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Authors

Carpenter, Daniel P
Esterling, Kevin M
Lazer, David MJ

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Friends, Brokers, and Transitivity: Who Informs Whom in Washington Politics?

Daniel P. Carpenter
Harvard University

Kevin M. Esterling
University of California, Riverside

David M. J. Lazer
Harvard University

Why and how do groups share information in politics? Most studies of information exchange in politics focus on individual-level attributes and implicitly assume that communication between any two policy actors is independent of the larger communication network in which they are embedded. We develop a theory stating that the decision of any lobbyist to inform another lobbyist is heavily conditioned upon their mutual relationships to third parties. We analyze over 40,000 dyadic relationships among lobbyists, government agencies, and congressional staff using sociometric data gathered in the 1970s health and energy policy domains. The results cohere with recent findings that lobbyists disproportionately inform those with similar preferences and show in addition that political communication is *transitive*: holding constant the degree of preference similarity, a lobbyist is more likely to communicate with another lobbyist if their relationship is brokered by a third party.

While many students of lobbying focus attention on the communication of information between private groups and Congress or executive agencies, the importance of information sharing *among* lobbyists, to and from their valued “contacts,” has long been recognized (Bauer, de Sola Pool, and Dexter 1972, 325; Heclo 1978, 103; Milbrath 1963, 260). The complexity of contemporary policies and the sheer scale of interest representation create incentives for groups to invest in staff that develop contacts with other groups to gain policy-relevant information (Heinz et al. 1993, 381; Kingdon 1984, 133; Polsby 1984, 167; Salisbury 1991, 378). An interest group’s success in establishing good contacts affects, among other things, its stature and influence in policy making (Heclo 1978, 103), and its access to congressional committees and to agencies (Carpenter, Esterling, and Lazer 1998).

The study of this contact making and communication in politics, however, is curiously bifurcated. A “behavioral” tradition asserts that the similarity of the policy *preferences* between sender and receiver is the primary determinant of who

informs whom in politics, a basic finding of the signaling theory (Ainsworth 1993; Austen-Smith 1993; Kollman 1998) and the mobilization of bias theory of communication (Hall 1996; Hojnacki and Kimball 1998; Huckfeldt and Sprague 1987; Kingdon 1989; Kollman 1997; Peterson 1992). A distinct “structural” tradition argues that a policy actor’s communication choices also depend heavily upon the larger pattern of communication choices of others with whom she interacts (e.g., Heclo 1978; Heinz et al. 1993; Huckfeldt 1983; Knoke et al. 1996; Laumann and Knoke 1987; see Thatcher 1998). These two literatures seem to speak past each other. Studies of policy network formation rarely consider the role of actors’ preferences over policies.¹ Studies that adopt the behavioral perspective generally neglect any social effects that are external to the immediate exchange relationship (Heclo 1978, 102).

In this article, we demonstrate that social network effects drive communication choices in politics *over and above* preference similarity and other individual-level determinants. Given the complexity of contemporary interest representation and policy issues, interest groups and other policy actors often communicate with others in order to *discover* their preferences among policy alternatives (Jones 2001, 102; Polsby 1984, 14; Salisbury 1991; Smith 1984, 46; Truman 1951). Groups often seek out others whose opinion they trust on complex issues in order to develop a coherent interpretation of a policy, a nonpreference-based mechanism consistent with the structural tradition. The implication is that preferences and social trust independently should contribute to communication patterns in the aggregate as issues come and go.

In order to make the concept of social trust operational, we focus upon the concept of *network transitivity*—if it is the case that actor A talks to actor C and that actor C talks to actor B, then actors A and B should have more trust and so be more likely to share information with one another, despite redundancies in the exchange relationship (Holland and Leinhardt 1971). Using the data of Laumann and Knoke (1987), we examine tens of thousands of individual dyads—the presence or absence of communication links between two policy actors A and B. These dyads involve potential information exchanges among lobbyists, between lobbyists and bureaucrats, between lobbyists and Congress, and so on. Holding constant preference similarity, we state hypotheses that stand as critical tests between social trust and informational efficiency theories of network structure effects.

Our theoretical and empirical analyses of transitivity and brokerage expand and improve on the original analyses of policy communication networks in Laumann and Knoke’s *The Organizational State* (1987). In their analysis, all of the determinants of communication are individual attributes of the actors, rather than structural characteristics of the local network in which those actors are

¹ Recent studies of political networks in the structural tradition have begun to include actors’ preferences as exogenous variables; Koenig and Braunniger’s (1998) study of German policy networks represents a thorough attempt. For an attempt to model formally the emergence of a policy network from actors’ preferences, see Stokman and Zeggelink (1996).

embedded. In our model, contacts with third-party actors (“C”) are a crucial determinant of the presence or absence of communication between two actors (“A” and “B”). In this sense, we add a microlevel structural component to Laumann and Knoke’s analysis of communication networks. Our aim is to shed long overdue attention upon transitivity, which is a core construct of communication theory and social network theory emanating from the mathematical graph-theoretic results of Holland and Leinhardt (1971).²

More generally, our results offer two lessons for the study of political communication. First, our results support the behavioral arguments of the signaling and mobilization of bias theories that lobbyists seek out those with similar preferences to exchange information. Second, our results show that the communication network in which policy actors are embedded is a crucial factor in explaining political communication and that the redundant transitivity exchange patterns associated with social trust appear to be more robust predictors of information exchange than structural patterns associated with informational efficiency. Quite clearly, network structure—or who knows whom—does matter in Washington politics, even after accounting for policy preferences.

The Purposes of Political Communication

It is a common if implicit assumption in much of the institutional literature that policy choice spaces are well defined across issues (Jones 2001, 87). If the choice space is well defined, policy actors gather information from others in order to reduce uncertainty in their decision making (see Jones 2001, 87; Jones 1999). In this case, the similarity of actors’ preferences should largely determine their exchange of information. Two separate but complementary theories supply the logic. Signaling models predict that information is transmitted credibly to the extent that the sender and receiver share policy preferences (Ainsworth 1993, 46–48; Austen-Smith 1993, 817; Crawford and Sobel 1982, 1437; Kollman 1998, 61).³ Alternatively, mobilization of bias theory argues that providing information subsidizes the receiver’s activities, enabling her to become active in an issue at lower cost; groups strategically provide information to those with similar interests (e.g., Hall 1996, 87; Hall and Wayman 1990, 803; Hojnacki and Kimball 1998, 778; Kingdon 1989).

² Although less important than our theoretical and empirical departures from Laumann and Knoke, we also offer what we believe to be methodological improvements over their analysis. Laumann and Knoke analyzed the path distance between actors in their data using OLS. Essentially, this was equivalent to analyzing binary data using OLS, which produces biased and inconsistent estimates. In addition, Fernandez and Gould (1994) develop and test a theory of brokerage among lobbyists to explain variation in groups’ perceived influence in the social network. In contrast, we model contact making among groups rather than a group’s perceived influence.

³ Austen-Smith and Wright (1992) argue that interest groups have the greatest incentive to contact those who are inclined to disagree with them. If this theory is true, then preference similarity should be negatively associated with communication in the models below.

Given the complexity of contemporary policies, however, a policy issue will have a well-defined choice space only if the policy is recurrent or if the policy issue has a clear ideological structure (e.g., see Hinich and Munger 1996; Poole and Rosenthal 1993). When an issue is both complex and newly emergent, the choice space often is unstructured, and policy actors will engage in discussion in order to establish a frame of reference within which preferences may be defined (Jones 2001, 102; Kollman 1998, 103; Laumann and Knoke 1987, 206; Salisbury 1990, 225; Smith 1984, 46; Truman 1951, 19).⁴ To the extent that communication is for the purpose of constructing a framework, policy preferences cannot logically explain the choice of communication partners. Instead, a group will consider whether another group seems to have sound or creative ideas in order to impose meaning on a complex problem (see Smith 1984). To the extent that policy communication is this sort of mutual construction of issue interpretations, social properties such as friendship, trust, sharing common frames of reference, and other social similarities will increase the likelihood of communication, all else equal (Fernandez and Gould 1994, 1460).

Social Trust and Network Transitivity

To make the concept of “social trust” operational, we turn to social network theory. The social structure of a communication network may have two possible effects: enabling the efficient transmission of information and creating and maintaining social capital and social trust (Laumann and Knoke 1987, 215). In the efficiency view of networks, the network simply operates as a passive conduit of information. In the social capital view of networks, the network itself affects the transaction cost of maintaining ties and affects the degree of social interaction among, and the relative familiarity of, potential exchange partners (Putnam 1995, 71; Schneider et al. 1997a, b). When interest groups are communicating with each other, they are building up and maintaining trust and familiarity through their social interaction.

Given that communication networks may have these two possible effects, we use theoretically identifiable configurations of ties among actors in the network in order to state competing informational efficiency and social trust hypotheses regarding the structure of the emergent networks among interest groups. Following a long tradition in network analysis (Fernandez and Gould 1994; Holland and Leinhardt 1971; Wasserman and Faust 1994), the key social structural unit we use to measure the impact of the social structure on the ties between two actors is the *triad*. Specifically, we examine for each directed dyad (say, A to B) its relationship with every third party (C) in the political communication network in

⁴For example, an environmental group first needs a framework to understand that the intent of the market mechanism at the heart of an emissions trading plan is to reduce emissions (rather than say to capitulate to industry demands); given such a framework, the group may try to find information regarding the probability that emissions would in fact be reduced.

which it is embedded. The question we ask is: *How does A and B's configuration of relationships with every other actor in the system affect the probability that A talks to B?*

In order to create measures of “third-party relationships” we generate counts of every possible configuration of every dyad’s relationships with all third parties in the larger communication network. With directed data—or data in which ties need not be symmetric—a given third party may have one of 16 possible relationships with a dyad (see Figure 1). In each case in Figure 1, A is the hypothesized “sender” of policy information, and B is the hypothesized “recipient.” Our structural hypotheses below state predictions for the probability of A initiating contact with B for different subsets of these relationships to third party information brokers (actor C). We propose two models for social capital effects, a *facilitator* model, and a *transitivity* model. In these two models the third party plays the role of a social broker who can increase interaction and build up trust between A and B. We also propose an informational efficiency model, where groups seek to maximize the information they receive given a number of ties they invest in.

Facilitator Model

In this model, we consider those triads where C communicates information to both A and B (see, e.g., triad 6 in Figure 1). In this case, C is in a position to build an alliance between A and B, perhaps by providing a common frame of reference between A and B and coordinating the relationship in other ways.⁵ A and B are therefore more likely to talk not only because of C’s coalition efforts, but also because they are more likely to have a common outlook on policy matters through C’s policy-framing efforts.

HI: *The probability of A to B transmission is **positively** related to the number of third parties they both receive information from (triads 6, 8, 14, and 16 predict an A to B tie).*

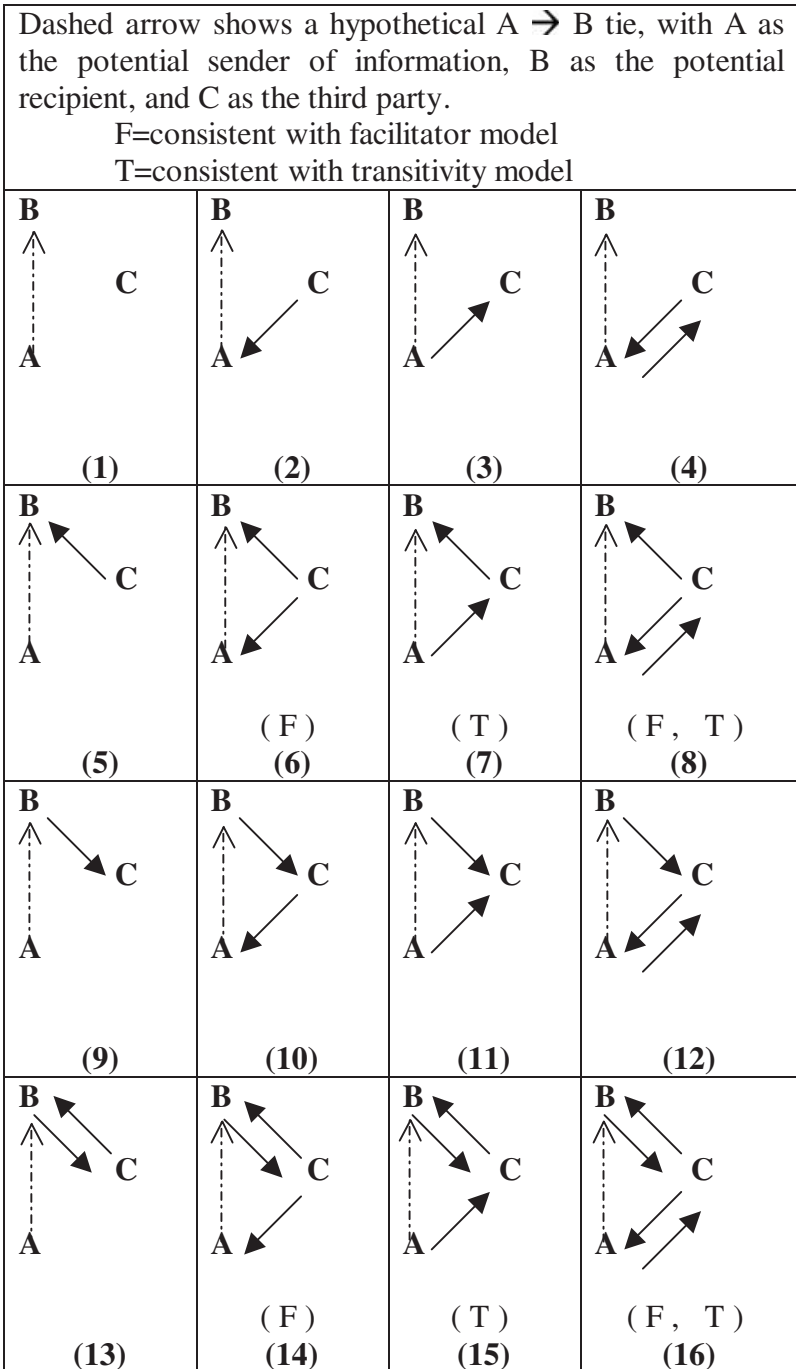
Transitivity Model

Building on work by Heider (1946) on the cognitive structure of affect, research on networks extended the idea of transitivity (e.g., enemies of enemies are friends; friends of friends are friends; etc.) to the structure of social relations (Cartwright and Harary 1956; Newcomb 1953). Davis, Holland, and Leinhardt (e.g., see Davis 1967, 1970; Holland and Leinhardt 1971, 1981) subsequently

⁵In this model and the next, notice the argument is not that the third party actually acts as a facilitator or broker, but rather is in a structural position in the social network to play these roles. This kind of theory based on social structure is common in social network analysis (see Fernandez and Gould 1994, 1460).

FIGURE 1

Relationships of Dyads with Third Parties



demonstrated that transitivity, where an A to C tie combined with a C to B tie, was associated with a much higher probability of an A to B tie.

Transitivity has a particularly compelling interpretation in a strategic informational context, such as in the interest group universe. In this setting groups are constantly searching for good sources of information. That is, interest groups are not simply transmitting information about politics and policy, but also about who are reliable sources of information. Presumably, most interest groups consider their sources of information to be reliable (otherwise, why get information from them?) and report this to other groups with whom they communicate. There is thus a dynamic tendency to create transitive relationships: A communicates to B, which is satisfied with the information it gets from A, and reports this to C, which subsequently seeks information from A.

H2: *The probability of A to B transmission is **positively** related to the number of third parties to whom A sends information and from whom B receives information (triads 7, 8, 15, and 16).*

Informational Efficiency

In this model, we assume ties will emerge where they provide the maximum quantity of nonredundant factual information. That is, each group assesses the informational “value added” of each tie or potential tie, and if a tie is providing little new information (or, information that is mostly redundant), that tie will be dropped.⁶ The informational efficiency model predicts that B will not seek information from A if it is already getting information from A indirectly through a third party, or if much of the information A is passing on is from third parties from whom B already gets information. In short, the informational efficiency model predicts exactly the opposite pattern of results than the facilitator and transitivity models:

H3: *The probability of A to B transmission is **negatively** related to the number of third parties to whom A sends information and from whom B receives information (triads 7, 8, 15, and 16) as well as to the number of third parties both receive information from (triads 6, 8, 14, and 16).*

Inclusion of triads 6, 7, and 8, and 14, 15, and 16 in the statistical model allows critical tests between the informational efficiency model and the facilitator and transitivity models.⁷ In addition, both the facilitator and the transitivity models

⁶Milbrath emphasizes the budget constraint interest groups face in forming their networks: “Once made, contacts require at least minimum maintenance. . . . Lobbyists who take the maintenance of their contacts seriously . . . must devote a good deal of time to it—so much that they can keep up only a small circle of contacts” (1963, 264).

⁷It is more difficult to conduct critical tests between the facilitator and transitivity models, because these models do not predict that the absence of brokerage or transitivity should necessarily lead to reduced information transmission below the unconnected baseline (triad 1).

predict triad 16 will induce an A to B tie, and so we expect the marginal effect of triad 16 will be particularly large and will diverge the most from the informational efficiency predictions.

Data

The data for this study were collected in the 1980s under the massive political networks project of Laumann and Knoke, published in *The Organizational State* (1987). The authors chose two policy arenas in which significant and sustained engagement occurred over vital national issues in the 1970s and 1980s—health policy and energy policy. In the summer of 1981, the authors surveyed informants from an exhaustive list of influential lobbying organizations, government agencies, and congressional committees involved in D.C. health and energy politics.⁸ In energy politics, their sample of lobbying organizations includes production companies (Texaco and Ford Motor Company), trade associations and research firms (the American Nuclear Energy Council and the Gas Research Institute), environmental and citizens groups (the American Automobile Association and the Sierra Club), labor unions (United Mine Workers), state government agencies, and staff from 37 congressional committees and subcommittees involved in national energy policy. In health politics, the sample includes industry associations (such as the American Insurance Association and the Pharmaceutical Manufacturers Association), professional societies (American College of Cardiology, American Medical Association), health interest groups (Coalition for Health Funding, Arthritis Foundation), as well as more general interest groups, business firms, and relevant government agencies and congressional committees.

Organizational and Network Variables

The data set contains an extensive battery of internal organizational characteristics on each group, agency and committee, such as operating budget, number of staff, number of staff employed to monitor Washington affairs, organizational structure (voting rules, centralization, etc.), as well as interest, activity, and preference measures on issues within the energy and health policy domains. The Laumann-Knoke data set also documents the full network of communication ties from each of these groups to every other, and we use these measures to construct the dependent variables as well as the triadic independent variables. Specifically, a tie from organization A to organization B is coded 1 on the dependent variable if (1) A reports “regularly or routinely” discussing important energy/health

⁸The sample of organizations is not a probability sample drawn from a known population, but rather is an exhaustive list of organizations that are consequential or highly visible in health care or energy lobbying. Laumann and Knoke used this method of nonrandom random selection since there is no known universe for sampling health lobbying organizations, and since it avoids selecting organizations on their degree of connectedness (1987, 95).

matters with B or (2) A reports giving “confidential advice” to B; otherwise the tie is coded 0.⁹ The triadic independent variables are simply a count of the number of each type of triadic relationship in which A and B are embedded, using these same communication measures (see Figure 1).

Controls

The model controls for other theoretical determinants of communication (see appendix). For reasons we set out above, we include a measure of the *Preference similarity* of the dyad across a series of policy lobbying events (such as a committee markup or an agency notice before a final rule) on which both sender and receiver actively participated. In addition, we measure the *Interest similarity* and *Activity similarity* of the dyad, which may prompt groups to communicate even if they often disagree (Laumann and Knoke 1987, 220). In the model we control for whether the sender or receiver (or both) is a *Governmental actor*, since influential political actors are more likely to be contacted (Hojnacki and Kimball 1998, 779). We include variables measuring both organizations’ *Budget* since resources enable a group to extend its contacts (Hojnacki and Kimball 1998, 779), and the size of both groups’ FTE staff *Monitoring capacity* since Kollman (1998, 53) reports that staff size is the best measure of organizational capacity. Hansen (1991) shows that established players have incentives to provide credible information, so we control for the organization’s *Age* in the model. Finally, the models control for the supply side of contact making: we include the proportion of other groups in the population that share policy interests with the organization, which we term the group’s *Information supply*.

Results from Model Estimations: Energy Politics

The logit models of information transmission for energy politics appear in Tables 1a and 1b. Table 1a contains an analysis of information transmission among all organizations (lobbying, administrative, legislative, and other) in the energy policy domain. The left column of estimates excludes individual-level panel effects, while the right column of estimates presents estimates adjusted for individual-sender random effects.¹⁰ The incidence of information transmission among organizations in national energy politics is relatively low; transmission

⁹Note that in the vast majority of cases where there was confidential communication there also was regular and routine communication; running the analyses just on the latter did not substantively change the results.

¹⁰We would attach a note of caution to the random-effects estimates for the health sample, as convergence problems affected estimation of these models. We nonetheless prefer the random-effects estimator to the fixed-effects estimator for our logit analyses. It is worth noting that fixed-effects estimators perform no better here; the presence of triad count variables (without a differentiated error structure) makes convergence in the presence of fixed-effect dummy variables problematic.

TABLE 1A
 Model Estimates, Energy Data
 Dependent Variable is {A → B tie = 1, 0 otherwise}

Variable	Logit Model Standard Errors Clustered on Sender		Logit Random Effects Grouped on Sender	
	Coefficient	SE	Coefficient	SE
Issue Interest Dis-similarity	-.0055***	.0009	-.0052***	.0007
Activity Similarity	.0050	.0042	.0088**	.0030
Preference Similarity	1.0251***	.1447	1.2702***	.1186
Sender Information Supply	-.0941	.1536	-.2090	.2355
Receiver Information Supply	.7382**	.2728	.7374**	.2639
Year of Sender's Founding	.0001	.0001	.0001	.0002
Year of Receiver's Founding	.0000	.0001	.0000	.0001
Sender Budget (logged)	.0075	.0047	.0088	.0076
Receiver Budget (logged)	.0082 ⁺	.0043	.0086*	.0040
Sender Monitoring Capacity (logged)	.0878**	.0301	.1244**	.0498
Receiver Monitoring Capacity (logged)	.0440 ⁺	.0244	.0453 ⁺	.0246
Sender is Government Actor	.4602***	.1291	.9572***	.1776
Receiver is Government Actor	.4204***	.1017	.4948***	.0859
Triad 2 Count	-.0092	.0066	-.0063	.0045
Triad 3 Count	.01426***	.0033	.0078*	.0038
Triad 4 Count	-.0118	.0117	-.0305***	.0052
Triad 5 Count	.01928***	.0033	.01664***	.0027
Triad 6 Count (<i>simple facilitation</i>)	-.0106	.0081	-.0121 ⁺	.0074
Triad 7 Count (<i>simple transitivity</i>)	.1284***	.0127	.1150***	.0112
Triad 8 Count (<i>facilitation + transitivity</i>)	.1759***	.0154	.1963***	.0110
Triad 9 Count	-.0090**	.0035	-.0098***	.0028
Triad 10 Count	-.0469***	.01410	-.0440***	.0133
Triad 11 Count	.0253***	.0067	.0161**	.0059
Triad 12 Count	.0035	.0077	-.0084	.008391
Triad 13 Count	-.0080 ⁺	.0045	-.0090**	.0030
Triad 14 Count (<i>facilitation</i>)	.0244*	.0120	.0195 ⁺	.0100
Triad 15 Count (<i>transitivity</i>)	.0975***	.01493	.084356***	.008034
Triad 16 Count (<i>2-way facilitation + 2-way transitivity</i>)	.2767***	.01518	.2876***	.0090
Constant	-3.6594***	.3683	-3.6887***	.5645
$\ln(\sigma_u^2)$	—	—	-1.8081***	.2502
σ_u	—	—	.4049	.0507
ρ	—	—	.1409***†	.0303

⁺ $p \leq 0.10$; * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$.

Clustered Errors Model: N = 25,760; Wald $\chi^2_{(28)} = 2,958.9***$; Pseudo R² = .3583; (Standard Errors adjusted for disturbance term possibly not i.i.d. across sender's observations).

Random Effects Model: N = 25,760; N of Senders = 161; N obs. per sender = 160; Wald $\chi^2_{(28)} = 4,025.2***$; † LR $\rho = 0$, $\chi^2_{(1)} = 96.20$.

TABLE 1B

Model Estimates, Energy Data (Interest Groups Only)

Dependent Variable is {A → B tie = 1, 0 otherwise}

Variable	Logit Model Standard Errors Clustered on Sender		Logit Random Effects Grouped on Sender	
	Coefficient	SE	Coefficient	SE
Issue Interest Dis-similarity	-.0022 ⁺	.0012	-.0017 ⁺	.0010
Activity Similarity	-.0030	.0044	.0064	.0040
Preference Similarity	1.155***	.1624	1.274***	.1705
Sender Information Supply	-.0084	.1082	-.0354	.2508
Receiver Information Supply	.2909	.2261	.2957	.3291
Year of Sender's Founding	.0001	.0001	.0002	.0003
Year of Receiver's Founding	.0001	.0002	.0001	.0002
Sender Budget (logged)	.0129***	.0062	.0130 ⁺	.0076
Receiver Budget (logged)	.0122***	.0053	.0120*	.0052
Sender Monitoring Capacity (logged)	.1452**	.0455	.1996***	.0529
Receiver Monitoring Capacity (logged)	.1153***	.0318	.1113***	.0344
Triad 2 Count	-.0074	.0060	-.0048	.0057
Triad 3 Count	-.0191*	.0096	-.0302***	.0083
Triad 4 Count	-.0715***	.0091	-.0876***	.0087
Triad 5 Count	.0087 ⁺	.0046	.0072 ⁺	.0038
Triad 6 Count (<i>simple facilitation</i>)	-.0150	.0095	-.0173 ⁺	.0093
Triad 7 Count (<i>simple transitivity</i>)	.1881***	.0251	.1807***	.0222
Triad 8 Count (<i>facilitation + transitivity</i>)	.1999***	.0191	.2055***	.0156
Triad 9 Count	-.0503***	.0085	-.0499***	.0075
Triad 10 Count	-.0265	.0272	-.0299	.0272
Triad 11 Count	.0654**	.0201	.0562**	.0172
Triad 12 Count	.0424*	.0204	.0312 ⁺	.0167
Triad 13 Count	-.0534***	.0069	-.0537***	.0058
Triad 14 Count (<i>facilitation</i>)	.0088	.0170	.0038	.0157
Triad 15 Count (<i>transitivity</i>)	.2162***	.0194	.2103***	.0155
Triad 16 Count (<i>2-way facilitation + 2-way transitivity</i>)	.2671***	.0168	.2672***	.0131
Constant	-3.349***	.4346	-3.3318***	.6505
$\ln \sigma_u^2$	—	—	-2.0490***	.2978
σ_u	—	—	.33590***	.0534
ρ	—	—	-.1141***	.0301

⁺ $p \leq 0.10$; * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$.

Clustered Errors Model: $N = 15,750$; Wald $\chi^2_{(26)} = 2,010.91$ ***; Pseudo $R^2 = .370$; (Standard Errors adjusted for disturbance term possibly not i.i.d. across sender's observations).

Random Effects Model: $N = 15,750$; Wald $\chi^2_{(26)} = 2,488.62$ ***; N of Senders = 126; N of obs. per sender = 125; †LR $\rho = 0$, $\chi^2_{(1)} = 36.21$.

occurs in 20.7% of all dyads, and the following results must be interpreted in light of this fact.

Preferences and Resources

We reproduce Laumann and Knoke's findings that similar policy preferences ($p < .0001$) and a similar profile of issue involvement ($p < .0001$) are associated with a greater probability of communication.¹¹ Among the other dyadic control variables, sender resources appear to have an important effect upon information transmission, but the effect depends crucially upon the way in which "resources" are defined. The crucial resource is *not* the aggregate budget of the sender—the logged budget variable is statistically indistinguishable from zero—but the number of staff employed to monitor Washington politics. A one-point increase in the natural log of monitoring staff for the sender organization (A) is associated with a 1.1% increase in the probability of A-to-B signaling. These results are consistent with Kollman's assertion that staff size is a better measure of organizational capacity and group resources than the group's budget, given that many groups have in-kind contributions, volunteer help, and so on (Kollman 1998, 53). Finally, the effect of the information supply variable, which measures the proportion of other organizations in the network that share similar interests with the group, appears to reduce the propensity that A will talk to B. This is an intuitive result, since it suggests useful information is simply readily available from others in the policy community.

Brokerage: Transitivity and Facilitation

The results on triad variables in Table 2a present a fascinating portrait of the effect of communication structure in energy politics. First, the results offer a critical-test rejection of the informational efficiency model of political communication. Triads which the efficiency model would expect to have a negative relationship to information transmission are in fact positively related to A-to-B communicating. Triads 5, 7, 8, 14, 15, and 16 are positively related to the likelihood of A-to-B information transmission. In other words, the communications network in energy politics in the 1970s and 1980s is highly redundant. The more paths connecting A to B, the more likely A is to talk to B, other variables held constant.¹²

If the efficiency model poorly explains the triadic structure of policy communication, then which of the social broker models can better explain it? The facilitator model receives mixed support. Triad (6), which represents the simplest case

¹¹ As noted earlier, Laumann and Knoke (1987, 223) use path distance as their dependent variable, whereas we use dyadic information transmission. These are conceptually distinct, but empirically related, in that the transmission from A to B means that there is a path distance of one from A to B.

¹² As we note above, the "inefficiency" of the energy politics network does not necessarily indicate a lack of rationality; we argue that trust compels a certain amount of redundancy in the network.

TABLE 2A

Model Estimates, Health Data

Dependent Variable is {A → B tie = 1, 0 otherwise}

Variable	Logit Model Standard Errors Clustered on Sender		Logit Random Effects Grouped on Sender	
	Coefficient	SE	Coefficient	SE
Issue Interest Dis-similarity	-.0084***	.0014	-.0084***	.0009
Activity Similarity	.0009	.0058	.0010	.0054
Preference Similarity	.9278***	.1325	.9278***	.1048
Sender Information Supply	-.4260***	.0908	-.4260**	.1297
Receiver Information Supply	-.3319**	.1368	-.3319**	.1273
Year of Sender's Founding	-.0023*	.0010	-.0023**	.0007
Year of Receiver's Founding	-.0018	.0008*	-.0018*	.0007
Sender Budget (logged)	-.0047	.0067	-.0047	.0062
Receiver Budget (logged)	-.0053	.0061	-.0053	.0065
Sender Monitoring Capacity (logged)	-.0335	.0464	-.0335	.0388
Receiver Monitoring Capacity (logged)	-.0572	.0471	-.0572	.0408
Sender is Government Actor	.3208*	.1370	.3208**	.1157
Receiver is Government Actor	.1164	.1667	.1164	.1244
Triad 2 Count	-.0106	.0073	-.0106 ⁺	.0055
Triad 3 Count	.0342***	.0054	.0342***	.0029
Triad 4 Count	-.0045	.0142	-.0045	.0043
Triad 5 Count	.0274***	.0053	.0274***	.0046
Triad 6 Count (<i>simple facilitation</i>)	.0507**	.0158	.0507***	.0105
Triad 7 Count (<i>simple transitivity</i>)	.1521***	.0270	.1522***	.0169
Triad 8 Count (<i>facilitation + transitivity</i>)	.1855***	.0170	.1855***	.0112
Triad 9 Count	-.0005	.0056	-.0005	.0036
Triad 10 Count	-.0428*	.0208	-.0428*	.0186
Triad 11 Count	-.0085	.0116	-.0085	.0084
Triad 12 Count	.0341	.0237	.0341**	.0128
Triad 13 Count	.0078	.0072	.0078	.0045
Triad 14 Count (<i>facilitation</i>)	.0450***	.0128	.0450***	.0111
Triad 15 Count (<i>transitivity</i>)	.1631***	.0323	.1631***	.0147
Triad 16 Count (<i>2-way facilitation + 2-way transitivity</i>)	.2984***	.0174	.2984***	.0108
Constant	5.2405*	2.4801	5.241*	2.048
$\ln \sigma_u^2$	—	—	-14	##
σ_u	—	—	.000912	##
ρ	—	—	8.32e-07 [†]	##

⁺ $p \leq 0.10$; * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$.

Clustered Errors Model: N = 15,252; Wald $\chi^2_{(28)} = 2,722.97***$; Pseudo R² = .3453; (Standard Errors adjusted for disturbance term possibly not i.i.d. across sender's observations).

Random Effects Model: N = 15,252; N of Senders = 124; N of obs. per sender = 123; Wald $\chi^2_{(28)} = 2,889.94***$; ##—Standard Error not retrievable.

TABLE 2B
 Model Estimates, Health Data (Interest Groups Only)
 Dependent Variable is {A → B tie = 1, 0 otherwise}

Variable	Logit Model Standard Errors Clustered on Sender		Logit Random Effects Grouped on Sender	
	Coefficient	SE	Coefficient	SE
Issue Interest Dis-similarity	-.0085***	.0020	-.0062***	.0014
Activity Similarity	.0010	.0074	.0068	.0080
Preference Similarity	.6969***	.1851	.9791***	.1705
Sender Information Supply	-.5354***	.1485	.0293	.1602
Receiver Information Supply	-.4892**	.1653	-.5860***	.1687
Year of Sender's Founding	-.0014	.0018	-.0284	.0022
Year of Receiver's Founding	.0012	.0010	.0012	.0013
Sender Budget (logged)	.0061	.0087	-.0464***	.0097
Receiver Budget (logged)	-.0039	.0079	-.0046	.0087
Sender Monitoring Capacity (logged)	.0474	.0741	1.610***	.1164
Receiver Monitoring Capacity (logged)	-.0947	.0685	-.1411*	.0618
Triad 2 Count	-.0046	.0092	-.0336***	.0089
Triad 3 Count	-.0121	.0145	-.3357***	.0226
Triad 4 Count	-.0425	.0298	-.1593***	.0121
Triad 5 Count	.0343***	.0082	.0223***	.0066
Triad 6 Count (<i>simple facilitation</i>)	.0207	.0174	.0524**	.0160
Triad 7 Count (<i>simple transitivity</i>)	.2343***	.0449	-.1192***	.0397
Triad 8 Count (<i>facilitation + transitivity</i>)	.1931***	.0266	.2410***	.0188
Triad 9 Count	-.0599***	.0148	-.0506***	.0129
Triad 10 Count	.0258	.0483	-.0344	.0428
Triad 11 Count	.1094***	.0257	-.2340***	.0326
Triad 12 Count	.1533***	.0342	.0988***	.0302
Triad 13 Count	-.0131	.0111	-.0178 ⁺	.0095
Triad 14 Count (<i>facilitation</i>)	.0704***	.0195	.0012	.0210
Triad 15 Count (<i>transitivity</i>)	.2947***	.0354	-.0462	.0353
Triad 16 Count (<i>2-way facilitation + 2-way transitivity</i>)	.3147***	.0226	.3335***	.0178
Constant	-2.276	4.294	52.2524***	5.1109
$\ln \sigma_u^2$	—	—	1.2512***	.1191
σ_u	—	—	1.8693***	.1114
ρ	—	—	.7775***	.0206

⁺ $p \leq 0.10$; * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$.

Clustered Errors Model: N = 9,702; Wald $\chi^2_{(26)} = 1,428.44$ ***; Pseudo R² = .3025; (Standard Errors adjusted for disturbance term possibly not i.i.d. across sender's observations).

Random Effects Model: N = 9,702; Wald $\chi^2_{(26)} = 1,231.53$ ***; #Senders = 99; N of obs. per sender = 98; [†]LR $\rho = 0$, $\chi^2_{(1)} = 120.03$.

of what we call facilitator brokerage (where the third party C sends both to A and to B, but no other ties exist) has a negative but insignificant coefficient. Triads (8) and (16) are significantly positive (as we discuss below), but the transitivity model would predict a positive relationship for these triads as well, so their explanatory power alone cannot be attributed to the facilitator model. The other triad for which the facilitator model makes a unique positive prediction is triad (14), which is positive and significant. The substantive impact of this variable, however, is quite small. Relative to the presence of other triads, a standard deviation increase (2.74) in triads of the form of (14) leads to a 0.7% increase in the probability of information transmission from A to B.¹³

For energy politics, it is clearly the transitivity model that emerges as most robust from our logit analyses, and this model stands as the clearest contradiction of the informational efficiency model. All four triads for which the transitivity model predicts a positive relationship to transmission have positive and significant coefficients in both the nonpanel estimation and the random-effects estimation. The key triads for interpretive purposes are (7) and (15), for which only the transitivity model makes a positive coefficient prediction (as the broker C is not jointly sending information to the sender A and the recipient B). Both are significantly positive. Relative to the prevalence of other triads, a standard deviation increase (2.74) in triads of the form (7) is associated with a 4.1% increase in the probability of information transmission from A to B. Similarly, a standard deviation increase (3.69) in triads of the form (15) is associated with a 4.2% increase in A-to-B transmission, or just over 20% of the dependent variable mean.

We can also assess the relative influence of transitivity and facilitation by comparing coefficients for triads (6) and (7) and triads (14) and (15). A Wald test for linear restrictions rejects the null hypothesis of equivalence between the coefficient for triad (6) (pure facilitation) and the coefficient for triad (7) (pure transitivity) [Wald χ^2 value = 95.36; Pr < .0000]. There is statistical evidence, then, that transitivity in the form of triad (7) has a greater positive effect upon information transmission than facilitation brokerage in the form of triad (6). A similar conclusion follows from comparison of triads (14) and (15). The Wald test [Wald χ^2 value = 15.21; Pr = .0001] rejects the null hypothesis of equivalence between the facilitator triad (14) and the transitivity triad (15).

Our evidence does not warrant an entire dismissal of the facilitation model for energy politics, however; in combination with the transitivity model, it appears to work rather well. The triads with the largest effect upon information transmission are those which contain transitivity *and* a facilitator. The best example of such an effect is triad (8), in which A-to-C and C-to-B ties exist—which makes for transitivity. The presence of a C-to-A tie in this triad is crucial, however,

¹³ Notice that, because of the sparseness of the networks, the average counts for triads with a significant number of ties (triads 6–8, 10–12, 14–16) is very low (averages between 1.45 and 4.19). The implication is that these types of relationships are relatively rare, but we show that their presence has a large effect on transmission.

because it signifies a relationship of information trade (and hence greater trust) between A and C. Comparing triad (8) to triad (7), where no C-to-A tie exists, shows the importance of transitivity that is augmented by A's increased trust in C. The equivalence of the coefficients for triads (7) and (8) can be rejected at the .05 level of significance [Wald χ^2 value = 5.06; Pr = .0245]. The marginal effects of this variable are also impressive. The presence of just one additional triad of the form (8) leads to a 2.1% increase in the probability of information transmission. The hypothesis that the effect of triad (15) equals that of triad (16) can be rejected much more easily [Wald χ^2 value = 68.16; Pr < .0000.], and the addition of a single triad of the form (16) yields a 3.3% increase in the probability of A-to-B transfer. In short, when there is two-way communication between the sender of information (A) and the broker (C), transitivity becomes much more powerful.

Estimations for the Private-Organization-Only Sample

Table 1b reports logit analyses for the sample restricted to information transmission between private energy lobbying groups themselves. In other words, no government agency, congressional committee, or any other public entity is included, either as a sender or receiver of information. (It is important to note, however, that government organizations are still counted in the construction of the triad variables for these regressions.) For the energy policy domain, this exclusion results in the deletion of 10,010 dyads from the sample, leaving 15,750 group-to-group dyads.

The results generally echo those in Table 1a, though with several noteworthy caveats. First, preference similarity, issue profile similarity, and sender resources all retain their support. Second, the results for the triads are substantively identical to those for the full sample save for one adjustment. It is no longer the case that, between groups only, facilitation adds to the effect of transitivity. The equivalence between triads (7) and (8) in the random-effects model cannot be rejected by means of a Wald test [Wald χ^2 value = .03; Pr = .8713]. The equivalence of effects for triads (15) and (16) can be rejected in the random-effects model [Wald χ^2 value = 3.38; Pr = .0660], but not in the nonpanel model. What this implies is that brokerage may matter most when congressional committees or government bureaucracies are involved in information transfer. Because signaling legislators or bureaucrats may entail a greater need for trust, a well-informed broker may play an important role. More broadly, the robustness of the transitivity triads across our estimations points to the social logic of trust for information flow in national energy politics.

Results from Model Estimations: Health Politics

The results from estimation of the logit models for information transmission in health politics appear in Tables 2a and 2b. They offer a picture of communication that is similar but not identical to that in national energy politics in the 1970s and

1980s. The frequency of dyadic information transfer among organizations in national health politics—transfer occurred in 19.3% of possible dyads—does not differ substantially from the frequency in energy politics (20.7%).

Resources and Preferences

The most active groups in health politics were the “usual suspects”: large, well-organized groups such as the American Medical Association and the Health Insurance Association of America. It is not the case, however, that organizations with large budgets or monitoring resources are more likely to transmit information to other groups in health policy. The logit estimates of Table 2a show that sender budget and monitoring capacity are *negatively* (but insignificantly) associated with A-to-B ties. The models do show that older organizations are more likely to send ties, an effect that was absent in the energy politics models.

The preference similarity ($p < .0001$) and similarity of profile of issue involvement ($p < .0001$) variables again emerge as positive and robust. Again, the positive and robust effect of preference similarity throughout all models estimated in health and energy politics provides strong support for the “friendly lobbying” and the strategic signaling models of political communication, even while taking into account the larger social structure. Interestingly, in contrast to the energy results, the effect of the information supply variable (again, measuring the potential supply of information from others in the network) in the health sample appears to enhance communication between A and B; we cannot readily explain this apparent difference between energy and health, and it suggests there may be different norms at work in the two domains.

The Importance of Transitivity and Facilitation

The estimates for the triadic count variables are similar to those for the energy sample. Once again, positive coefficients on triads (5–8) and (13–16) allow us to confidently reject the informational efficiency model of communication and again conclude that a high degree of redundancy exists in health policy communication networks. A Wald test strongly rejects the null hypothesis that the sum of the coefficients for triads (5) through (8) is zero [Wald χ^2 value = 148.76; Pr < .0000] and a similar result obtains for triads (13) through (16) [Wald χ^2 value = 191.63; Pr < .0000].

As in the energy politics network, the relative effect of facilitation and transitivity can be assessed through Wald tests to test for the equivalence of different triad effects. While the simple facilitator effect (6) is positive and significant ($p < .001$), the transitivity triad (7) has a coefficient more than twice that of the facilitator triad (6). A Wald test again rejects equivalence of the two coefficients ($\chi^2 = 14.31$; Pr = .0002). A similar difference may be observed in comparing the coefficients for triads (14) and (15) ($\chi^2 = 34.05$; Pr < .0000). Again, however, the transitivity effect appears strongest when it is augmented by facilitation. The

effect for triad (8) is stronger than that of triad (7) [$\chi^2 = 5.87$; Pr = .0154], and the effect of triad (16) is stronger than that of (15) [$\chi^2 = 49.26$; Pr < .0000]. In particular, the effects of the facilitator-transitivity triads are substantive. Controlling for the presence of all other types of triads, the addition of a single additional triad of the form (8) boosts the probability of A-B signaling by 2.3%, while the addition of a single triad of form (16) increases the signaling probability by 3.9%. Standard deviation increases in the count of these triads—2.66 for triad (8) and 3.29 for triad (16)—render appreciable boosts in the likelihood of communication (7.0% for triad (8) and 16.1% for triad (16)).

Results from the Private-Organizations-Only Sample

When dyads involving government senders and receivers are dropped from the sample, 5,550 observations are deleted, leaving 9,702 for analysis. The difference in the results mimics the case for energy politics. Preference and profile of issue involvement continue to be large and significant. One noticeable difference from the full-sample estimation is that the age effects disappear entirely; between private organizations alone, older groups are not more likely to send and receive information than younger ones (perhaps less so in the case of recipients).

The results for the triad counts are largely the same as for the full sample, with two exceptions. First, simple facilitation (6), while still positive, is not significant. Second, just as with the energy data, in the private-only sample for health facilitation no longer seems to augment the effect of transitivity. The coefficient for triad (7) is actually larger than that for triad (8), although a Wald test cannot reject their equivalence [$\chi^2 = .47$; Pr = .4944]. Likewise, the coefficients for triad (15) and triad (16) are almost identical, an appearance which the Wald test supports [$\chi^2 = .11$; Pr = .7358].

Discussion

The independent effect of transitivity suggests the explanatory importance of network effects in communication choices over and above the specific attributes of sender and receiver.¹⁴ The transmission of information from a sender A to a receiver B is enhanced when an (informationally redundant) transitive relationship prevails through a third party C. When the government is a participant, the likelihood of communication will be even further enhanced when the sender and the broker trade information with one another. In Washington politics and elsewhere, the decision to communicate is not dependent entirely on strategic considerations driven by the attributes of the two actors. The decision of one actor

¹⁴ Another issue facing our estimations is what network theorists have called mutuality: the log-odds of a B-to-A tie on the probability that an A-to-B tie is formed (Wasserman and Faust 1994). We have included the B-to-A tie as a blunt measure of mutuality in our logit models, and while the effect of mutuality is significant, our fundamental results are unchanged (analyses available upon request). We thank an anonymous reviewer for bringing this issue to our attention.

to inform another depends heavily upon the presence of others. The statistical dependence across dyads has a theoretically recognizable structure, transitivity, a configuration likely to induce communication based on trust and social commonalities.

Our analysis offers a cautionary methodological note. Analyses that omit social network effects will retrieve biased and inconsistent estimates of the effect of individual level independent variables upon information transmission. In separate analyses (not reported), we find that including triad variables in the logit analyses *decreases* the estimated coefficients for the preference similarity and monitoring capacity variables. Including the structural variables decreases the preference similarity coefficients by 12% for the energy sample, and 21% for health, and slashes the monitoring capacity coefficients by 47% for energy and 107% for health. In addition, the aggregate effects of these structural variables are considerable. Although inference about the total explanatory model in logit models is difficult, adding triad variables boosts the pseudo- R^2 of the logit model for the energy sample almost three-fold, from .13 to .36, an increase of over 22 percentage points in explained variance. For the health sample, the increase in pseudo- R^2 more than doubles from .16 in the nontriad model to .35 in the triad model.

Skeptical readers might ask whether our triad results are simply picking up unmeasured preference similarity or other interorganizational factors that affect signaling. Of course, if triad (7) is positively related merely because of C, then other triads where ties between A, B, and C prevail must also be positively related to A-to-B communication. Our results show there is simply *no monotonic relationship between the number of third-party ties that exist between A and B and the likelihood of communication between A and B*, nor would our theory posit any such relationship. Some triads where three ties exist with a third-party C indeed are associated with *reduced* communication (triad 10), while some triads with only one tie increase signaling (triad 3).¹⁵ A more general objection is that the causal arrow for our triad results simply runs the other way. Perhaps the existence of an A-to-B tie makes some triads more likely and others less likely. It strains credulity, however, to believe that an A-to-B tie could *both* induce two-way information exchange between A and C *and* between B and C *and also reduce* the probability of B-to-C-to-A transmission. Our theory is able to explain much of the nuanced and nonmonotonic results of the triad variables we employ in our study.¹⁶

¹⁵ Relative to the presence of other triads, a standard deviation increase in triads of form (10) leads to a 1.5% point reduction in the probability of A-B information transfer. The combined logic of transitivity and brokered trust explain why this is so. Triad (10) represents the *reverse* of transitivity; if triad (10) existed and A sent information to B, it would represent a cycle of transmission. But notice that in triad (10), A does not send information to the third party C, and so C cannot inform B of A's value as an exchange partner.

¹⁶ In addition, we reestimated these models using Wasserman and Pattison's (1995) P* regression methods, which take into account the potential endogenous effects that may come from the full configuration of network relationships. We found substantively similar results (analyses available from the authors on request).

Conclusion

Theoretically and empirically, our aim has been to demonstrate the importance of structural approaches to information transmission in national politics. While noteworthy differences in patterns of information transfer exist across the national health and energy policy domains, our analyses nonetheless uncover some important similarities. First, whether in health politics or energy politics, and whether the sample includes all organizations in a policy arena or just private organizations, preference similarity is an important determinant of information transmission in national politics. We show that “lobbying friends” prevails not only between private organized interests and politicians—as Kollman (1997), Hojnacki and Kimball (1998), and Hall (1996) have previously shown—but that friendly information transmission prevails *between organized interests themselves*. The robustness of this conclusion across two policy arenas, and across numerous specifications of our statistical models, adds further support to the “friendly lobbying” argument.

Second, more importantly, our analyses have unearthed a pervasive social logic to political communication. As analysts of political communication have shown—and as private lobbyists, members of Congress, and agency bureaucrats surely know—the transmission of information from one actor to another does not occur in a social vacuum. The presence of numerous actors in any political setting strongly conditions the exchange of information between any pair of policy actors. We have posited three mechanisms by which the presence of “third parties” might affect dyadic communication patterns, and we find that political transitivity best explains the results.

The results support our theory that social trust is an important mechanism that determines communication choices independently of the strategic communication logics driven by preference similarity. Communication among interest groups indeed can help groups reduce uncertainty in the likely effects of alternatives, but communication in politics is not limited to uncertainty reduction (see Jones 2001). Communication driven by trust, social commonality, and transitive relationships can enable political actors to develop general understandings of policy alternatives or the frame of reference within which preferences are defined. Indeed, as Heclo (1978, 102) asserts, issue network activists often have a substantive, intellectual interest in policies, rather than a purely material interest. To the extent this is true, then transitivity and other social network effects are likely responsible for communication choices more generally, even in instances where actors possess distinct interests and preferences. In this sense, participation in a policy community where actors’ interests are intimately linked can affect communication in ways that simply cannot be envisioned in models that only consider individual-level attributes.

Appendix

Dyadic variables (Standard Deviations in parentheses)

Issue Interest Dissimilarity: Groups were asked on a 0-to-5 scale their level of interest in a list of issues (no interest to major interest). This variable is the sum of the absolute differences of responses to these items of the members of the dyad. Energy mean 133.35 (35.47); health mean 111.76 (33.72). *Activity Similarity*: Groups reported their activity on a list of events (e.g., bill on geothermal energy; the nomination of agency head). This is the count of events in which both members of the dyad were jointly active. Energy mean 10.62 (9.48); health mean 4.22 (5.94). *Preference Similarity*: Groups were asked their position in events (if any). This is the percent of events in which members of the dyad had the same position. Energy mean .253 (.203); health mean .333 (.306). *Organization's Year of Founding*: Year of establishment. Energy mean 1923 (165); health mean 1939 (36). *Organization's Budget (logged)*: Dues + grants + fees + endowment. Energy mean 4.88 (6.86); health mean 10.12 (6.92). *Organization's (logged) Monitoring Capacity*: Number of staff employed to monitor Washington and government affairs. Energy mean .69 (1.05); health mean .98 (.95). *Organization's Information Supply*: Percent of other organizations in policy arena that shared interests with the organization. Energy mean 50.5% (16.9); health mean 43.7% (22.4). *Organization Public Actor*: Scored 1 if the organization is either a government bureaucracy or a congressional committee. Energy mean 21.7% (41.2); health mean 20.2% (40.1). For triadic variable measurements, see Figure 1; descriptive statistics available on request. Note: data from Laumann and Knoke (1987).

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Daniel P. Carpenter is professor of government, Harvard University, Cambridge, MA (dcarpenter@latte.harvard.edu). Kevin M. Esterling is assistant professor of political science, University of California—Riverside, Riverside, CA (kevin.esterling@ucr.edu). David M. J. Lazer is associate professor of public policy, John F. Kennedy School of Government, Harvard University (David_Lazer@harvard.edu).