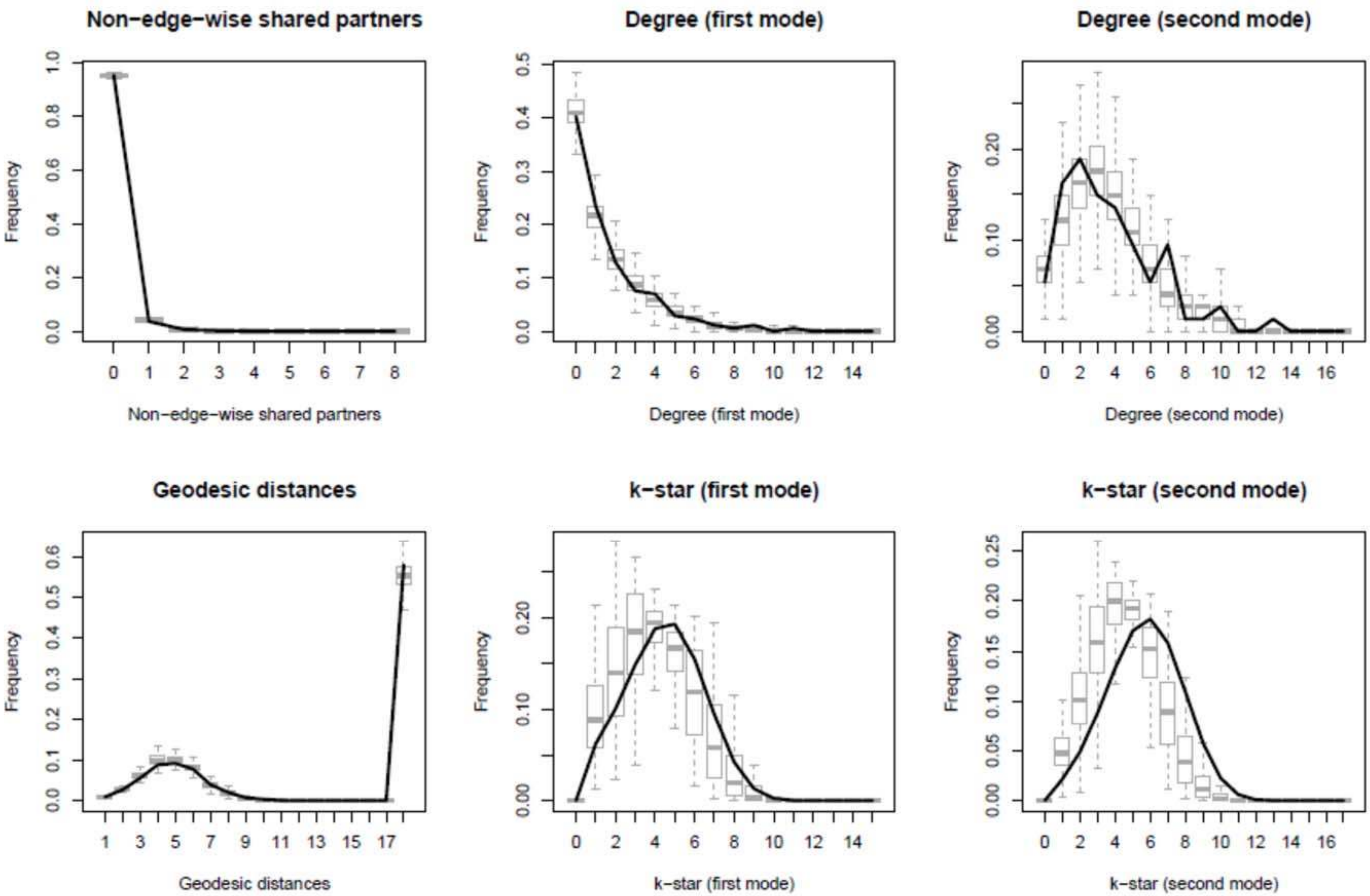


Non−edge−wise shared partners
Frequency
Non−edge−wise shared partners
Degree (first mode)
Frequency
Degree (first mode)
Degree (second mode)
Frequency
Degree (second mode)
Geodesic distances
Frequency
Geodesic distances
k−star (first mode)
Frequency
k−star (first mode)
k−star (second mode)
Frequency
k−star (second mode)

Model 4

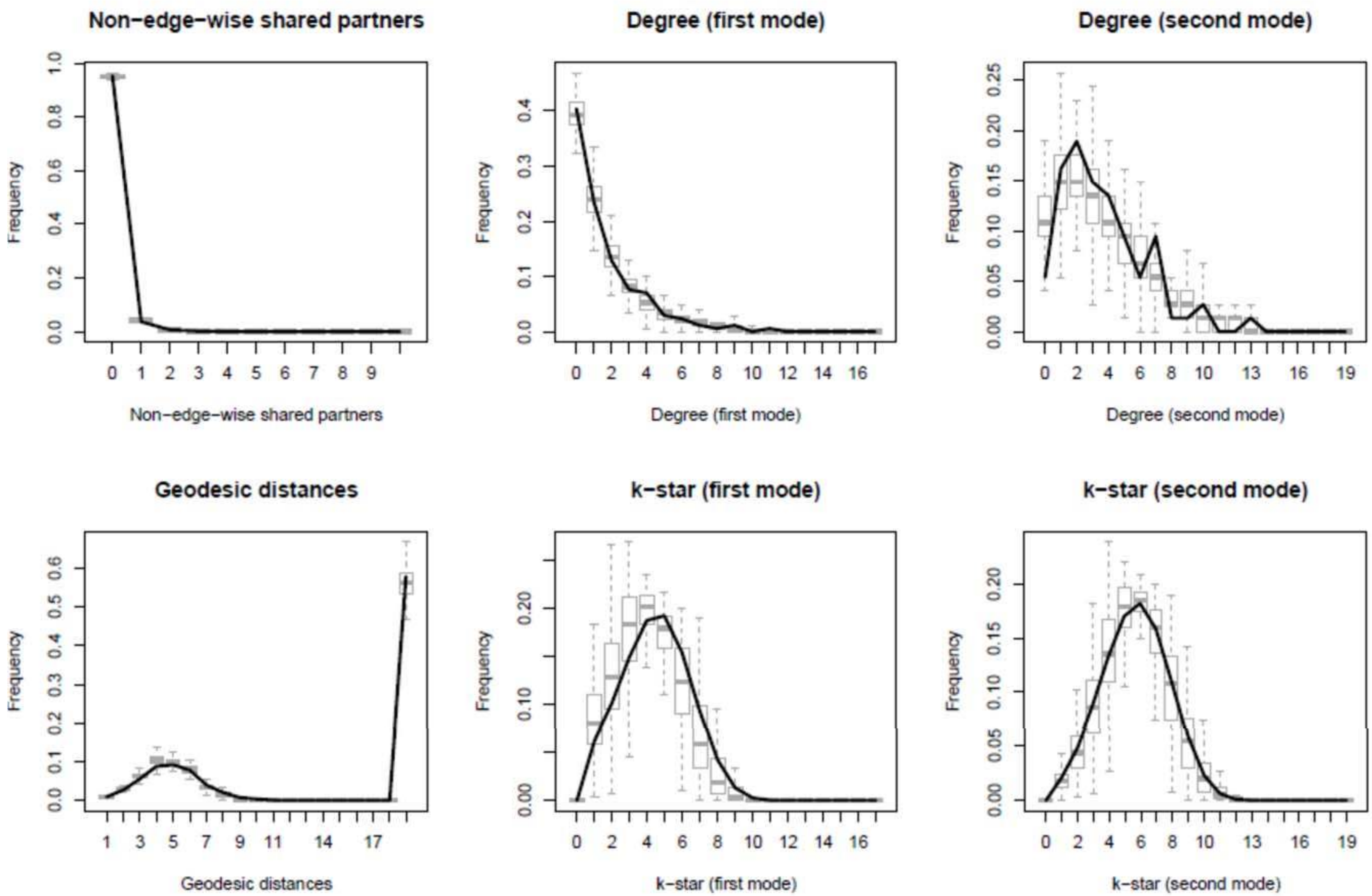

Non−edge−wise shared partners
Degree (first mode)
Degree (second mode)
Geodesic distances
k−star (first mode)
k−star (second mode)
Frequency
Non−edge−wise shared partners
Degree (first mode)
Degree (second mode)
Geodesic distances
k−star (first mode)
k−star (second mode)

Model 5

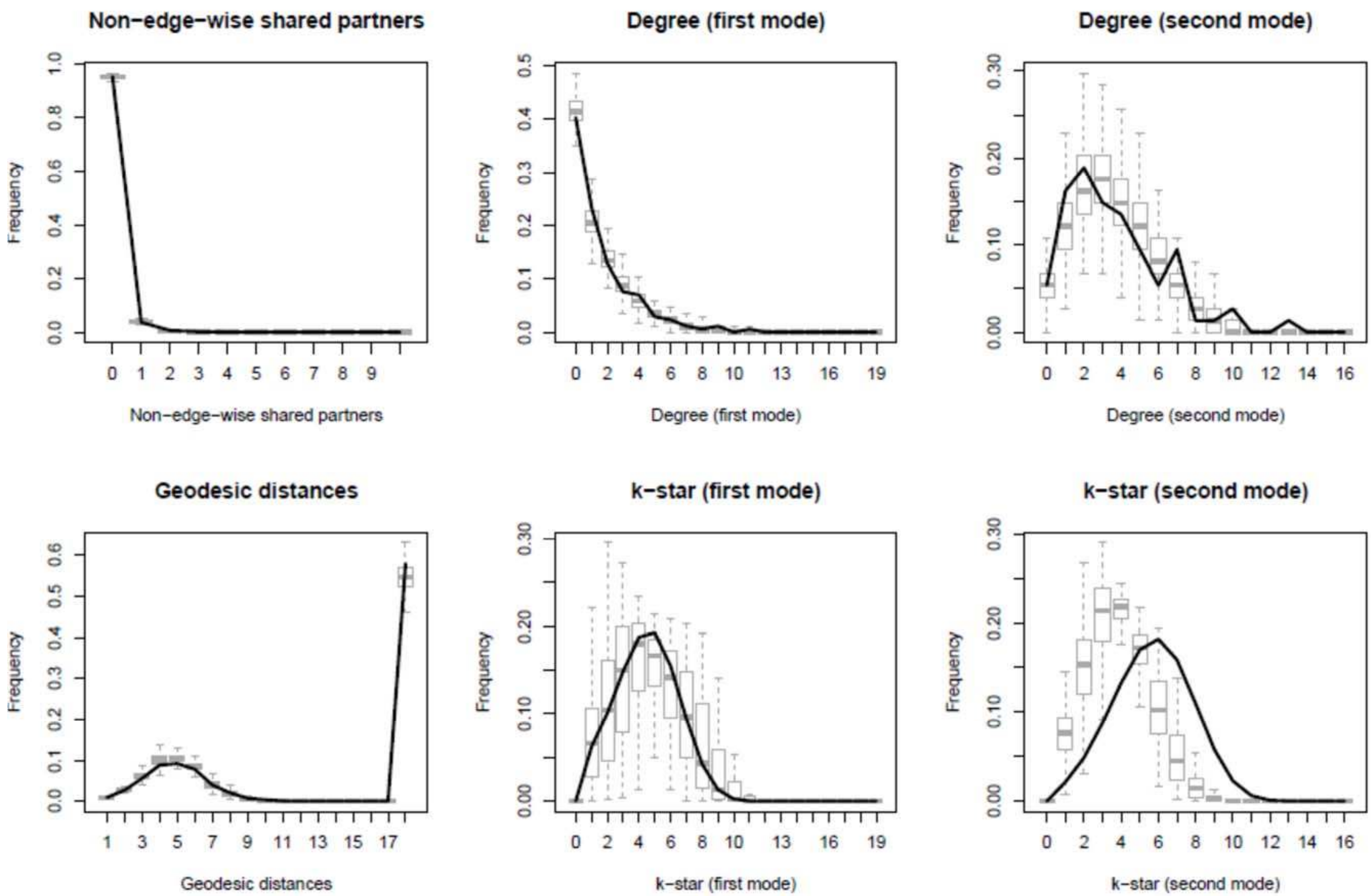


Non−edge−wise shared partners
Degree (first mode)
Degree (second mode)
Geodesic distances
k−star (first mode)
k−star (second mode)
Frequency

Model 6

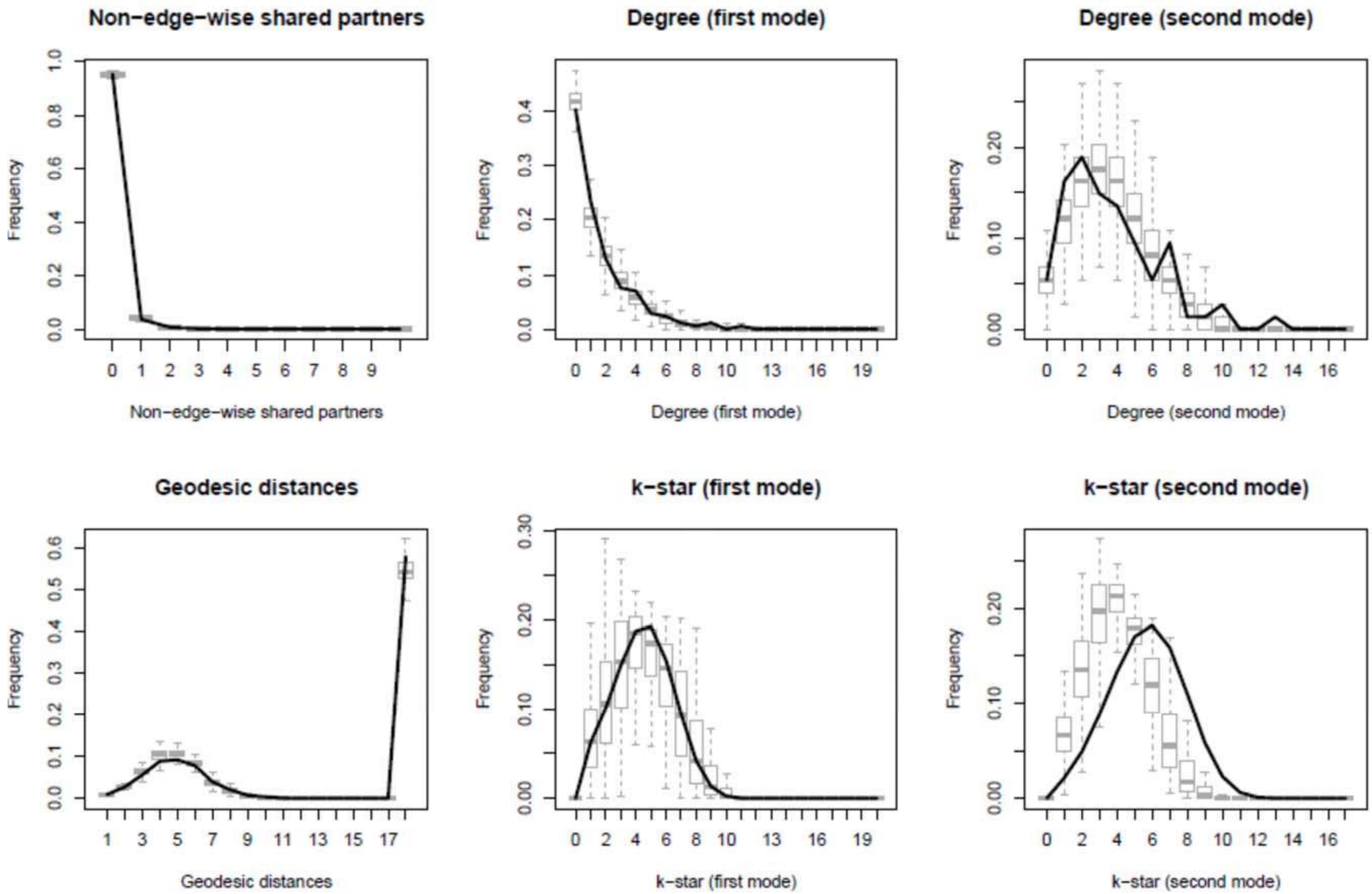

Non−edge−wise shared partners
Frequency
Non−edge−wise shared partners
Degree (first mode)
Frequency
Degree (first mode)
Degree (second mode)
Frequency
Degree (second mode)
Geodesic distances
Frequency
Geodesic distances
k−star (first mode)
Frequency
k−star (first mode)
k−star (second mode)
Frequency
k−star (second mode)

Model 7



Non−edge−wise shared partners
Degree (first mode)
Degree (second mode)
Geodesic distances
k−star (first mode)
k−star (second mode)
Frequency

Model 8


Non−edge−wise shared partners
Frequency
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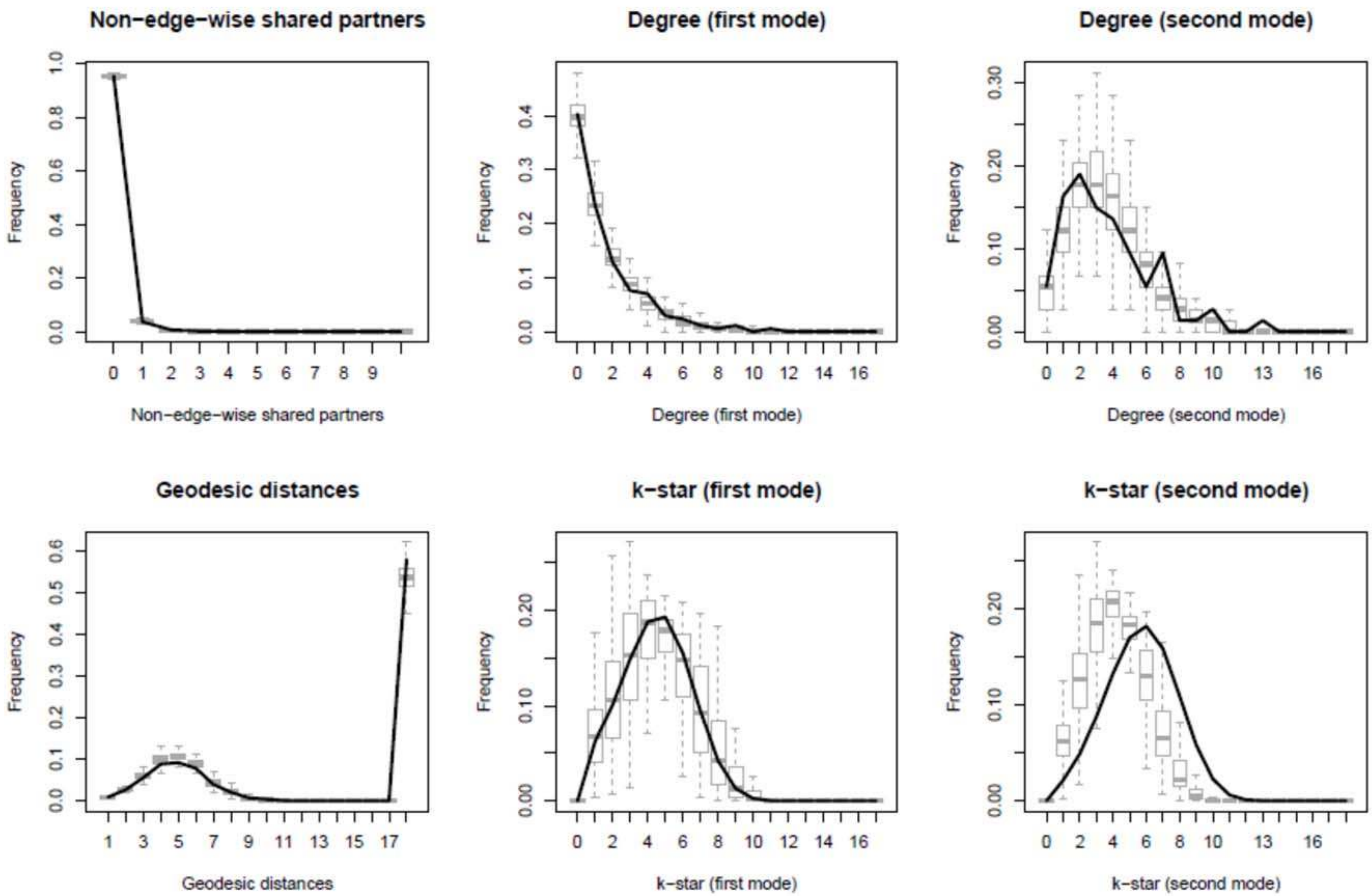
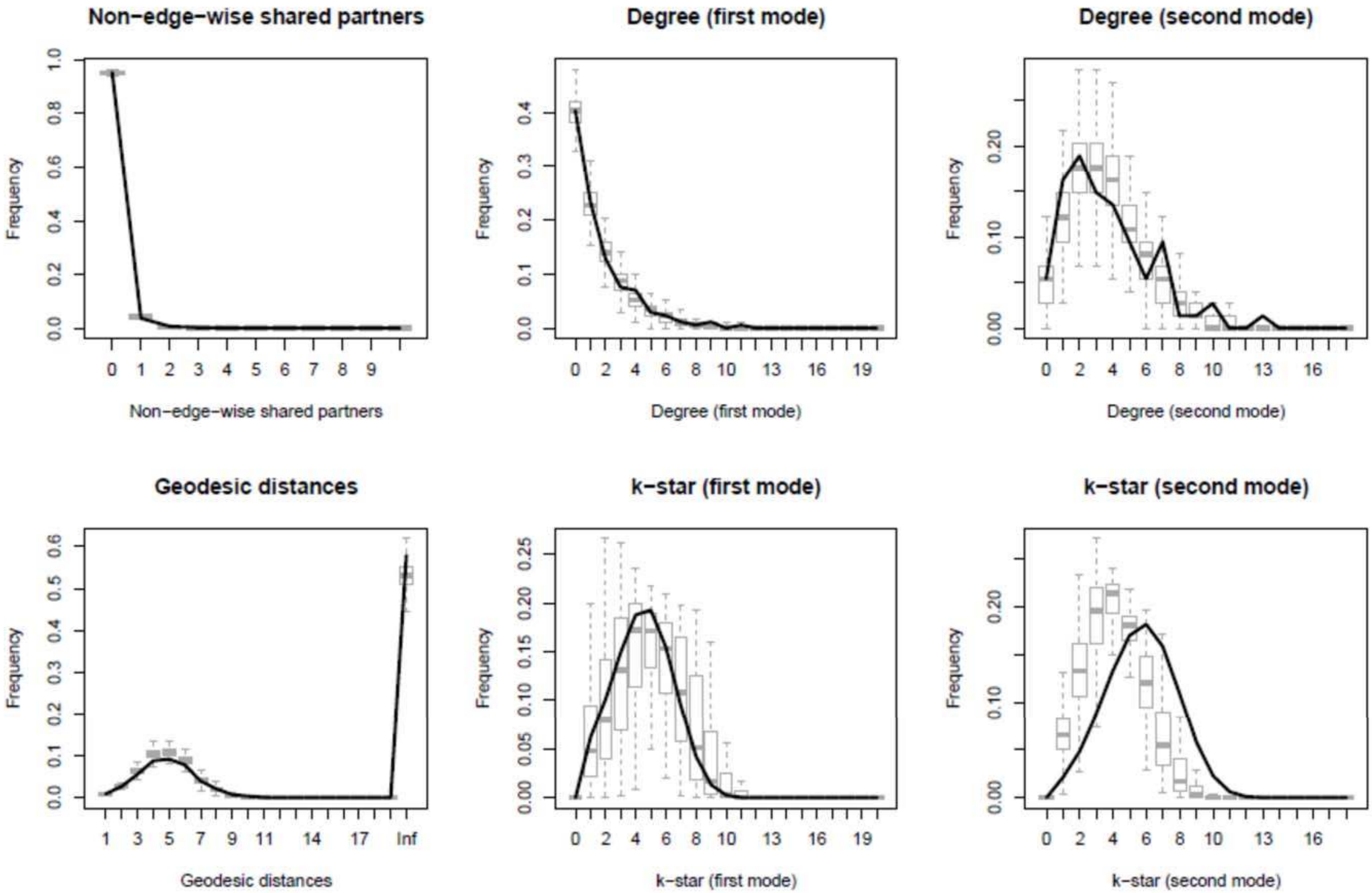
0 1 2 3 4 5 6 7 8 9
Non−edge−wise shared partners
Degree (first mode)
Frequency
0.0 0.1 0.2 0.3 0.4
0 2 4 6 8 10 13 16 19
Degree (first mode)
Degree (second mode)
Frequency
0.00 0.10 0.20
0 2 4 6 8 10 12 14 16
Degree (second mode)
Geodesic distances
Frequency
0.0 0.1 0.2 0.3 0.4 0.5 0.6
1 3 5 7 9 11 13 15 17
Geodesic distances
k−star (first mode)
Frequency
0.00 0.10 0.20 0.30
0 2 4 6 8 10 13 16 19
k−star (first mode)
k−star (second mode)
Frequency
0.00 0.10 0.20
0 2 4 6 8 10 12 14 16
k−star (second mode)

Model 9

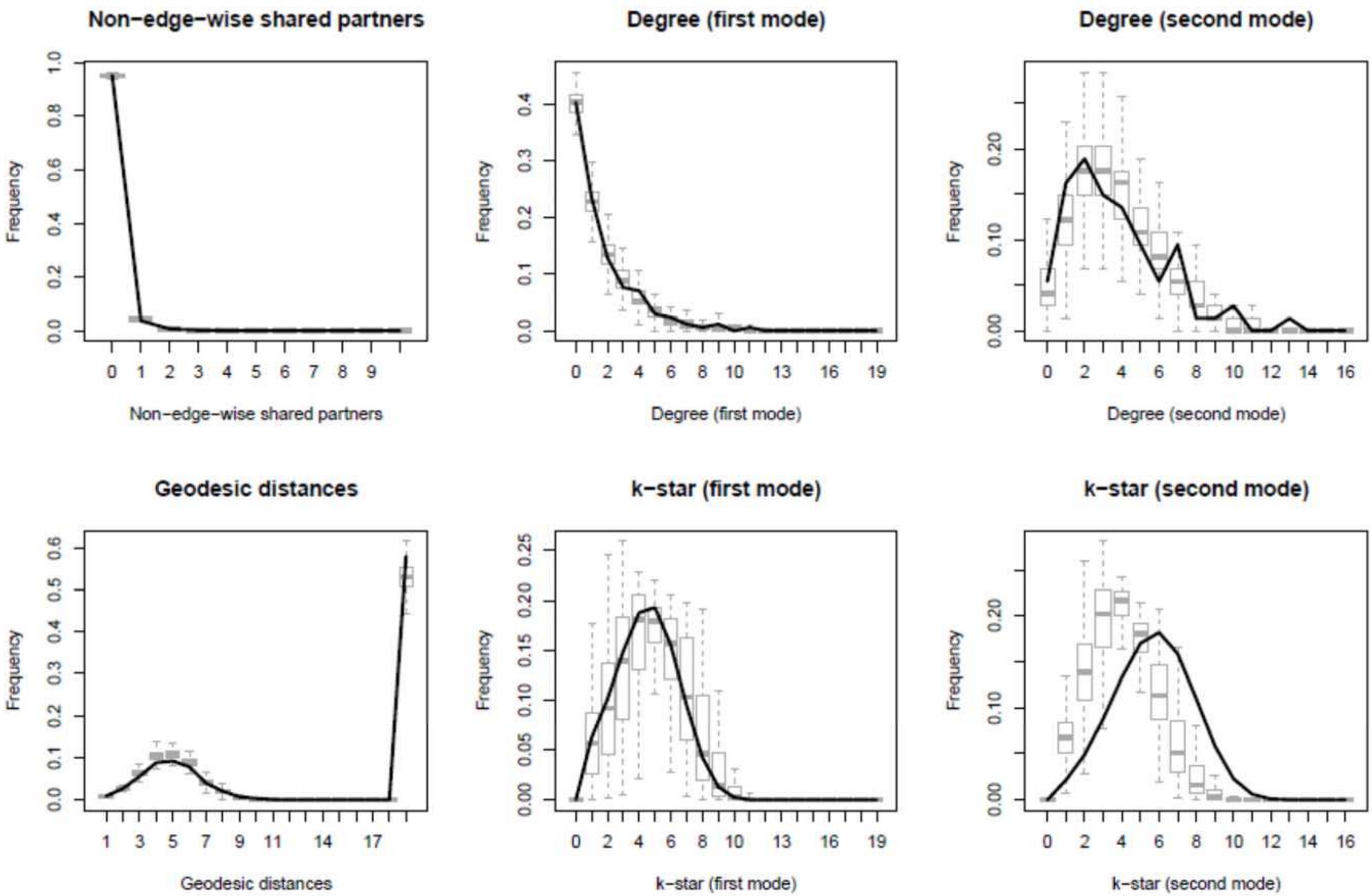


Non−edge−wise shared partners
Frequency
0.0
0.2
0.4
0.6
0.8
1.0
0 1 2 3 4 5 6 7 8 9
Non−edge−wise shared partners
Degree (first mode)
Frequency
0.0
0.1
0.2
0.3
0.4
0 2 4 6 8 10 12 14 16
Degree (first mode)
Degree (second mode)
Frequency
0.00
0.10
0.20
0.30
0 2 4 6 8 10 13 16
Degree (second mode)
Geodesic distances
Frequency
0.0
0.1
0.2
0.3
0.4
0.5
0.6
1 3 5 7 9 11 13 15 17
Geodesic distances
k−star (first mode)
Frequency
0.00
0.10
0.20
0 2 4 6 8 10 12 14 16
k−star (first mode)
k−star (second mode)
Frequency
0.00
0.10
0.20
0 2 4 6 8 10 13 16
k−star (second mode)

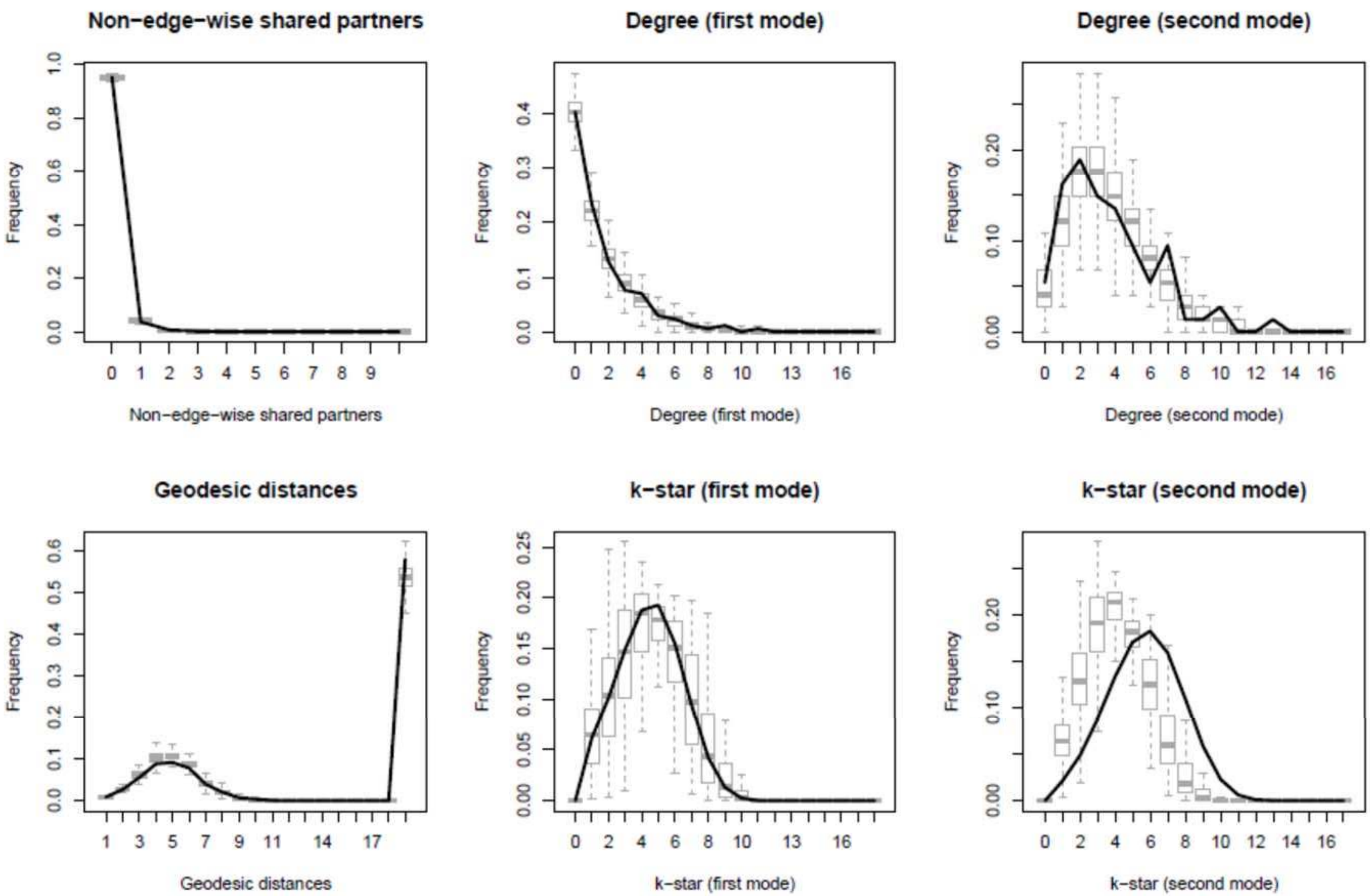
Model 10


Non−edge−wise shared partners
Frequency
Non−edge−wise shared partners
Degree (first mode)
Frequency
Degree (first mode)
Degree (second mode)
Frequency
Degree (second mode)
Geodesic distances
Frequency
Geodesic distances
k−star (first mode)
Frequency
k−star (first mode)
k−star (second mode)
Frequency
k−star (second mode)

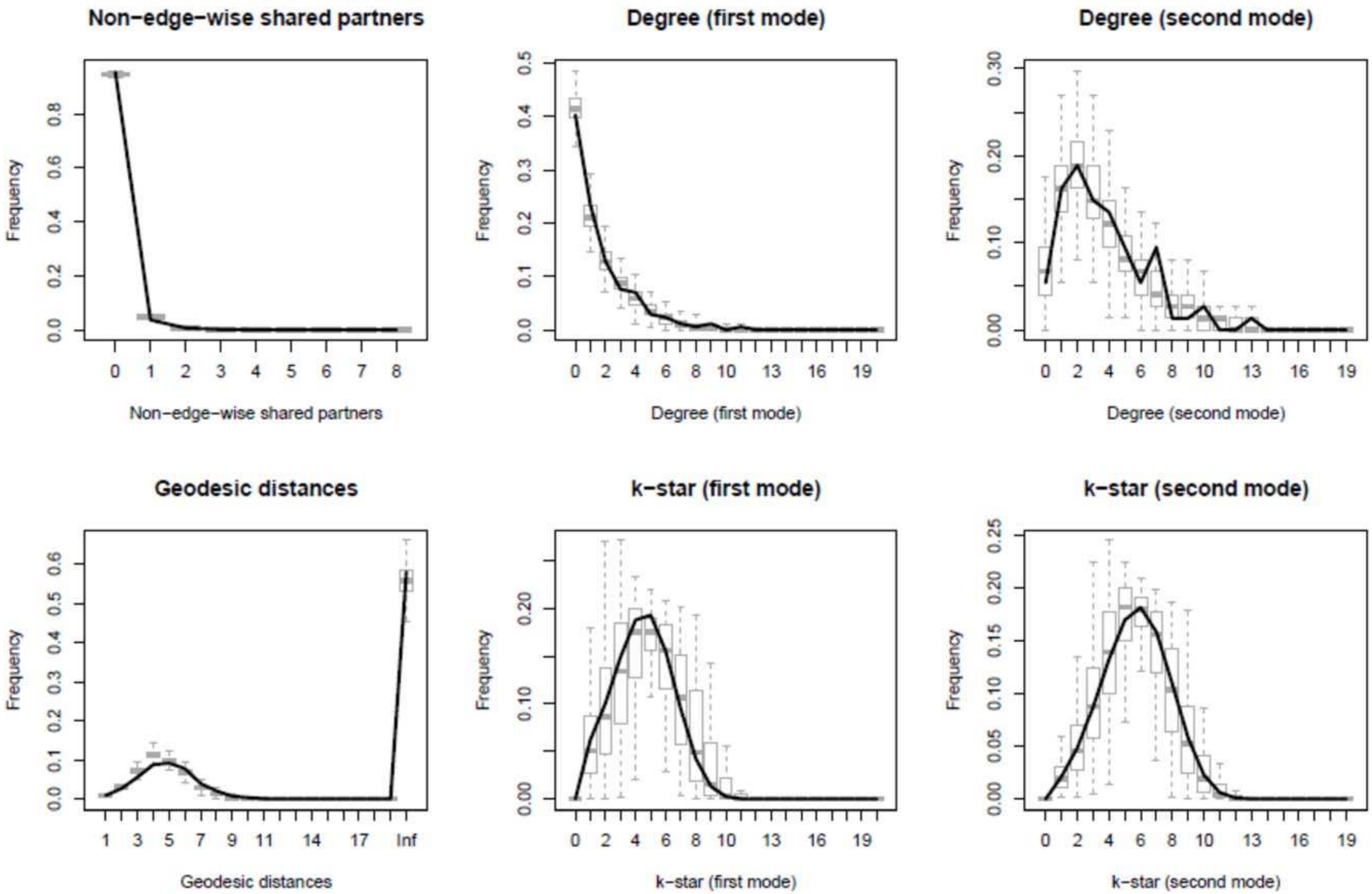
Model 11


Non−edge−wise shared partners
Degree (first mode)
Degree (second mode)
Geodesic distances
k−star (first mode)
k−star (second mode)
Frequency
Non−edge−wise shared partners
Degree (first mode)
Degree (second mode)
Geodesic distances
k−star (first mode)
k−star (second mode)

Model 12

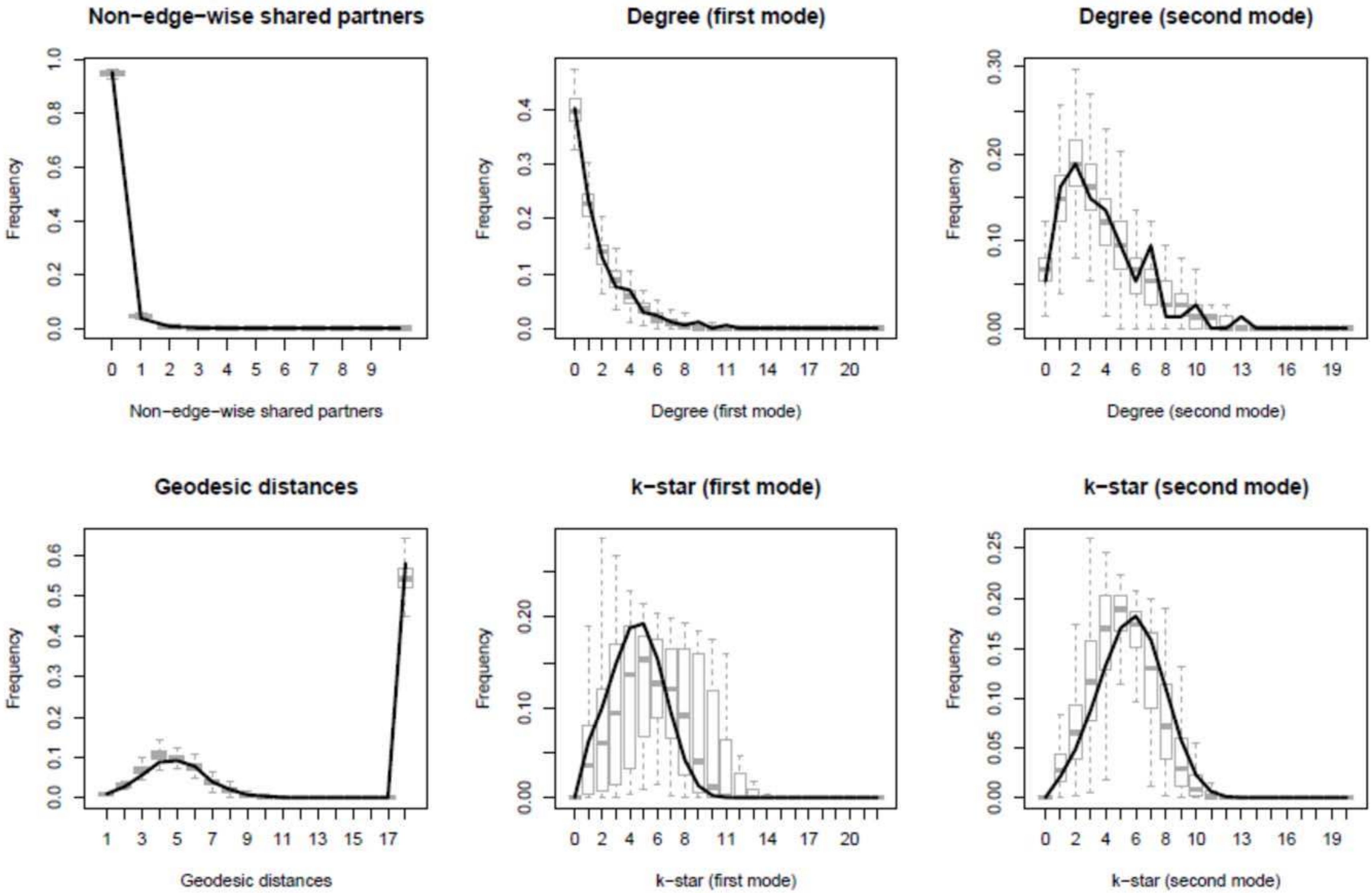

Non−edge−wise shared partners
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 1 2 3 4 5 6 7 8 9
Non−edge−wise shared partners
Degree (first mode)
Frequency
0.0 0.1 0.2 0.3 0.4
0 2 4 6 8 10 13 16
Degree (first mode)
Degree (second mode)
Frequency
0.00 0.10 0.20
0 2 4 6 8 10 12 14 16
Degree (second mode)
Geodesic distances
Frequency
0.0 0.1 0.2 0.3 0.4 0.5 0.6
1 3 5 7 9 11 14 17
Geodesic distances
k−star (first mode)
Frequency
0.00 0.05 0.10 0.15 0.20 0.25
0 2 4 6 8 10 13 16
k−star (first mode)
k−star (second mode)
Frequency
0.00 0.10 0.20
0 2 4 6 8 10 12 14 16
k−star (second mode)

Model 13

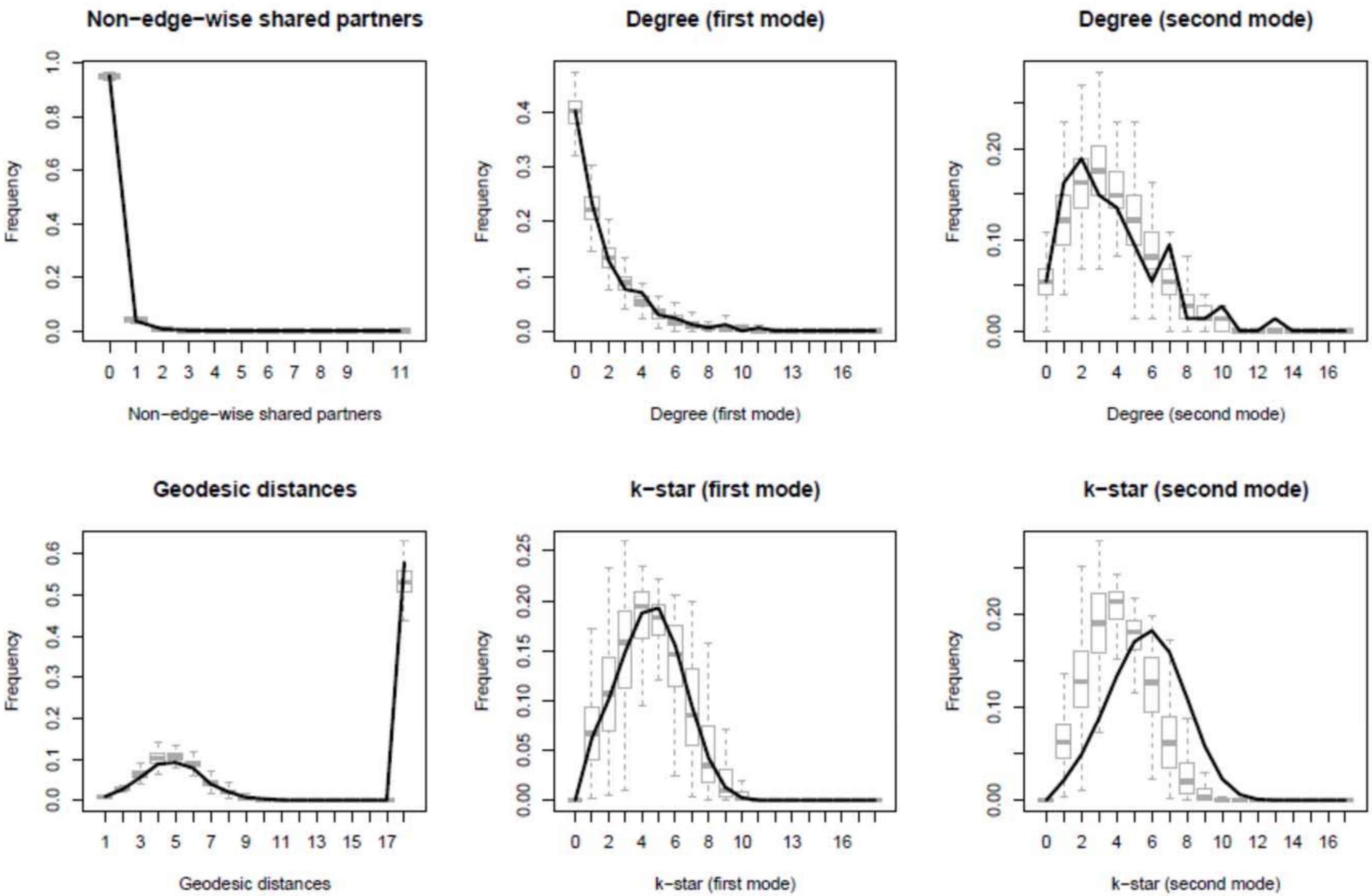


Non−edge−wise shared partners
Frequency
0.0 0.2 0.4 0.6 0.8
0 1 2 3 4 5 6 7 8
Non−edge−wise shared partners
Degree (first mode)
Frequency
0.0 0.1 0.2 0.3 0.4 0.5
0 2 4 6 8 10 13 16 19
Degree (first mode)
Degree (second mode)
Frequency
0.00 0.10 0.20 0.30
0 2 4 6 8 10 13 16 19
Degree (second mode)
Geodesic distances
Frequency
0.0 0.1 0.2 0.3 0.4 0.5 0.6
1 3 5 7 9 11 14 17 Inf
Geodesic distances
k−star (first mode)
Frequency
0.00 0.10 0.20
0 2 4 6 8 10 13 16 19
k−star (first mode)
k−star (second mode)
Frequency
0.00 0.05 0.10 0.15 0.20 0.25
0 2 4 6 8 10 13 16 19
k−star (second mode)

Model 14

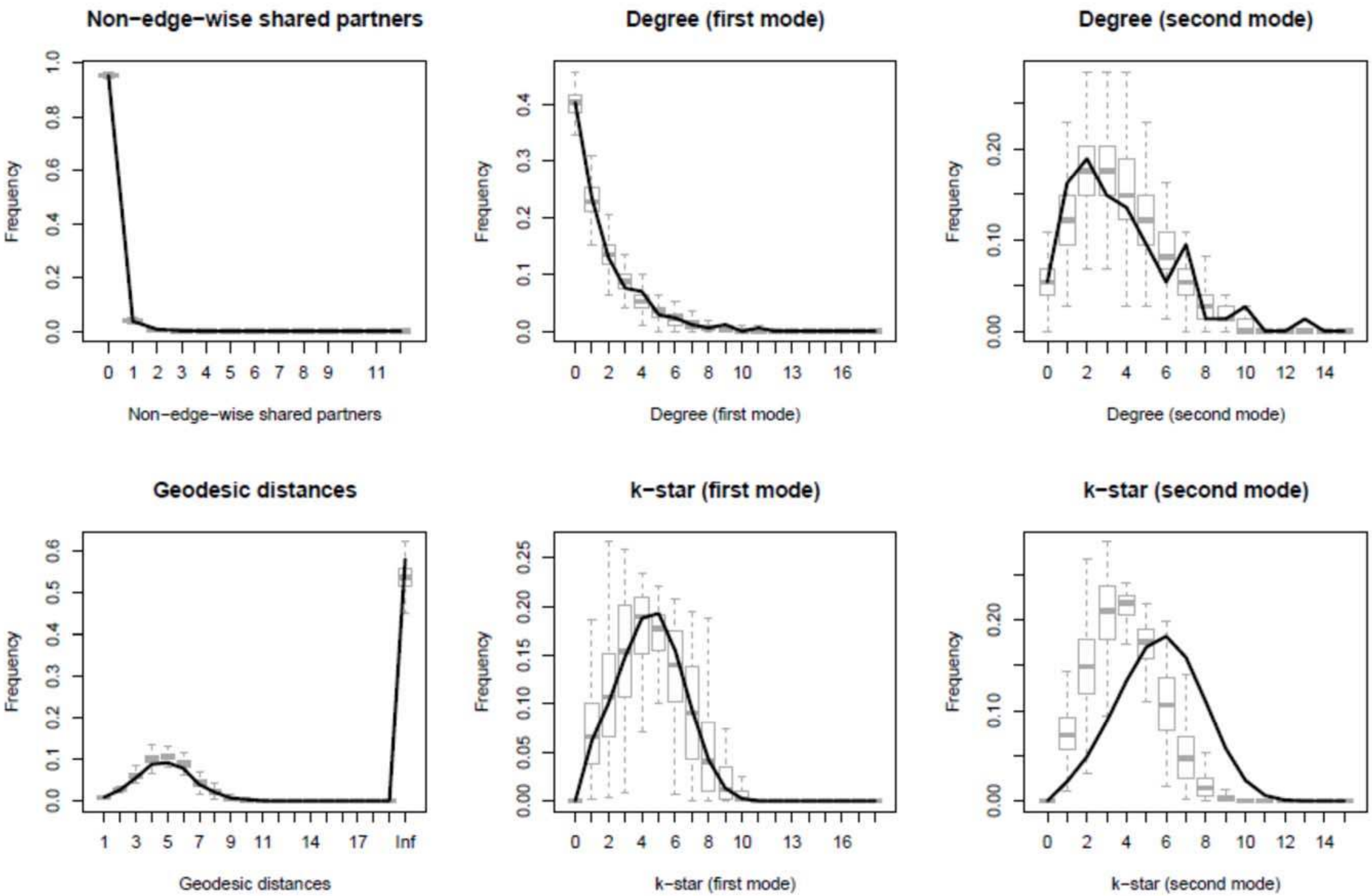

Non−edge−wise shared partners
Frequency
1.0 0.8 0.6 0.4 0.2 0.0
0 1 2 3 4 5 6 7 8 9
Non−edge−wise shared partners
Degree (first mode)
Frequency
0.4 0.3 0.2 0.1 0.0
0 2 4 6 8 11 14 17 20
Degree (first mode)
Degree (second mode)
Frequency
0.30 0.20 0.10 0.00
0 2 4 6 8 10 13 16 19
Degree (second mode)
Geodesic distances
Frequency
0.6 0.5 0.4 0.3 0.2 0.1 0.0
1 3 5 7 9 11 13 15 17
Geodesic distances
k−star (first mode)
Frequency
0.20 0.10 0.00
0 2 4 6 8 11 14 17 20
k−star (first mode)
k−star (second mode)
Frequency
0.25 0.20 0.15 0.10 0.05 0.00
0 2 4 6 8 10 13 16 19
k−star (second mode)

Model 15

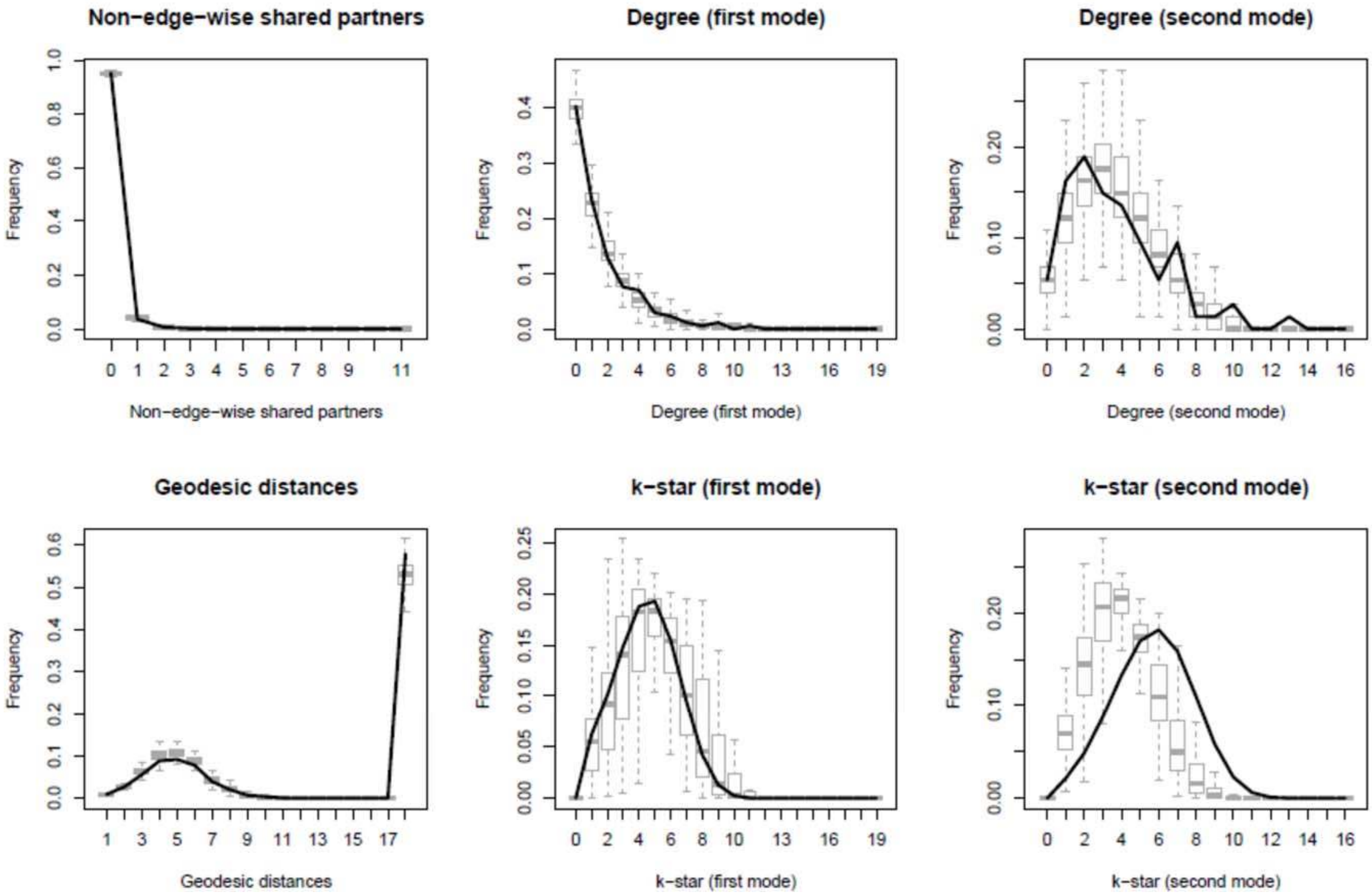


Non−edge−wise shared partners
Frequency
Non−edge−wise shared partners
Degree (first mode)
Frequency
Degree (first mode)
Degree (second mode)
Frequency
Degree (second mode)
Geodesic distances
Frequency
Geodesic distances
k−star (first mode)
Frequency
k−star (first mode)
k−star (second mode)
Frequency
k−star (second mode)

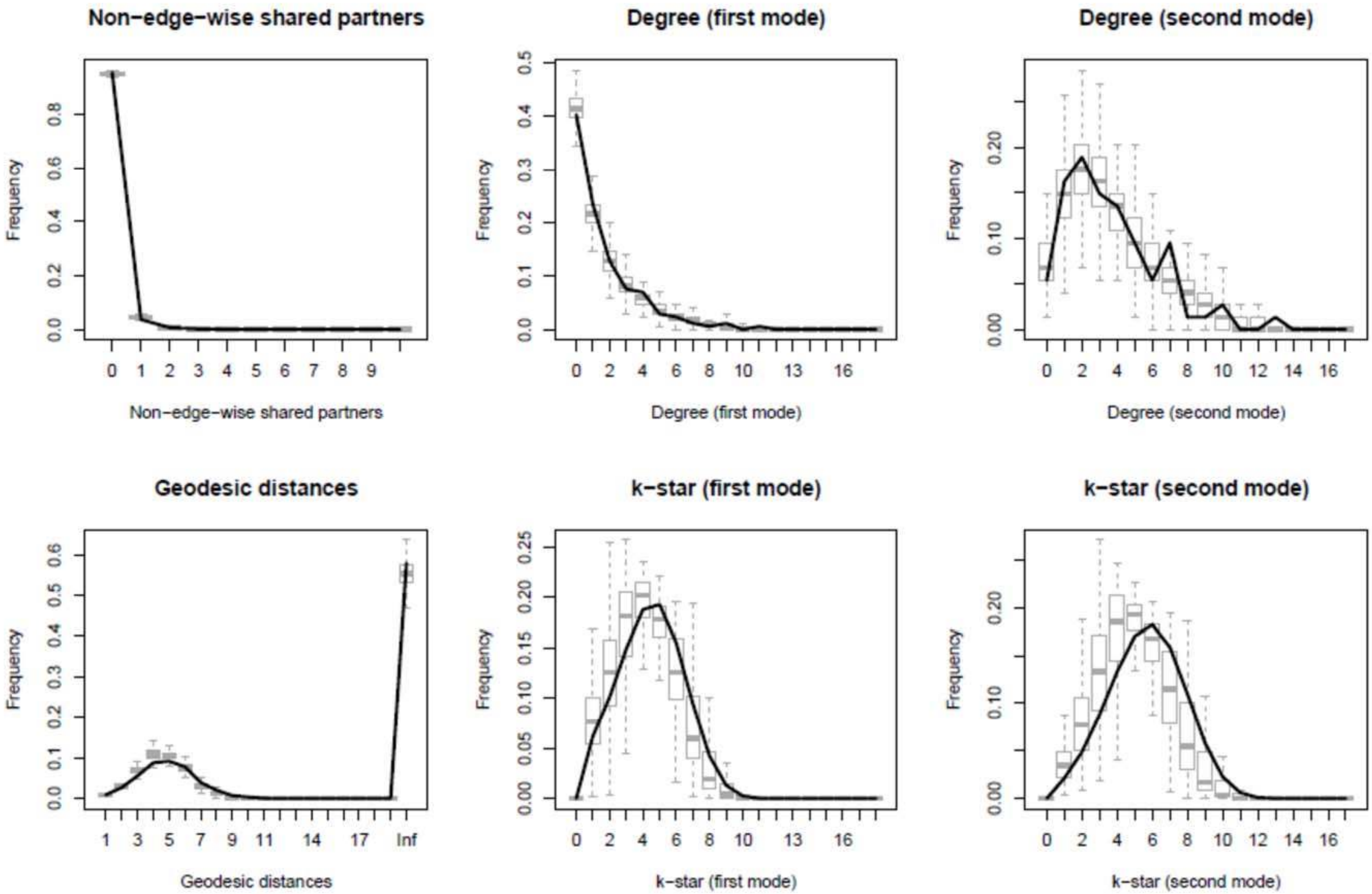
Model 16


Non−edge−wise shared partners
Degree (first mode)
Degree (second mode)
Geodesic distances
k−star (first mode)
k−star (second mode)
Frequency
Non−edge−wise shared partners
Degree (first mode)
Degree (second mode)
Geodesic distances
k−star (first mode)
k−star (second mode)

Model 17

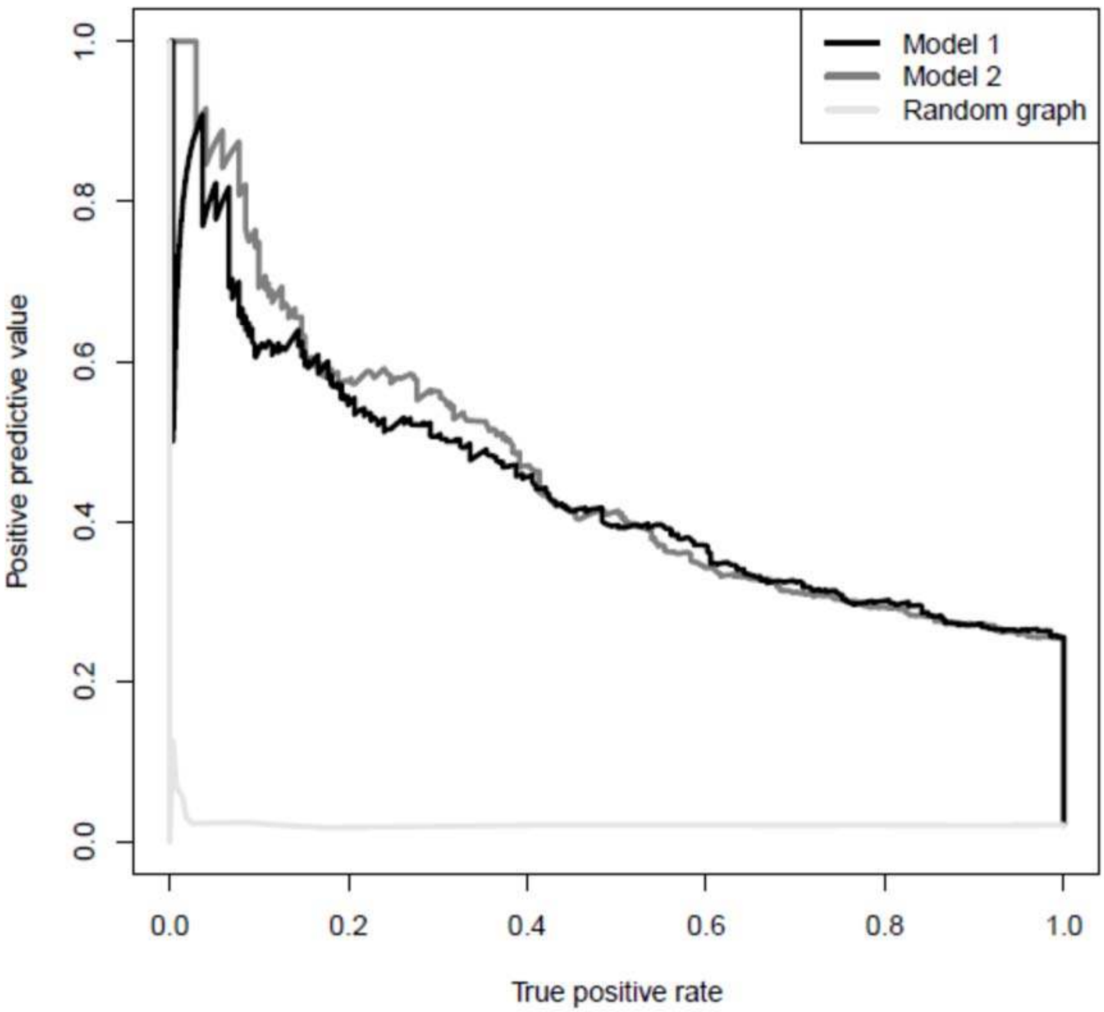

Non−edge−wise shared partners
Frequency
Non−edge−wise shared partners
Degree (first mode)
Frequency
Degree (first mode)
Degree (second mode)
Frequency
Degree (second mode)
Geodesic distances
Frequency
Geodesic distances
k−star (first mode)
Frequency
k−star (first mode)
k−star (second mode)
Frequency
k−star (second mode)

Model 18

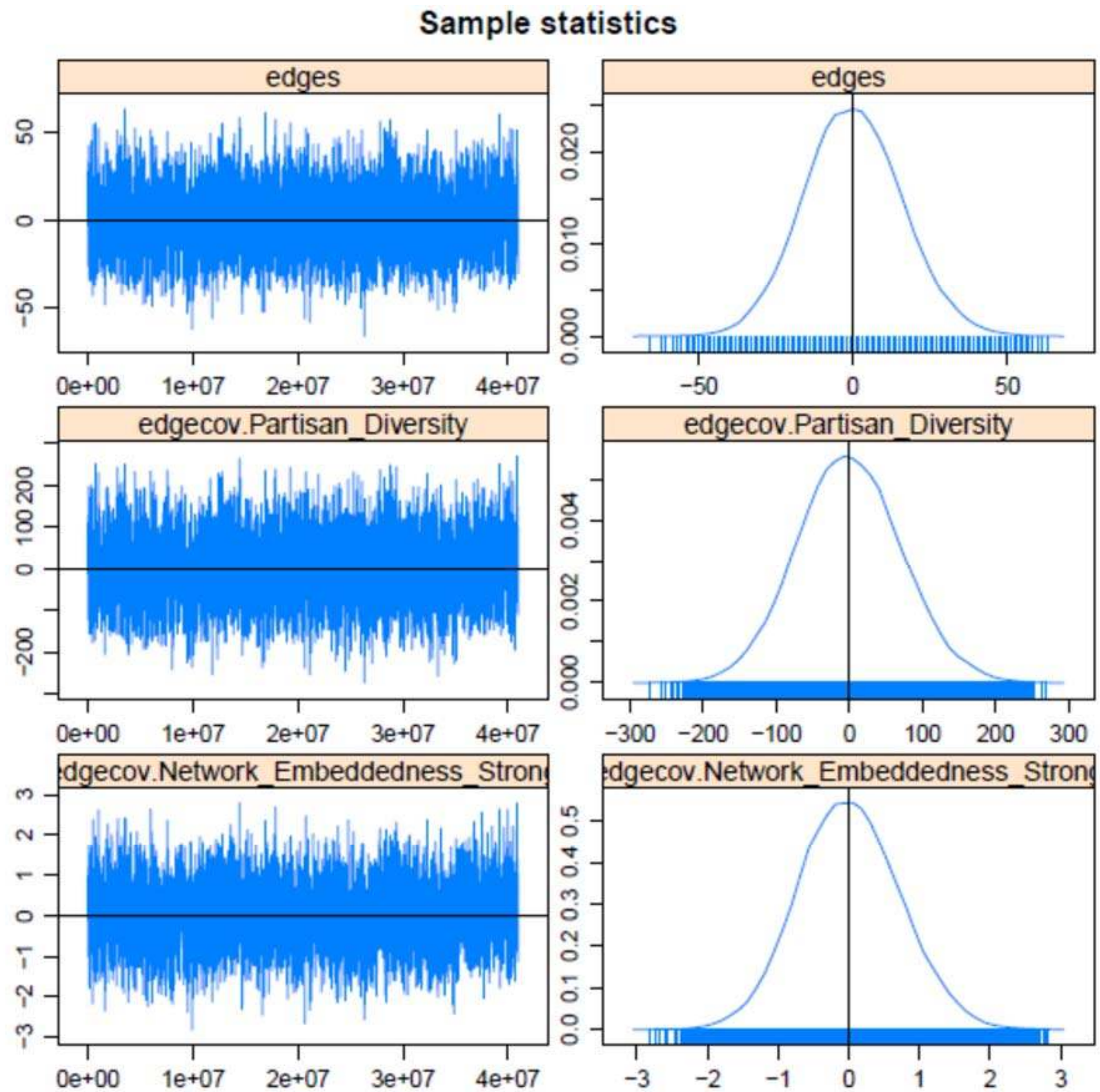


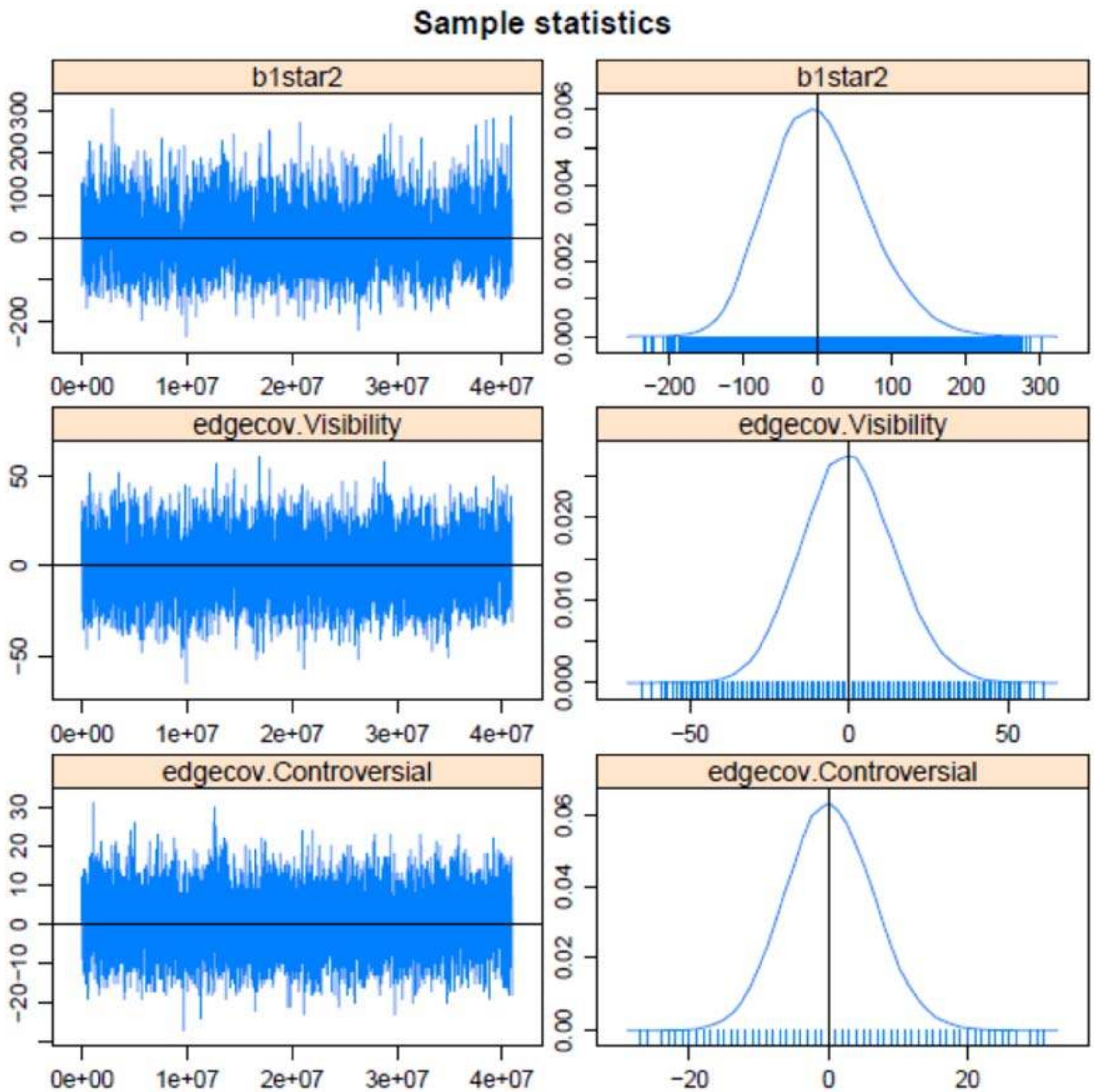
Non−edge−wise shared partners
Frequency
0.0
0.2
0.4
0.6
0.8
0 1 2 3 4 5 6 7 8 9
Non−edge−wise shared partners
Degree (first mode)
Frequency
0.0
0.1
0.2
0.3
0.4
0.5
0 2 4 6 8 10 13 16
Degree (first mode)
Degree (second mode)
Frequency
0.00
0.10
0.20
0 2 4 6 8 10 12 14 16
Degree (second mode)
Geodesic distances
Frequency
0.0
0.1
0.2
0.3
0.4
0.5
0.6
1 3 5 7 9 11 14 17 Inf
Geodesic distances
k−star (first mode)
Frequency
0.00
0.05
0.10
0.15
0.20
0.25
0 2 4 6 8 10 13 16
k−star (first mode)
k−star (second mode)
Frequency
0.00
0.10
0.20
0 2 4 6 8 10 12 14 16
k−star (second mode)

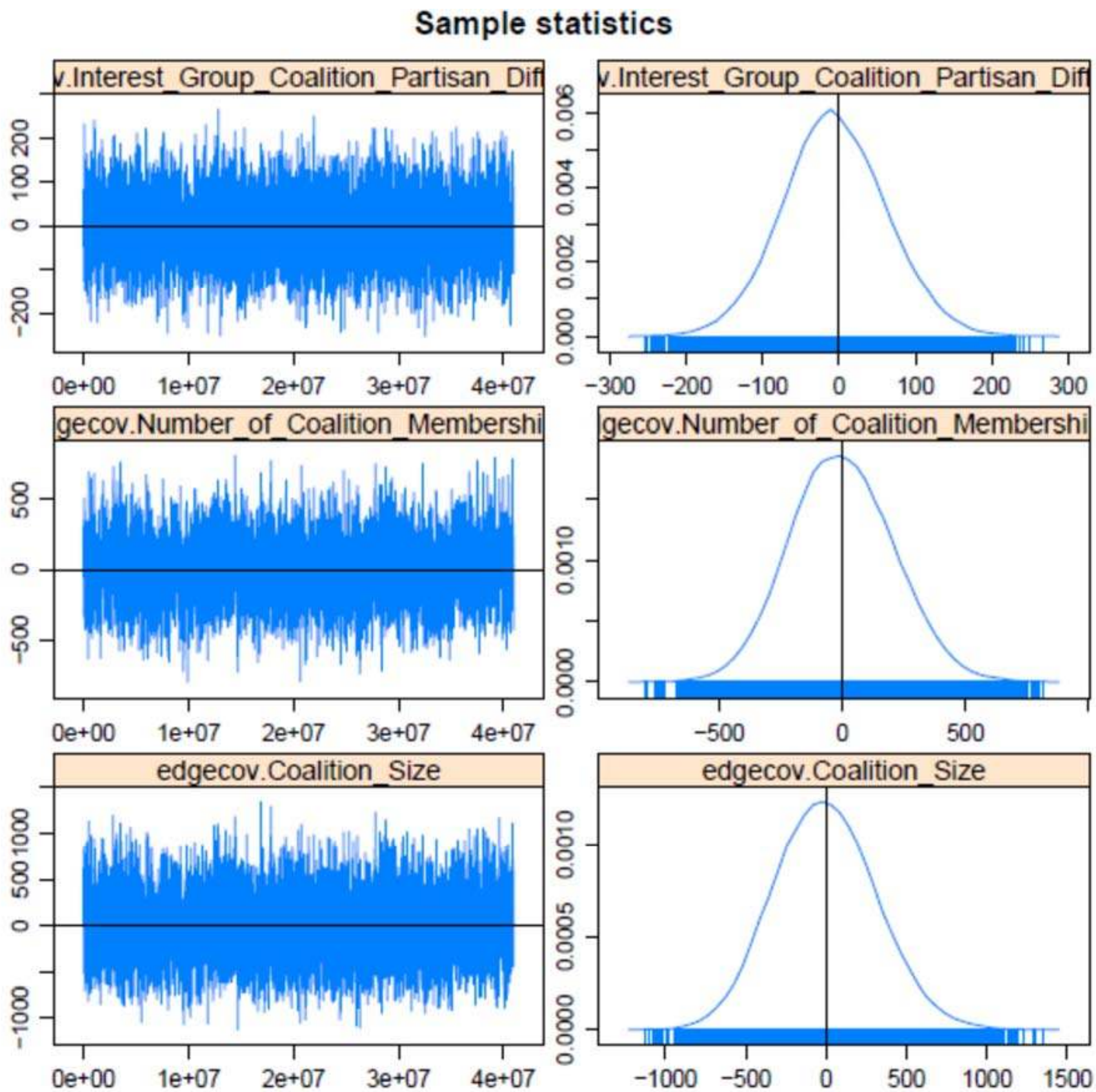
Online Appendix 7. Precision-Recall Curves for Models 1 and 2

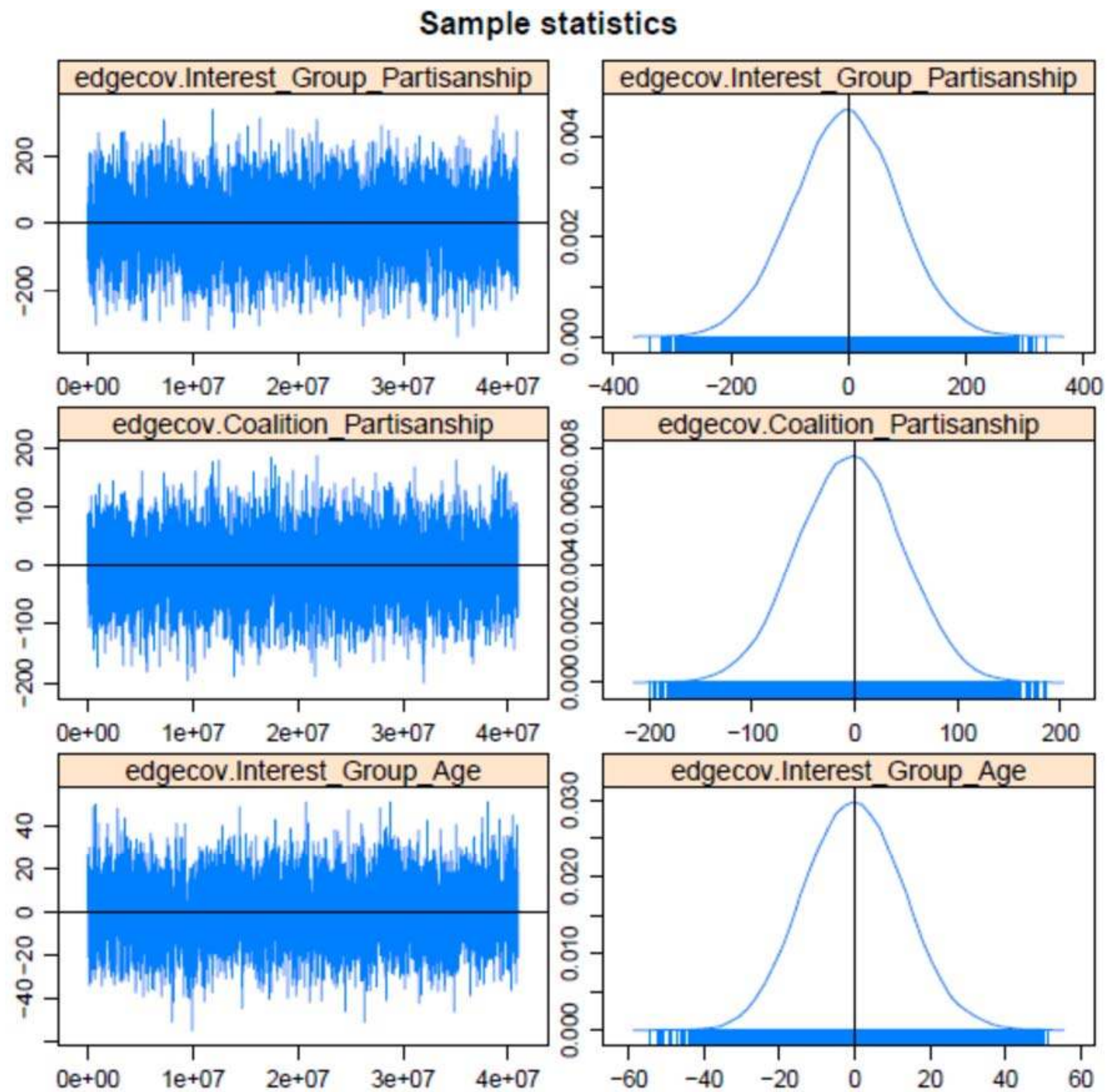


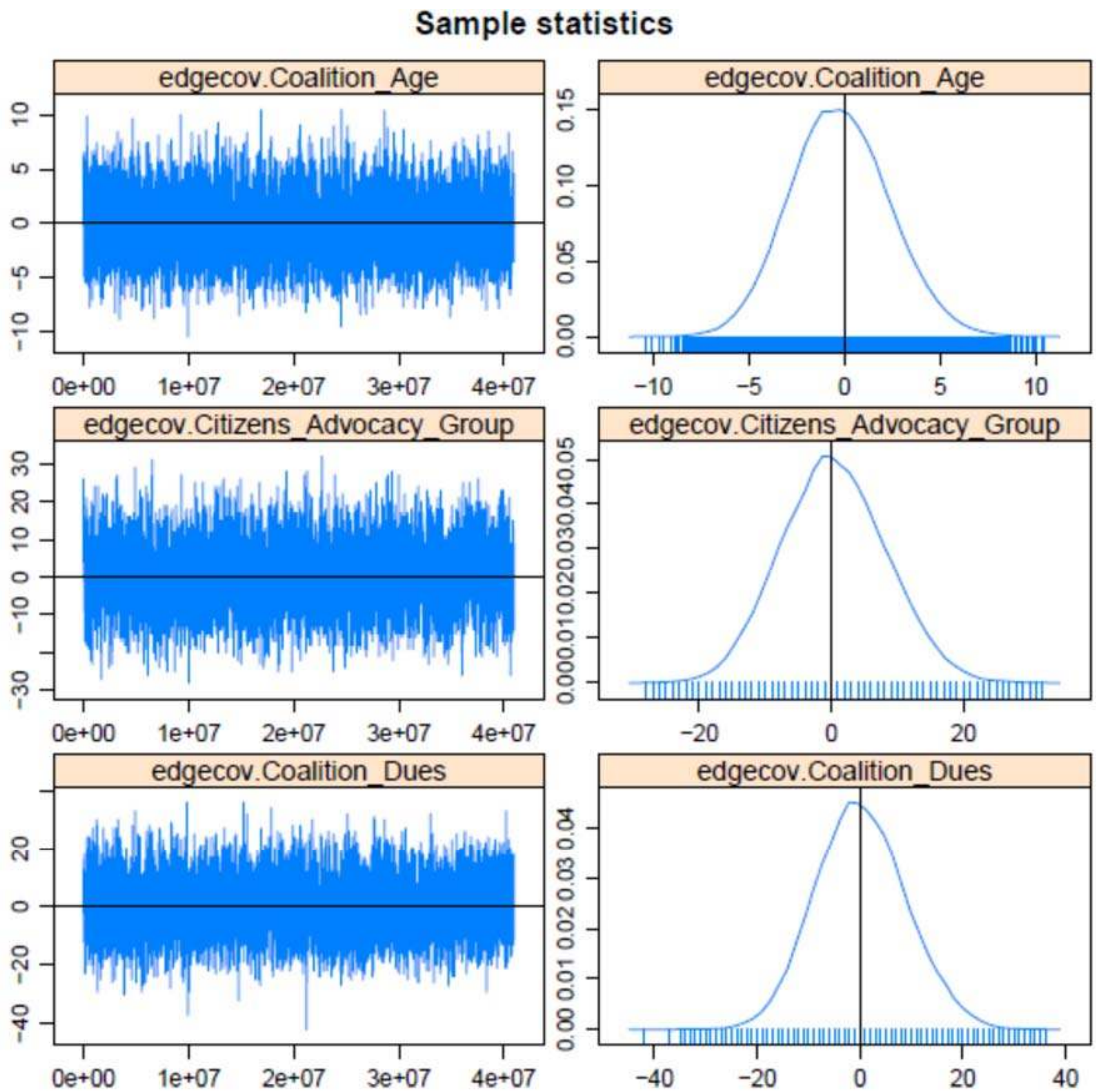
Online Appendix 8. MCMC Diagnostics for Model 1

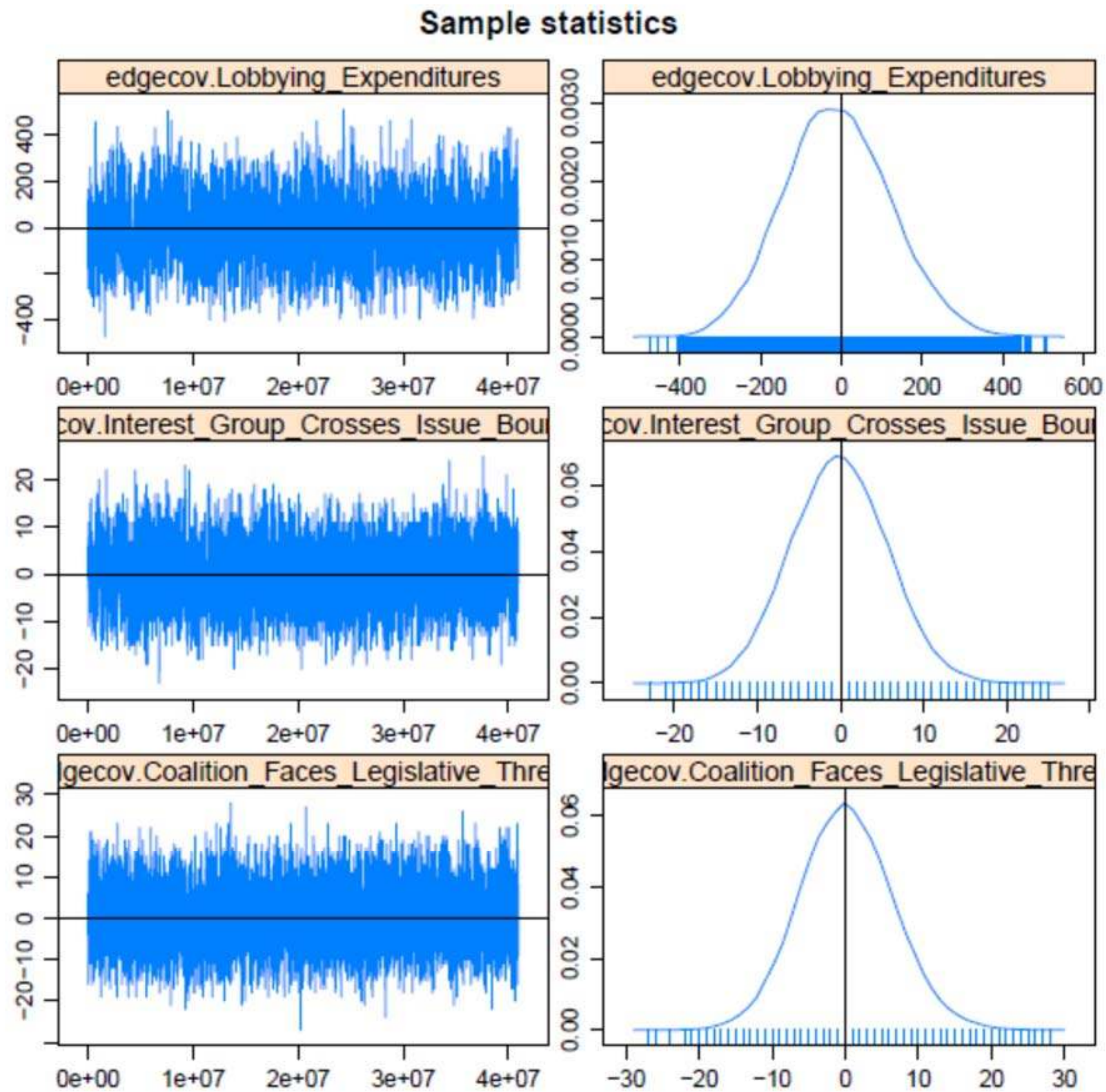


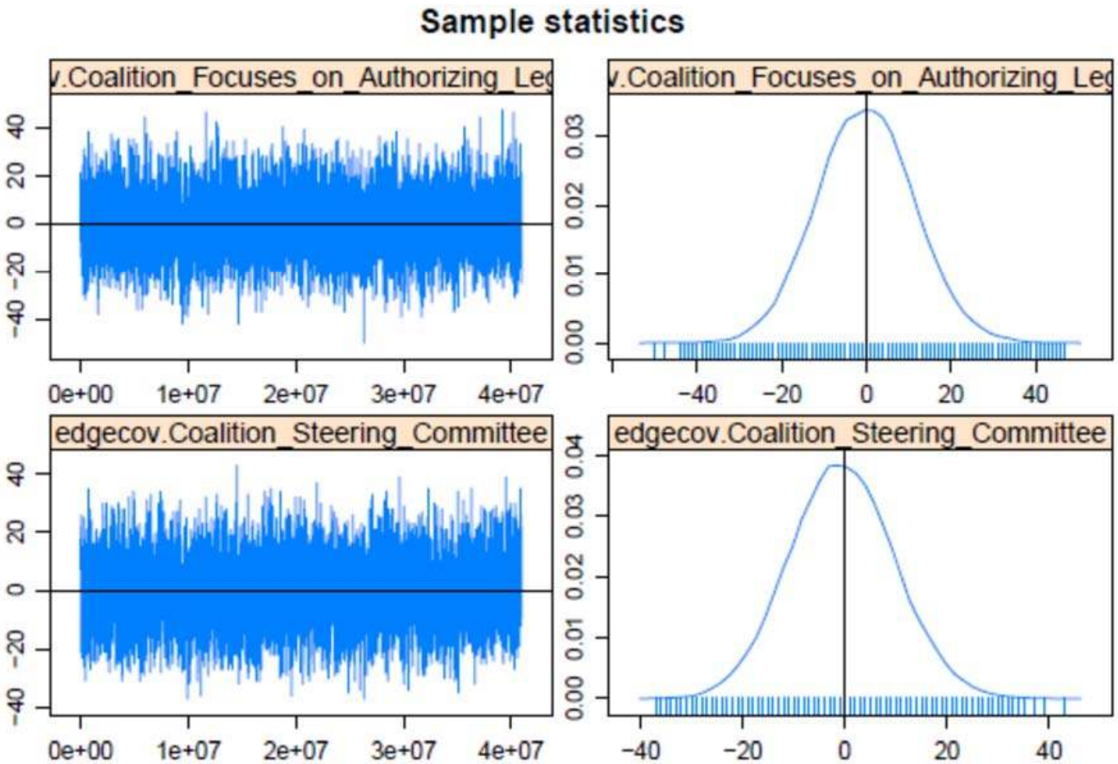

Sample statistics
b1star2
edgecov.Visibility
edgecov.Controversial


Sample statistics
v.Interest_Group_Coalition_Partisan_Diff
gecov.Number_of_Coalition_Membershi
edgecov.Coalition_Size


Sample statistics
edgecov.Interest_Group_Partisanship
edgecov.Interest_Group_Partisanship
edgecov.Coalition_Partisanship
edgecov.Coalition_Partisanship
edgecov.Interest_Group_Age
edgecov.Interest_Group_Age
0e+00
1e+07
2e+07
3e+07
4e+07


Sample statistics
edgecov.Coalition_Age
edgecov.Coalition_Age
edgecov.Citizens_Advocacy_Group
edgecov.Citizens_Advocacy_Group
edgecov.Coalition_Dues
edgecov.Coalition_Dues


Sample statistics
edgecov.Lobbying_Expenditures
edgecov.Lobbying_Expenditures
cov.Interest_Group_Crosses_Issue_Bou
cov.Interest_Group_Crosses_Issue_Bou
lgecov.Coalition_Faces_Legislative_Thre
lgecov.Coalition_Faces_Legislative_Thre
0e+00
1e+07
2e+07
3e+07
4e+07


Sample statistics
v.Coalition_Focuses_on_Authorizing_Leg
v.Coalition_Focuses_on_Authorizing_Leg
edgecov.Coalition_Steering_Committee
edgecov.Coalition_Steering_Committee
0e+00
1e+07
2e+07
3e+07
4e+07
-40
-20
0
20
40
0.00
0.01
0.02
0.03
0.04

Online Appendix 9. Alternative Measures of Network Embeddedness

The measure of network embeddedness we employ in the main manuscript (Models 1-4) and in most versions of the Online Appendix (Models 5-6 and 11-18) is the number of connections focal group i has to other groups k outside the focal coalition j, standardized by the number of potential connection i and any k can have at most:

$$\text{strong embeddedness}_{ij} = \frac{\sum_{i \in U} \sum_{j \in V} \sum_{k \in U} \sum_{l \in V} [i \neq k][j \neq l] N_{ij} N_{kj} N_{il} N_{kl}}{\sum_{i \in U} \sum_{j \in V} \sum_{k \in U} \sum_{l \in V} [i \neq k][j \neq l] N_{ij} N_{kj}}$$

where N_{ij} denotes the membership status (0 or 1) of interest group i in coalition j and square brackets denote an indicator function that equals 1 if the condition inside the brackets is true and 0 if it is false. Effectively, this notion of network embeddedness captures *strong* embeddedness in the sense that the number of outside coalition memberships a focal group shares with the other members of the focal coalition is taken into account. That is, outside shared membership with another group through 10 different coalitions can make up for not being connected to 10 other groups (compared to being connected to each of them through one single outside coalition each).

Alternatively, one could test for *weak* embeddedness, which means that the co-membership strength with any other group is not taken into account. This version of network embeddedness is used in Models 7 and 8 in the Online Appendix.

$$\text{weak embeddedness}_{ij} = \frac{\sum_{i \in U} \sum_{j \in V} \sum_{k \in U} [i \neq k] (N_{ij} N_{kj} [\sum_{l \in V} [j \neq l] N_{il} N_{kl} > 0])}{\sum_{i \in U} \sum_{j \in V} \sum_{k \in U} [i \neq k] N_{ij} N_{kj}}$$

In this version, any additional group k with which i has an outside co-membership is counted equally. This puts a stronger emphasis on the weak ties a group maintains with other groups.

Alternatively, one could use communication between the members of a coalition as a proxy for network embeddedness. This variant of *communication* embeddedness is employed in Models 9 and 10 in the Online Appendix. Embeddedness of a focal group i in coalition j is measured as the fraction of other members of j with whom i has a communication tie.

$$\text{communication embeddedness}_{ij} = \frac{\sum_{i\in U}\sum_{j\in V}\sum_{k\in U}[i \neq k]N_{ij}N_{kj}X_{ik}}{\sum_{i\in U}\sum_{j\in V}\sum_{k\in U}[i \neq k]N_{ij}N_{kj}}$$

where Xdenotes a square $|U| \times |U|$ sociomatrix with elements $X_{ik} = 1$ if group i maintains a communication tie to group k and $X_{ik} = 0$ otherwise. It should be noted that causality can be bidirectional with this alternative formulation of embeddedness: communication embeddedness may trigger leadership contributions, but leadership contributions could also cause groups to become more embedded in the communication network.

Finally, Models 11 and 12 in the Online Appendix are based on a variant of strong network embeddedness that computes embeddedness only for within- or only for cross-partisan ties. To accomplish this, the equation for strong embeddedness is altered by multiplying the product by a dummy variable that is 1 if both i and k are on the same side (on different sides, respectively) of the partisan dimension and 0 otherwise.

Online Appendix 10. R Replication Code

```
# last change: 2017-05-18


# ==============================================================================
# Prepare workspace
# ==============================================================================

library("network")
library("sna")
library("ergm")
library("xergm")
library("texreg")
library("inline")
library("Rcpp")
library("ggplot2")
library("reshape2")

sessionInfo()
# R version 3.3.0 (2016-05-03)
# Platform: x86_64-pc-linux-gnu (64-bit)
# Running under: Ubuntu 16.04.2 LTS
#
# locale:
#  [1] LC_CTYPE=en_GB.UTF-8       LC_NUMERIC=C
#  [3] LC_TIME=en_GB.UTF-8        LC_COLLATE=en_GB.UTF-8
#  [5] LC_MONETARY=en_GB.UTF-8    LC_MESSAGES=en_GB.UTF-8
#  [7] LC_PAPER=en_GB.UTF-8       LC_NAME=C
#  [9] LC_ADDRESS=C               LC_TELEPHONE=C
# [11] LC_MEASUREMENT=en_GB.UTF-8 LC_IDENTIFICATION=C
#
# attached base packages:
# [1] stats     graphics  grDevices utils     datasets  methods   base
#
# other attached packages:
#  [1] reshape2_1.4.1       Rcpp_0.12.3          inline_0.3.14
#  [4] texreg_1.36.23       xergm_1.8.2          GERGM_0.11.2
#  [7] rem_1.1.2            tnam_1.6.5           btergm_1.9.0
# [10] ggplot2_2.0.0        xergm.common_1.7.7   ergm_3.6.0
# [13] statnet.common_3.3.0 sna_2.3-2            network_1.13.0
#
# loaded via a namespace (and not attached):
#  [1] deSolve_1.12         gtools_3.5.0         lpSolve_5.6.13
#  [4] ergm.count_3.2.0     splines_3.3.0        lattice_0.20-33
#  [7] mstate_0.2.8         colorspace_1.2-6     flexsurv_0.7
# [10] stats4_3.3.0         tergm_3.4.0          mgcv_1.8-12
# [13] survival_2.39-4      nloptr_1.0.4         RColorBrewer_1.1-2
# [16] muhaz_1.2.6          speedglm_0.3-1       trust_0.1-7
# [19] plyr_1.8.3           stringr_1.0.0        robustbase_0.92-5
# [22] munsell_0.4.2        gtable_0.1.2         caTools_1.17.1
# [25] mvtnorm_1.0-5        coda_0.18-1          permute_0.8-4
# [28] parallel_3.3.0       DEoptimR_1.0-4       KernSmooth_2.23-15
# [31] ROCR_1.0-7           networkDynamic_0.9.0 statnet_2016.4
# [34] scales_0.3.0         gdata_2.17.0         vegan_2.3-1
# [37] RcppParallel_4.3.20  lme4_1.1-10          gplots_2.17.0
# [40] stringi_1.0-1        grid_3.3.0           quadprog_1.5-5
# [43] tools_3.3.0          bitops_1.0-6         magrittr_1.5
# [46] RSiena_1.1-232       cluster_2.0.4        MASS_7.3-45
# [49] Matrix_1.2-6         minqa_1.2.4          boot_1.3-17
# [52] igraph_1.0.1         nlme_3.1-128

burnin <- 10000      # MCMC burnin
```

```
sampsize <- 10000    # MCMC sample size
maxit <- 200         # number of MCMC MLE iterations
nsim <- 1000         # number of simulated networks for the GOF assessment
cores <- 3           # number of computing cores for parallel processing
seed <- 12345        # random seed for exact reproducibility
set.seed(seed)


# ==============================================================================
# Read CSV files and transform/manage data
# ==============================================================================

# leadership network
leader <- as.matrix(read.csv("Coalition_Leadership.csv", header = TRUE,
    row.names = 1, stringsAsFactors = FALSE))

# coalition non-membership matrix
nonmem <- as.matrix(read.csv("Coalition_Nonmembership.csv", header = TRUE,
    row.names = 1, stringsAsFactors = FALSE))
mem <- (nonmem * -1) + 1  # membership matrix

# several nodal attributes
attrib <- read.csv("Coalition_Node_Attributes.csv", header = TRUE)

# communication network: any kind of communication
comm.any <- as.matrix(read.table("Communication_Any.csv",
    stringsAsFactors = FALSE, sep = ",", header = TRUE, row.names = 1))

# communication network: occasional communication
comm.occ <- as.matrix(read.table("Communication_Occasional.csv",
    stringsAsFactors = FALSE, sep = ",", header = TRUE, row.names = 1))

# communication network: regular communication
comm.reg <- as.matrix(read.table("Communication_Regular.csv",
    stringsAsFactors = FALSE, sep = ",", header = TRUE, row.names = 1))

# attributes contain both groups and coalitions; they need to be separated
attrib.grp <- attrib[1:nrow(mem), ]
attrib.coal <- attrib[(nrow(mem) + 1): nrow(attrib), ]

# who founded which coalition?
founded <- as.matrix(read.csv("Founded.csv", header = TRUE, row.names = 1,
    stringsAsFactors = FALSE))


# ==============================================================================
# Create new model terms for multiplexity and diversity
# ==============================================================================


# impute NA values in communication
for (i in 1:nrow(comm.any)) {
  for (j in 1:ncol(comm.any)) {
    if (is.na(comm.any[i, j]) && !is.na(comm.any[j, i])) {
      comm.any[i, j] <- comm.any[j, i]  # impute from reciprocal dyad
    } else if (is.na(comm.any[j, i])) {
      comm.any[i, j] <- 0  # zero-impute if reciprocal dyad also NA
    }
    if (is.na(comm.reg[i, j]) && !is.na(comm.reg[j, i])) {
      comm.reg[i, j] <- comm.reg[j, i]
    } else if (is.na(comm.reg[j, i])) {
      comm.reg[i, j] <- 0
    }
```

```
    if (is.na(comm.occ[i, j]) && !is.na(comm.occ[j, i])) {
      comm.occ[i, j] <- comm.occ[j, i]
    } else if (is.na(comm.occ[j, i])) {
      comm.occ[i, j] <- 0
    }
  }
}


# H1: network embeddedness

# compute co-occurrence of coalition membership among coalition members
cpp.comember.strong <- cxxfunction(signature(mat = "matrix"), plugin = "Rcpp",
    body = '
  IntegerMatrix mem = as<IntegerMatrix>(mat);
  int rows = mem.nrow();
  int cols = mem.ncol();
  Rcpp::NumericMatrix comemb = NumericMatrix(rows, cols);
  int realized;
  int possible;
  for (int i = 0; i < cols; i++) {
    for (int j = 0; j < rows; j++) {
      realized = 0;
      possible = 0;
      for (int k = 0; k < rows; k++) {
        for (int l = 0; l < cols; l++) {
          if (j != k && i != l && mem(j, i) == 1 && mem(k, i) == 1) {
            possible++;
            if (mem(k, l) == 1 && mem(j, l) == 1) {
              realized++;
            }
          }
        }
      }
      //std::cout << i << " " << j << " " << realized << " " << possible << "\\n";
      if (possible == 0.0) {
        comemb(j, i) = 0.0;
      } else {
        comemb(j, i) = double(realized) / double(possible);
      }
    }
  }
  return(wrap(comemb));
')

Network_Embeddedness_Strong <- cpp.comember.strong(mem)

# compute share of other members with whom i has at least one co-membership
cpp.comember.weak <- cxxfunction(signature(mat = "matrix"), plugin = "Rcpp",
    body = '
  IntegerMatrix mem = as<IntegerMatrix>(mat);
  int rows = mem.nrow();
  int cols = mem.ncol();
  Rcpp::NumericMatrix comemb = NumericMatrix(rows, cols);
  int realized;
  int nummembers;
  for (int i = 0; i < cols; i++) {
    nummembers = 0;
    for (int k = 0; k < rows; k++) {
      if (mem(k, i) == 1) {
        nummembers++;
      }
    }
```

```
    for (int j = 0; j < rows; j++) {
      realized = 0;
      bool kiscomem;
      for (int k = 0; k < rows; k++) {
        kiscomem = false;
        for (int l = 0; l < cols; l++) {
          if (j != k && i != l && mem(j, i) == 1 && mem(k, i) == 1) {
            if (mem(k, l) == 1 && mem(j, l) == 1) {
              kiscomem = true;
              realized++;
              break;
            }
          }
        }
      }
      //std::cout << i << " " << j << " " << realized << " " << nummembers << "\\n";
      if (nummembers < 2.0) {
        comemb(j, i) = 0.0;
      } else {
        comemb(j, i) = double(realized) / double(nummembers - 1);
      }
    }
  }
  return(wrap(comemb));
')

Network_Embeddedness_Weak <- cpp.comember.weak(mem)


# communication density of others in current coalition
cpp.commdensity <- cxxfunction(signature(mat = "matrix", comm = "matrix"),
    plugin = "Rcpp", body = '
  IntegerMatrix mem = as<IntegerMatrix>(mat);
  IntegerMatrix com = as<IntegerMatrix>(comm);
  int rows = mem.nrow();
  int cols = mem.ncol();
  Rcpp::NumericMatrix cd = NumericMatrix(rows, cols);
  int realized;
  int possible;
  for (int i = 0; i < cols; i++) {
    for (int j = 0; j < rows; j++) {
      realized = 0;
      possible = 0;
      for (int k = 0; k < rows; k++) {
        if (j != k && mem(j, i) == 1 && mem(k, i) == 1) {
          possible++;
          if (com(j, k) == 1) {
            realized++;
          }
        }
      }
      // std::cout << realized << " " << possible << "\\n";
      if (possible == 0.0) {
        cd(j, i) = 0.0;
      } else {
        cd(j, i) = double(realized) / double(possible);
      }
    }
  }
  return(wrap(cd));
')

commdensity <- cpp.commdensity(mem, comm.any)
```

```
# H2: diversity

cpp.diversity <- cxxfunction(signature(mat = "matrix", attribute = "integer"),
    plugin = "Rcpp", body = '
  IntegerMatrix mem = as<IntegerMatrix>(mat);
  IntegerVector at = as<IntegerVector>(attribute);
  int rows = mem.nrow();
  int cols = mem.ncol();
  Rcpp::NumericMatrix diversity = NumericMatrix(rows, cols);
  for (int i = 0; i < cols; i++) {
    for (int j = 0; j < rows; j++) {
      double sum = 0.0;
      int counter = 0;
      for (int k = 0; k < rows; k++) {
        if (mem(j, i) == 1 && mem(k, i) == 1) {
          counter++;
          sum = sum + at[k];
        }
      }
      double mean = sum / counter;
      double sqsum = 0.0;
      for (int k = 0; k < rows; k++) {
        if (mem(j, i) == 1 && mem(k, i) == 1) {
          sqsum = sqsum + ((mean - at[k]) * (mean - at[k]));
        }
      }
      if (counter == 0) {
        diversity(j, i) = 0;
      } else {
        diversity(j, i) = sqrt(sqsum / counter);
      }
    }
  }
  return(wrap(diversity));
')

# diversity measures
Partisan_Diversity <- cpp.diversity(mat = mem,
    attribute = attrib.grp$Conservative_Lean_of_Organization)
diversity.lobspend <- cpp.diversity(mat = mem,
    attribute = attrib.grp$Lobbying_Spending_by_Organization)
diversity.infrep <- cpp.diversity(mat = mem,
    attribute = attrib.grp$Organizations_Influence_Reputation)
diversity.outshealth <- cpp.diversity(mat = mem,
    attribute = attrib.grp$Organization_Identified_Primarily_Outside_Health)
diversity.citadv <- cpp.diversity(mat = mem,
    attribute = attrib.grp$Organization_is_Citizens_Advocacy_Organization)
diversity.age <- cpp.diversity(mat = mem,
    attribute = attrib.grp$Years_Since_Founding_of_Organization_Coalition)

# interaction terms comembership * diversity
Diversity_X_Embeddedness_Strong <-
    Network_Embeddedness_Strong * Partisan_Diversity
Diversity_X_Embeddedness_Weak <-
    Network_Embeddedness_Weak * Partisan_Diversity
commdensity.diversity <- commdensity * Partisan_Diversity

# dependent variable and structural zeros and ones
leader <- network(leader, directed = FALSE, bipartite = TRUE)  # DV
# model 1: non-members are structural zeros:
nonmem <- network(nonmem, directed = FALSE, bipartite = TRUE)
```

```
nonmem2 <- as.matrix(nonmem)
nonmem2[founded == 1] <- 1  # model 2, non-members and founders = struct. zeros
sum(mem * founded)  # 136 additional structural zeros
sum((mem * founded) * as.matrix(leader))  # 102 leadership ties are removed
# model 3: in addition to nonmem as structural zeros, model founders who are
# also leaders as structural ones, i.e., constrain founders to be leaders:
founderleader <- as.matrix(leader) * founded


# ===============================================================================
# Create model terms for control variables
# ===============================================================================

# issue controversy
Controversial <- matrix(rep(attrib.coal$Issue_is_Highly_Controversial,
    nrow(as.matrix(leader))), nrow = nrow(as.matrix(leader)), byrow = TRUE)
Diversity_X_Controversial <- Partisan_Diversity * Controversial

# coalition visibility
Visibility <- matrix(rep(attrib.coal$Coalition_in_Public,
    nrow(as.matrix(leader))), nrow = nrow(as.matrix(leader)), byrow = TRUE)
Diversity_X_Visibility <- Partisan_Diversity * Visibility

# three-way interaction: diversity x embeddedness within or across parties
cpp.comember.strong.party <- cxxfunction(signature(mat = "matrix",
    cl = "IntegerVector", cross = "bool"), plugin = "Rcpp", body = '
  IntegerMatrix mem = as<IntegerMatrix>(mat);
  IntegerVector conslean = as<IntegerVector>(cl);
  bool crossparty = as<bool>(cross);
  int rows = mem.nrow();
  int cols = mem.ncol();
  Rcpp::NumericMatrix comemb = NumericMatrix(rows, cols);
  int realized;
  int possible;
  for (int i = 0; i < cols; i++) {
    for (int j = 0; j < rows; j++) {
      realized = 0;
      possible = 0;
      for (int k = 0; k < rows; k++) {
        if ((crossparty == false && (conslean(j) < 0 && conslean(k) < 0) ||
                                    (conslean(j) >= 0 && conslean(k) >= 0)) ||
            (crossparty == true && (conslean(j) < 0 && conslean(k) >= 0) ||
                                    (conslean(j) >= 0 && conslean(k) < 0))) {
          for (int l = 0; l < cols; l++) {
            if (j != k && i != l && mem(j, i) == 1 && mem(k, i) == 1) {
              possible++;
              if (mem(k, l) == 1 && mem(j, l) == 1) {
                realized++;
              }
            }
          }
        }
      }
      // std::cout << realized << " " << possible << "\\n";
      if (possible == 0.0) {
        comemb(j, i) = 0.0;
      } else {
        comemb(j, i) = double(realized) / double(possible);
      }
    }
  }
  return(wrap(comemb));
')
```

```
cpp.comember.weak.party <- cxxfunction(signature(mat = "matrix",
    cl = "IntegerVector", cross = "bool"), plugin = "Rcpp", body = '
  IntegerMatrix mem = as<IntegerMatrix>(mat);
  IntegerVector conslean = as<IntegerVector>(cl);
  bool crossparty = as<bool>(cross);
  int rows = mem.nrow();
  int cols = mem.ncol();
  Rcpp::NumericMatrix comemb = NumericMatrix(rows, cols);
  int realized;
  int nummembers;
  for (int i = 0; i < cols; i++) {
    nummembers = 0;
    for (int k = 0; k < rows; k++) {
      if (mem(k, i) == 1) {
        nummembers++;
      }
    }
    for (int j = 0; j < rows; j++) {
      realized = 0;
      bool kiscomem;
      for (int k = 0; k < rows; k++) {
        kiscomem = false;
        if ((crossparty == false && (conslean(j) < 0 && conslean(k) < 0) ||
                                    (conslean(j) >= 0 && conslean(k) >= 0)) ||
            (crossparty == true && (conslean(j) < 0 && conslean(k) >= 0) ||
                                    (conslean(j) >= 0 && conslean(k) < 0))) {
          for (int l = 0; l < cols; l++) {
            if (j != k && i != l && mem(j, i) == 1 && mem(k, i) == 1) {
              if (mem(k, l) == 1 && mem(j, l) == 1) {
                kiscomem = true;
                realized++;
                break;
              }
            }
          }
        }
      }
      //std::cout << i << " " << j << " " << realized << " " << nummembers << "\\n";
      if (nummembers < 2.0) {
        comemb(j, i) = 0.0;
      } else {
        comemb(j, i) = double(realized) / double(nummembers - 1);
      }
    }
  }
  return(wrap(comemb));
')

Network_Embeddedness_Weak_SameParty <- cpp.comember.weak.party(mem,
    attrib.grp$Conservative_Lean_of_Organization_Coalition, FALSE)
Network_Embeddedness_Weak_CrossParty <- cpp.comember.weak.party(mem,
    attrib.grp$Conservative_Lean_of_Organization_Coalition, TRUE)
Network_Embeddedness_Strong_SameParty <- cpp.comember.strong.party(mem,
    attrib.grp$Conservative_Lean_of_Organization_Coalition, FALSE)
Network_Embeddedness_Strong_CrossParty <- cpp.comember.strong.party(mem,
    attrib.grp$Conservative_Lean_of_Organization_Coalition, TRUE)
Diversity_X_Embeddedness_Weak_SameParty <-
    Partisan_Diversity * Network_Embeddedness_Weak_SameParty
Diversity_X_Embeddedness_CrossParty <-
    Partisan_Diversity * Network_Embeddedness_Weak_CrossParty

# Number_of_Coalition_Memberships: outdegree centrality of groups in the
```

```
# membership network
rs <- rowSums(mem)
Number_of_Coalition_Memberships <- matrix(NA, nrow = nrow(mem),
    ncol = ncol(mem))
for (i in 1:nrow(Number_of_Coalition_Memberships)) {
  Number_of_Coalition_Memberships[i, ] <- rs[i]
}

# Coalition_Size: indegree centrality of coalitions in the membership network
cs <- colSums(mem)
Coalition_Size <- matrix(NA, nrow = nrow(mem), ncol = ncol(mem))
for (i in 1:ncol(Coalition_Size)) {
  Coalition_Size[, i] <- cs[i]
}

# commpart.indeg: indegree centrality in the communication network; count number
# of comm. partners in same coal. and divide by num. of coal. members excl. ego
# (notes: NAs need to be replaced first; the matrix is transposed, i.e.,
# communication flows from columns to rows, so this needs to be transposed)
for (i in 1:nrow(comm.any)) {
  for (j in 1:ncol(comm.any)) {
    if (is.na(comm.any[i, j]) && !is.na(comm.any[j, i])) {
      comm.any[i, j] <- comm.any[j, i]  # impute from reciprocal dyad
    } else if (is.na(comm.any[j, i])) {
      comm.any[i, j] <- 0  # zero-impute if reciprocal dyad also NA
    }
    if (is.na(comm.reg[i, j]) && !is.na(comm.reg[j, i])) {
      comm.reg[i, j] <- comm.reg[j, i]
    } else if (is.na(comm.reg[j, i])) {
      comm.reg[i, j] <- 0
    }
    if (is.na(comm.occ[i, j]) && !is.na(comm.occ[j, i])) {
      comm.occ[i, j] <- comm.occ[j, i]
    } else if (is.na(comm.occ[j, i])) {
      comm.occ[i, j] <- 0
    }
  }
}
commpart.outdeg.any <- matrix(0, nrow = nrow(mem), ncol = ncol(mem))  # any com.
commpart.indeg.any <- commpart.outdeg.any  # indegree, any type of communication
commpart.outdeg.reg <- commpart.outdeg.any # outdegree, regular communication
commpart.indeg.reg <- commpart.outdeg.any  # indegree, regular communication
for (i in 1:nrow(mem)) {
  for (j in 1:ncol(mem)) {
    if (mem[i, j] == 1) {
      members <- which(mem[, j] == 1)  # all members of this coalition

      # any communication
      comm.subset <- comm.any[members, members]  # comm. partners in this coal.

      groupi <- which(rownames(comm.subset) == rownames(mem)[i])
      indeg.coal <- sum(comm.subset[groupi, ])  # indegree of group i in coal.
      commpart.indeg.any[i, j] <- indeg.coal / (sum(mem[, j]) - 1)

      outdeg.coal <- sum(comm.subset[, groupi])  # outdegree of group i in coal.
      commpart.outdeg.any[i, j] <- outdeg.coal / (sum(mem[, j]) - 1)

      # regular communication
      comm.subset <- comm.reg[members, members]  # comm. partners in this coal.

      groupi <- which(rownames(comm.subset) == rownames(mem)[i])
      indeg.coal <- sum(comm.subset[groupi, ])  # indegree of group i in coal.
      commpart.indeg.reg[i, j] <- indeg.coal / (sum(mem[, j]) - 1)
```

```
      outdeg.coal <- sum(comm.subset[, groupi])  # outdegree of group i in coal.
      commpart.outdeg.reg[i, j] <- outdeg.coal / (sum(mem[, j]) - 1)
    }
  }
}

# Interest_Group_Coalition_Partisan_Differential: absolute difference in
# conservatism group vs. coalition
# set the node attribute for re-use with the absdiff term
set.vertex.attribute(leader, "Partisanship",
    attrib$Conservative_Lean_of_Organization_Coalition)
Interest_Group_Coalition_Partisan_Differential <- matrix(NA,
    nrow = nrow(as.matrix(leader)), ncol = ncol(as.matrix(leader)))
cl <- attrib$Conservative_Lean_of_Organization_Coalition
cl.ig <- cl[1:nrow(as.matrix(leader))]
cl.coal <- cl[(nrow(as.matrix(leader)) + 1):length(cl)]
for (i in 1:length(cl.ig)) {
  for (j in 1:length(cl.coal)) {
    Interest_Group_Coalition_Partisan_Differential[i, j] <- abs(cl.ig[i] -
        cl.coal[j])
  }
}

# Interest_Group_Partisanship: conservatism of the group
Interest_Group_Partisanship <- matrix(NA, nrow = nrow(mem), ncol = ncol(mem))
for (i in 1:ncol(mem)) {
  Interest_Group_Partisanship[, i] <-
      attrib.grp$Conservative_Lean_of_Organization_Coalition
}

# Coalition_Partisanship: conservatism of the coalition
Coalition_Partisanship <- matrix(NA, nrow = nrow(mem), ncol = ncol(mem))
for (i in 1:nrow(mem)) {
  Coalition_Partisanship[i, ] <-
      attrib.coal$Conservative_Lean_of_Organization_Coalition
}

# Lobbying_Expenditures: lobbying expenditure of organization
Lobbying_Expenditures <- matrix(NA, nrow = nrow(mem), ncol = ncol(mem))
for (i in 1:ncol(mem)) {
  Lobbying_Expenditures[, i] <- attrib.grp$Lobbying_Spending_by_Organization
}

# Coalition_Dues: does the coalition collect dues?
Coalition_Dues <- matrix(NA, nrow = nrow(mem), ncol = ncol(mem))
for (i in 1:nrow(mem)) {
  Coalition_Dues[i, ] <- attrib.coal$Coalition_Collects_Dues
}

# Coalition_Faces_Legislative_Threat: coalition responding to legislative threat
Coalition_Faces_Legislative_Threat <- matrix(NA, nrow = nrow(mem),
    ncol = ncol(mem))
for (i in 1:nrow(mem)) {
  Coalition_Faces_Legislative_Threat[i, ] <-
      attrib.coal$Coalition_Responding_to_Legislative_Threat
}

# Coalition_Focuses_on_Authorizing_Legislation
Coalition_Focuses_on_Authorizing_Legislation <- matrix(NA, nrow = nrow(mem),
    ncol = ncol(mem))
for (i in 1:nrow(mem)) {
  Coalition_Focuses_on_Authorizing_Legislation[i, ] <-
```

```
      attrib.coal$Coalition_Focuses_on_Authorizing_Legislation
}

# Interest_Group_Crosses_Issue_Boundary:
# organization primarily active outside health domain
Interest_Group_Crosses_Issue_Boundary <- matrix(NA, nrow = nrow(mem),
    ncol = ncol(mem))
for (i in 1:ncol(mem)) {
  Interest_Group_Crosses_Issue_Boundary[, i] <-
      attrib.grp$Organization_Identified_Primarily_Outside_Health
}

# Citizens_Advocacy_Group: organization is citizens' advocacy organization
Citizens_Advocacy_Group <- matrix(NA, nrow = nrow(mem), ncol = ncol(mem))
for (i in 1:ncol(mem)) {
  Citizens_Advocacy_Group[, i] <-
      attrib.grp$Organization_is_Citizens_Advocacy_Organization
}

# Coalition_Steering_Committee: coalition has a steering committee
Coalition_Steering_Committee <- matrix(NA, nrow = nrow(mem), ncol = ncol(mem))
for (i in 1:nrow(mem)) {
  Coalition_Steering_Committee[i, ] <-
      attrib.coal$Coalition_Has_Steering_Committee
}

# Interest_Group_Age: centuries since organization was founded
Interest_Group_Age <- matrix(NA, nrow = nrow(mem), ncol = ncol(mem))
for (i in 1:ncol(mem)) {
  Interest_Group_Age[, i] <- 0.01 *
      attrib.grp$Years_Since_Founding_of_Organization_Coalition
}

# Coalition_Age: centuries since coalition was founded
Coalition_Age <- matrix(NA, nrow = nrow(mem), ncol = ncol(mem))
for (i in 1:nrow(mem)) {
  Coalition_Age[i, ] <- 0.01 *
      attrib.coal$Years_Since_Founding_of_Organization_Coalition
}


# ==============================================================================
# Estimate ERGMs
# ==============================================================================

# model 1: non-members as structural zeros
model.1 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
```

```
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 2: non-members as structural zeros, founders who are leaders as
# structural ones
model.2 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)) + offset(edgecov(founderleader)),
    offset.coef = c(-Inf, Inf), eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 3: same as model 1, but with diversity x embeddedness interaction
model.3 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    + edgecov(Diversity_X_Embeddedness_Strong)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
```

```
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 4: same as model 2, but with diversity x embeddedness interaction
model.4 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    + edgecov(Diversity_X_Embeddedness_Strong)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)) + offset(edgecov(founderleader)),
    offset.coef = c(-Inf, Inf), eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# models in the main manuscript
htmlreg(list(model.1, model.2, model.3, model.4), single.row = TRUE,
    file = "Models 1-4.html")


# model 5: non-members and founders as structural zeros
model.5 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
```

```
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem2)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 6: no structural zeros at all
model.6 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    , eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 7: substituting strong for weak embeddedness in model 1
model.7 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Weak)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
```

```
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 8: substituting strong for weak embeddedness in model 3
model.8 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Weak)
    + edgecov(Diversity_X_Embeddedness_Weak)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

htmlreg(list(model.5, model.6, model.7, model.8), single.row = TRUE,
    custom.model.names = paste("Model", 5:8), file = "Models 5-8.html")

# model 9: like model 1, but using communication density instead of network
# embeddedness
model.9 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(commdensity)
    # controls
    + b1star(2)
    + edgecov(Visibility)
```

```
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 10: like model 3, but using communication density instead of network
# embeddedness
model.10 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(commdensity)
    + edgecov(commdensity.diversity)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 11: network embeddedness only in the same party (within-party ties)
model.11 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong_SameParty)
    # controls
    + b1star(2)
```

```
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 12: network embeddedness only across parties (cross-party ties)
model.12 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong_CrossParty)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

htmlreg(list(model.9, model.10, model.11, model.12), single.row = TRUE,
    custom.model.names = paste("Model", 9:12), file = "Models 9-12.html")

# model 13: only main effects and endogenous model terms
model.13 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
```

```
    # controls
    + b1star(2)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 14: like model 13, but with number of coalition memberships
model.14 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    # controls
    + b1star(2)
    + edgecov(Number_of_Coalition_Memberships)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 15: add five other diversity variables to model 1
model.15 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    + edgecov(diversity.age)
    + edgecov(diversity.lobspend)
    + edgecov(diversity.citadv)
    + edgecov(diversity.outshealth)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

# model 16: like model 1, but interaction between visibility and diversity
model.16 <- ergm(
    leader ~
    + edges
```

```
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Diversity_X_Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

htmlreg(list(model.13, model.14, model.15, model.16), single.row = TRUE,
    custom.model.names = paste("Model", 13:16), file = "Models 13-16.html")

# model 17: like model 1, but interaction between controversial and diversity
model.17 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    # controls
    + b1star(2)
    + edgecov(Visibility)
    + edgecov(Diversity_X_Controversial)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Number_of_Coalition_Memberships)
    + edgecov(Coalition_Size)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)
```

```
# model 18: coalition two-stars instead of number of coalition memberships and
# coalition size (as these are collinear)
model.18 <- ergm(
    leader ~
    + edges
    # main effects
    + edgecov(Partisan_Diversity)
    + edgecov(Network_Embeddedness_Strong)
    # controls
    + b1star(2)
    + b2star(2)
    + edgecov(Visibility)
    + edgecov(Controversial)
    + edgecov(Interest_Group_Coalition_Partisan_Differential)
    + edgecov(Interest_Group_Partisanship)
    + edgecov(Coalition_Partisanship)
    + edgecov(Interest_Group_Age)
    + edgecov(Coalition_Age)
    + edgecov(Citizens_Advocacy_Group)
    + edgecov(Coalition_Dues)
    + edgecov(Lobbying_Expenditures)
    + edgecov(Interest_Group_Crosses_Issue_Boundary)
    + edgecov(Coalition_Faces_Legislative_Threat)
    + edgecov(Coalition_Focuses_on_Authorizing_Legislation)
    + edgecov(Coalition_Steering_Committee)
    + offset(edgecov(nonmem)),
    offset.coef = -Inf, eval.loglik = FALSE,
    control = control.ergm(MCMC.burnin = burnin, MCMC.samplesize = sampsize,
        seed = seed, MCMLE.maxit = maxit)
)

htmlreg(list(model.17, model.18), single.row = TRUE,  custom.model.names =
    paste("Model", 17:18), file = "Models 17-18.html")


# ==============================================================================
# Assess goodness of fit
# ==============================================================================

# boxplot diagrams
mygof <- function(model, number) {
  gf <- gof(model, nsim = nsim, statistics = c(nsp, b1deg, b2deg, geodesic,
      b1star, b2star, rocpr), ncpus = cores, parallel = "multicore",
      roc = FALSE)
  temp <- gf[1:6]
  class(temp) <- "gof"
  pdf(paste0("gof.", number, ".pdf"), width = 9, height = 6)
  plot(temp)
  dev.off()
  return(gf)
}

gof.1 <- mygof(model.1, 1)
gof.2 <- mygof(model.2, 2)
gof.2 <- mygof(model.3, 3)
gof.2 <- mygof(model.4, 4)
gof.2 <- mygof(model.5, 5)
gof.2 <- mygof(model.6, 6)
gof.2 <- mygof(model.7, 7)
gof.2 <- mygof(model.8, 8)
gof.2 <- mygof(model.9, 9)
gof.2 <- mygof(model.10, 10)
gof.2 <- mygof(model.11, 11)
```

```
gof.2 <- mygof(model.12, 12)
gof.2 <- mygof(model.13, 13)
gof.2 <- mygof(model.14, 14)
gof.2 <- mygof(model.15, 15)
gof.2 <- mygof(model.16, 16)
gof.2 <- mygof(model.17, 17)
gof.2 <- mygof(model.18, 18)

# precision-recall curves
gof.1[[7]]$auc.pr
gof.2[[7]]$auc.pr
pdf("pr.pdf")
plot(gof.2[[7]], col = "gray50", rgraph = FALSE, lwd = 3,
    main = "Precision-recall curves")
plot(gof.1[[7]], col = "black", rgraph = TRUE, random.col = "gray90", lwd = 3,
    add = TRUE)
legend("topright", legend = c("Model 1", "Model 2", "Random graph"),
    col = c("black", "gray50", "gray90"), lty = 1, lwd = 3)
dev.off()

# MCMC trace plots
pdf("mcmcdiag.pdf")
mcmc.diagnostics(model.1)
dev.off()


# ==============================================================================
# Estimate a random or fixed effects model
# ==============================================================================

rows <- nrow(as.matrix(leader))
cols <- ncol(as.matrix(leader))
ig <- matrix(rep(1:rows, cols), nrow = rows)
coal <- matrix(rep(1:cols, rows), ncol = cols, byrow = TRUE)

# create data frame
nm <- as.matrix(nonmem)
dat <- data.frame(
    leader = as.matrix(leader)[nm != 1],
    absdiff = Interest_Group_Coalition_Partisan_Differential[nm != 1],
    Partisan_Diversity = Partisan_Diversity[nm != 1],
    Network_Embeddedness_Strong = Network_Embeddedness_Strong[nm != 1],
    Interest_Group_Partisanship = Interest_Group_Partisanship[nm != 1],
    Coalition_Partisanship = Coalition_Partisanship[nm != 1],
    Interest_Group_Age = Interest_Group_Age[nm != 1],
    Coalition_Age = Coalition_Age[nm != 1],
    Citizens_Advocacy_Group = Citizens_Advocacy_Group[nm != 1],
    Coalition_Dues = Coalition_Dues[nm != 1],
    Lobbying_Expenditures = Lobbying_Expenditures[nm != 1],
    Interest_Group_Crosses_Issue_Boundary =
        Interest_Group_Crosses_Issue_Boundary[nm != 1],
    Coalition_Faces_Legislative_Threat = Coalition_Faces_Legislative_Threat[nm
        != 1],
    Coalition_Focuses_on_Authorizing_Legislation =
        Coalition_Focuses_on_Authorizing_Legislation[nm != 1],
    Coalition_Steering_Committee = Coalition_Steering_Committee[nm != 1],
    ig = ig[nm != 1],
    coal = coal[nm != 1]
)
dat$coal2 <- factor(dat$coal)  # fixed effect: create factor

# random effect in lme4: estimation does not converge
library("lme4")
```

```
model.19 <- glmer(
    leader
    ~ absdiff
    + Partisan_Diversity
    + Network_Embeddedness_Strong
    + Interest_Group_Partisanship
    + Coalition_Partisanship
    + Interest_Group_Age
    + Coalition_Age
    + Citizens_Advocacy_Group
    + Coalition_Dues
    + Lobbying_Expenditures
    + Interest_Group_Crosses_Issue_Boundary
    + Coalition_Faces_Legislative_Threat
    + Coalition_Focuses_on_Authorizing_Legislation
    + Coalition_Steering_Committee
    + (1 | coal),
    data = dat[, 1:17], family = binomial, nAGQ = 10
)
summary(model.19)

# random effect with glmmPQL: estimation converges, but don't trust the results;
# e.g., no model fit is reported... did it really converge?
library("MASS")
model.20 <- glmmPQL(
    leader
    ~ absdiff
    + Partisan_Diversity
    + Network_Embeddedness_Strong
    + Interest_Group_Partisanship
    + Coalition_Partisanship
    + Interest_Group_Age
    + Coalition_Age
    + Citizens_Advocacy_Group
    + Coalition_Dues
    + Lobbying_Expenditures
    + Interest_Group_Crosses_Issue_Boundary
    + Coalition_Faces_Legislative_Threat
    + Coalition_Focuses_on_Authorizing_Legislation
    + Coalition_Steering_Committee
    , random = ~ 1|coal
    , data = dat[, 1:17], family = binomial
)
summary(model.20)

# use GLM and fixed effect: model does not converge
model.21 <- glm(
    leader
    ~ absdiff
    + Partisan_Diversity
    + Network_Embeddedness_Strong
    + Interest_Group_Partisanship
    + Coalition_Partisanship
    + Interest_Group_Age
    + Coalition_Age
    + Citizens_Advocacy_Group
    + Coalition_Dues
    + Lobbying_Expenditures
    + Interest_Group_Crosses_Issue_Boundary
    + Coalition_Faces_Legislative_Threat
    + Coalition_Focuses_on_Authorizing_Legislation
    + Coalition_Steering_Committee
    + coal2
```

```
    , data = dat, family = binomial
)
summary(model.21)


# ===============================================================================
# Micro-level interpretation (= predicted probabilities)
# ===============================================================================

# create dyadic datasets
edgeprob.3 <- edgeprob(model.3)
edgeprob.4 <- edgeprob(model.4)
edgeprob.10 <- edgeprob(model.10)
edgeprob.16 <- edgeprob(model.16)
edgeprob.17 <- edgeprob(model.17)


# function for plotting facets with variable 1 conditional on variable 2
facets <- function(edgeprobs, mem, number, var1, var2, varname1, varname2) {
  # keep only those dyadic probabilities where there is no structural zero
  include <- logical(nrow(edgeprobs))
  for (r in 1:length(include)) {
    if (mem[edgeprobs$i[r], edgeprobs$j[r] - nrow(mem)] == 1) {
      include[r] <- TRUE
    } else {
      include[r] <- FALSE
    }
  }
  dyads <- edgeprobs[include == TRUE, ]

  # cut network embeddedness into slices
  dyads$v1 <- c(dyads[var1])[[1]]
  v2 <- c(dyads[var2])[[1]]
  v2.quantiles <- quantile(v2)
  v2 <- cut(v2, v2.quantiles, labels = names(v2.quantiles)[2:5])
  v2[is.na(v2)] <- "25%"
  dta <- transform(dyads, v2 = v2)

  # plot conditional probabilities with facets
  pdf(paste0("facets.", number, ".", varname1, ".pdf"))
  gp <- ggplot(data = dta, aes(x = v1, y = probability))
  print(gp + stat_smooth(method = "lm", fullrange = TRUE, color = "black") +
facet_wrap( ~ v2,
      ncol = 2) + xlab(varname1) + ylab("Probability") + ggtitle(
      paste0("Model ", number, ": ", varname1, " effect conditional on ",
      varname2)))
  dev.off()
}

facets(edgeprobs = edgeprob.3, mem = mem, number = 3,
       var1 = "edgecov.Partisan_Diversity[[i]]",
       var2 = "edgecov.Network_Embeddedness_Strong[[i]]",
       varname1 = "Partisan diversity", varname2 = "Network embeddedness")

facets(edgeprobs = edgeprob.3, mem = mem, number = 3,
       var2 = "edgecov.Partisan_Diversity[[i]]",
       var1 = "edgecov.Network_Embeddedness_Strong[[i]]",
       varname2 = "Partisan diversity", varname1 = "Network embeddedness")

facets(edgeprobs = edgeprob.4, mem = mem, number = 4,
       var1 = "edgecov.Partisan_Diversity[[i]]",
       var2 = "edgecov.Network_Embeddedness_Strong[[i]]",
       varname1 = "Partisan diversity", varname2 = "Network embeddedness")
```

```r
facets(edgeprobs = edgeprob.4, mem = mem, number = 4,
       var2 = "edgecov.Partisan_Diversity[[i]]",
       var1 = "edgecov.Network_Embeddedness_Strong[[i]]",
       varname2 = "Partisan diversity", varname1 = "Network embeddedness")

facets(edgeprobs = edgeprob.10, mem = mem, number = 10,
       var1 = "edgecov.Partisan_Diversity[[i]]",
       var2 = "edgecov.commdensity[[i]]", varname1 = "Partisan diversity",
       varname2 = "Communication density")

facets(edgeprobs = edgeprob.10, mem = mem, number = 10,
       var2 = "edgecov.Partisan_Diversity[[i]]",
       var1 = "edgecov.commdensity[[i]]", varname2 = "Partisan diversity",
       varname1 = "Communication density")


# predicted probabilities for visibility interaction (model 16)
include.16 <- logical(nrow(edgeprob.16))
for (r in 1:length(include.16)) {
  if (mem[edgeprob.16$i[r], edgeprob.16$j[r] - nrow(mem)] == 1) {
    include.16[r] <- TRUE
  } else {
    include.16[r] <- FALSE
  }
}
dyads.16 <- edgeprob.16[include.16 == TRUE, ]

dta <- data.frame(prob = dyads.16$probability,
                  pd = dyads.16$`edgecov.Partisan_Diversity[[i]]`,
                  vis = dyads.16$`edgecov.Visibility[[i]]`)

pdf(paste0("interaction.visibility.16.pdf"))
gp <- ggplot(data = dta, aes(x = pd, y = prob, linetype = factor(vis))) +
    stat_smooth(method = "lm", fullrange = TRUE, colour = "black")
gp + labs(linetype = "Visibility") + xlab("Partisan diversity") +
    ylab("Probability") + ggtitle(paste("Partisan diversity conditional on",
    "visibility of the coalition"))
dev.off()


# predicted probabilities for controversy interaction (model 17)
include.17 <- logical(nrow(edgeprob.17))
for (r in 1:length(include.17)) {
  if (mem[edgeprob.17$i[r], edgeprob.17$j[r] - nrow(mem)] == 1) {
    include.17[r] <- TRUE
  } else {
    include.17[r] <- FALSE
  }
}
dyads.17 <- edgeprob.17[include.17 == TRUE, ]

dta <- data.frame(prob = dyads.17$probability,
                  pd = dyads.17$`edgecov.Partisan_Diversity[[i]]`,
                  cv = dyads.17$`edgecov.Controversial[[i]]`)

pdf(paste0("interaction.controversy.17.pdf"))
gp <- ggplot(data = dta, aes(x = pd, y = prob, linetype = factor(cv))) +
    stat_smooth(method = "lm", fullrange = TRUE, colour = "black")
gp + labs(linetype = "Controversy") + xlab("Partisan diversity") +
    ylab("Probability") + ggtitle(paste("Partisan diversity conditional on",
                                        "controversialness of the coalition"))
dev.off()
```

```
# ==============================================================================
# Marginal effects plot using btergm and interplot
# ==============================================================================

pdf("marginal-effects-model3a.pdf", width = 6, height = 4)
marginalplot(model.3,
             var1 = "edgecov.Partisan_Diversity",
             var2 = "edgecov.Network_Embeddedness_Strong",
             inter = "edgecov.Diversity_X_Embeddedness_Strong",
             structzeromat = as.matrix(nonmem),
             ylab = "Partisan diversity",
             xlab = "Network embeddedness",
             rug = TRUE) + ggtitle("Model 3") + theme_bw()
dev.off()

pdf("marginal-effects-model3b.pdf", width = 6, height = 4)
marginalplot(model.3,
             var1 = "edgecov.Network_Embeddedness_Strong",
             var2 = "edgecov.Partisan_Diversity",
             inter = "edgecov.Diversity_X_Embeddedness_Strong",
             structzeromat = as.matrix(nonmem),
             xlab = "Partisan diversity",
             ylab = "Network embeddedness",
             rug = TRUE) + ggtitle("Model 3") + theme_bw()
dev.off()

pdf("marginal-effects-model4a.pdf", width = 6, height = 4)
marginalplot(model.4,
             var1 = "edgecov.Partisan_Diversity",
             var2 = "edgecov.Network_Embeddedness_Strong",
             inter = "edgecov.Diversity_X_Embeddedness_Strong",
             structzeromat = as.matrix(nonmem),
             ylab = "Partisan diversity",
             xlab = "Network embeddedness",
             rug = TRUE) + ggtitle("Model 4") + theme_bw()
dev.off()

pdf("marginal-effects-model4b.pdf", width = 6, height = 4)
marginalplot(model.4,
             var1 = "edgecov.Network_Embeddedness_Strong",
             var2 = "edgecov.Partisan_Diversity",
             inter = "edgecov.Diversity_X_Embeddedness_Strong",
             structzeromat = as.matrix(nonmem),
             xlab = "Partisan diversity",
             ylab = "Network embeddedness",
             rug = TRUE) + ggtitle("Model 4") + theme_bw()
dev.off()

pdf("marginal-effects-model10a.pdf", width = 6, height = 4)
marginalplot(model.10,
             var1 = "edgecov.Partisan_Diversity",
             var2 = "edgecov.commdensity",
             inter = "edgecov.commdensity.diversity",
             structzeromat = as.matrix(nonmem),
             ylab = "Partisan diversity",
             xlab = "Communication density",
             rug = TRUE) + ggtitle("Model 10") + theme_bw()
dev.off()

pdf("marginal-effects-model10b.pdf", width = 6, height = 4)
marginalplot(model.10,
```

```
             var1 = "edgecov.commdensity",
             var2 = "edgecov.Partisan_Diversity",
             inter = "edgecov.commdensity.diversity",
             structzeromat = as.matrix(nonmem),
             xlab = "Partisan diversity",
             ylab = "Communication density",
             rug = TRUE) + ggtitle("Model 10") + theme_bw()
dev.off()

pdf("marginal-effects-model16.pdf", width = 6, height = 4)
marginalplot(model.16,
             var1 = "edgecov.Partisan_Diversity",
             var2 = "edgecov.Visibility",
             inter = "edgecov.Diversity_X_Visibility",
             structzeromat = as.matrix(nonmem),
             ylab = "Partisan diversity",
             xlab = "Visibility of the coalition",
             point = TRUE,
             rug = FALSE) +
  ggtitle("Model 16") +
  theme_bw()
dev.off()

pdf("marginal-effects-model17.pdf", width = 6, height = 4)
marginalplot(model.17,
             var1 = "edgecov.Partisan_Diversity",
             var2 = "edgecov.Controversial",
             inter = "edgecov.Diversity_X_Controversial",
             structzeromat = as.matrix(nonmem),
             ylab = "Partisan diversity",
             xlab = "Controversy",
             point = TRUE,
             rug = FALSE) +
  ggtitle("Model 17") +
  theme_bw()
dev.off()


# save workspace to a file for later use
save.image(file = "leadership-lobbying.RData")
```