The Strength of Strong Ties : A Model of Contact-Making in Policy Networks with Evidence from U.S. Health Politics

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A MODEL OF CONTACT-MAKING IN POLICY NETWORKS WITH EVIDENCE FROM U.S. HEALTH POLITICS

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ABSTRACT

Interest groups establish contacts with each other as a way of gaining useful policy information, and in this article we develop and test a model to explain this political phenomenon. Our simulation model suggests that when few need information, groups will pursue an *acquaintance strategy* by investing time and resources in gaining 'weak tie' political acquaintances rather than in gaining 'strong tie' political friends, but that as the collective demand for information rises, groups increasingly follow a *chum strategy*, placing greater emphasis on establishing strong ties. We test these hypotheses in an analysis of inter-organizational contact-making in U.S. health politics, using the data of Laumann and Knoke (1987), with OLS regressions of average group contacts over lobbying events over time and maximum likelihood count models of contacts across interest groups. Both analyses show that as collective demand for information increases, interest groups place greater priority on establishing strong ties, even while controlling for organizational attributes such as budget, mobilization capacity and organization age. The results suggest some conditions where policy networks in the aggregate are less likely to distribute information efficiently, and, in particular, that policy networks are less efficient at distributing information when information is most in demand.

KEY WORDS • acquaintance • information • interest groups • weak ties

'More than mere technical experts, network people are policy activists who know each other through the issues. Those who emerge to positions of wider leadership . . . are experts in using experts, victuallers of knowledge in a world hungry for right decisions.' – Hugh Heclo (1978: 103)

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More than two decades ago, Hugh Heclo (1978) called the attention of political science scholars to the importance of 'issue networks' in any explanation of the development of modern public policy. Peak associations and 'iron triangles' alone could not explain the dynamic of U.S. policy development. Heclo (1978: 104) writes:

> Increasingly, it is through networks of people who regard each other as knowledgeable, or at least as needing to be answered, that public policy issues tend to be refined, evidence debated, and alternative options worked out – though rarely in any controlled, well-organized way.

In subsequent decades, however, political science has developed surprisingly little theory to explain how it is these networks evolve among interest groups and other political organizations. Networks are not designed, but are the concatenation of myriad rational decisions as to whether to talk or not to talk, to acquaint or not to acquaint (e.g. Knoke 1990; Knoke et al. 1996; Verbrugge 1977; Padgett and Ansell 1993). Without a theory of how these individual decisions are made, one may conclude with Heclo that contemporary lobbying politics is disorderly and unpredictable, creating problems for democratic governance.

The interest group research has shown that congruence of policy interests is an important determinant of who talks with whom in policy networks (Hojnacki and Kimball 1998; Koenig and Braunninger 1998). Here we examine how organized groups allocate their time in establishing different *types* of contacts (which we label strong and weak ties) in a network. Allocation of time among contacts is an important facet of the lobbyist's job, determining in part how informed he or she is on current policy issues.[1] Lobbyists find this access to policy information critical; in particular, they may get 'access' to policy-makers by virtue of their demonstrated ability to convey credible and useful information to Congress or the bureaucracy (Milbrath 1963; Bauer et al. 1972; Heclo 1978; Hansen 1991). Given limited time, lobbyists face a trade-off between developing and maintaining trusted informational contacts ('strong ties') and more distant acquaintances ('weak ties'). To optimize the trade-off between strong and weak ties, we argue that interest groups must take into account a general rule of political and social life: friends help their friends first, their acquaintances later (see Uzzi 1996). We demonstrate in this article that as the collective demand for information among interest groups increases, *lobbyists will invest more time in making strong ties than in making weak ties*.

In earlier work, Granovetter (1977) has shown that weak ties distribute information more efficiently than strong ties, since strong ties tend empirically to be intra-clique and so less likely to provide new information. Our analysis offers an amendment to Granovetter's 'strength of weak ties' argument: in competitive informational environments, which often characterize national level health politics, information tends to be concentrated in the relatively inefficient strong tie network. Our theory and analysis therefore suggest conditions for the relative efficiency or inefficiency of the distribution of information in an issue network. In this argument, one important aspect of Heclo's problem of issue networks for national policy development is conditional: in some identifiable circumstances, policy information is likely to be undersupplied and so debates on important policy topics are likely to be relatively under-informed.[2]

To formally establish these conditions, we develop a simulation model and test the implications of the model with data on the communications network connecting national-level health policy lobbyists in the 1980s. These data were collected by Laumann and Knoke in their study *The Organizational State* (1987). Using these data, we test our theory in two ways. Our first test examines the evolution of a single policy network over time, covering 85 lobbying events in health politics in the 1970s. We find that the greater the interest among groups in the lobbying event, the greater the average strong-tie investments of groups involved in that event. Our second test compares lobbying organizations. Using maximum likelihood count regressions, we find that groups involved in events that many other groups are also interested in (i.e. events with greater demand for information) tend to invest in more strong ties.

We develop these findings in five sections. We first outline the assumptions underlying our approach to the study of policy networks. In Section II we develop a simulation model of contact-making based on these principles and derive model implications. We offer hypotheses from these implications in Section III and discuss the data we use to test them. In Section IV we review the results of our statistical analyses of contact-making in the health policy domain. In the conclusion we discuss the broader implications of these findings for the study of policy networks.

I. Lobbying and Networks

Interest groups seek to maximize their chances of being informed on the issues in which they are interested (see, e.g., Milbrath 1963; Bauer et al. 1972; Hansen 1991; Austen-Smith 1992; Austen-Smith and Wright 1992, 1994; Rasmussen 1993). Being informed, on both substantive and tactical issues, increases interest groups' ability to manage and control the policy process. We develop a micro-level model of how interest groups develop contacts in order to maximize the amount of information they obtain through these contacts. We build on Boorman's (1975) ground-breaking work on competitive information search in an employment context. Like Boorman, we assume that much useful policy information is socially distributed in the lobbying community, and that groups acquire information largely through contacts with other groups (Heclo 1978).[3] Often the maintenance of contacts with other groups can yield more useful information and at lower cost than conducting research anew for each policy issue. As Bauer et al. state, interest groups are 'nodes in the communications process', and as a general consequence, 'what they knew or failed to learn, what they heard or did not hear, what they said or failed to say, had a profound effect on what other people learned, heard, or said' (1972: 325).[4]

How do interest groups go about choosing contacts? Granovetter's 'strength of weak ties' hypothesis (1973) suggests that lobbyists are better off investing time in acquaintances (or 'weak ties') because they are more likely to hear new or novel policy information through weak ties than through strong ties. This hypothesis follows from an empirically observed feature of networks: strong ties tend to be densely socially interconnected, and so the information that flows through strong ties tends to be redundant. In contrast, weak ties tend to act as bridges between tightly knit cliques, and so it is through 'weak ties' that novel information diffuses most rapidly across a network (see also Schneider et al. 1997: 1205 and Browne 1988: 55).

The extent to which groups gain information through social contacts, however, depends critically on the social rules and incentives for information-sharing in policy networks. We argue that, in competitive information environments, there is a tendency for friends to share information with their close and trusted friends before they share information with acquaintances. This social rule is well illustrated by a lobbyist interviewed in the classic study of Milbrath:

> My contacts trust me, and I think their trust is well placed. Most of the things they tell me are not of a secret nature; it's just a development that they have discovered which they think I would be interested in. It is very difficult to get information if you go out digging for it. . . . Actually, you get much better information from people who know you, know what your interests are, and know that they can trust you. (1963: 260)

And as Granovetter notes (1982: 113): 'Weak ties provide people with access to information and resources beyond those available in their own social circles; but strong ties have greater motivation to be of assistance and are typically more easily available.'

There are three reasons why strong ties might receive preferential treatment in the context of policy networks. First, there is a 'bandwidth constraint': there are limits to how many others one can communicate with in a day.[5] That is, typically one cannot simply broadcast a bit of information to all of one's contacts who might benefit from having that information instantly. Instead, one will communicate that information over a period of time to one's contacts. Given this constraint, each actor will need to prioritize who receives information first.

Second, even if a source had unlimited capacity to convey information, the source would be more likely to know that a given strong tie was interested in a piece of information than a given weak tie, as the Milbrath quote above suggests.

Third, if possession of asymmetric information confers a distributional or political advantage in politics (e.g. Austen-Smith and Wright 1992 and Hansen 1991), then a source would likely give that information to strong ties before giving it to a weak tie or acquaintance.

A concrete illustration from recent national level health policy helps to establish the argument.[6] The expected number of managed care plans that will leave the Medicare program in a given year, and hence the number of elderly who are likely to lose coverage in their chosen plan, is based on the content of different reform proposals before Congress. These proposals often involve relatively arcane topics, such as risk adjustment methodology, capitated payment rates, program user fees, and mandated prescription drug coverage. Assume that the American Association of Health Plans (AAHP), the leading trade association for managed care plans and health maintenance organizations (HMOs), knows the number of plans that will exit the Medicare program based on the different proposals before Congress. The AAHP faces high costs of communicating policy

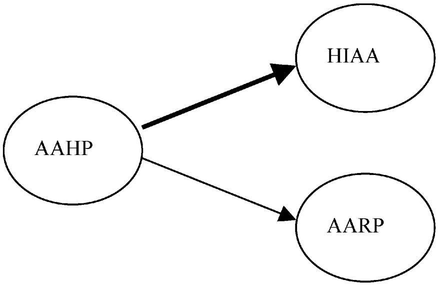

Figure 1. Illustration of strong tie priority rule

information on these arcane topics, since the various political and policy ramifications of various proposals might require an afternoon session to explain. Furthermore, assume the AAHP has a strong tie to the Health Insurance Association of America (HIAA) and a weak tie to AARP (formerly known as the American Association for Retired Persons). In this case, the AAHP is more likely to know that HIAA wants to know about managed care exit, is more inclined to invest the time and resources to explain the topic to HIAA, and is more inclined to confer the potential benefits for knowing this information to HIAA, when compared to the AARP. That is, the AAHP will likely send information to HIAA before it sends information to the AARP.

The ‘strength of weak ties’ hypothesis and the ‘strong tie priority’ rule together imply that there is a trade-off between seeking to gain better or more novel information through establishing weak ties, and seeking to increase the priority one’s contacts place in sending you information. It is also reasonable to assume that a trusted friendship requires more time to form and maintain than an acquaintance; a lobbyist can make more weak than strong ties, but the added expense of strong ties brings preferential treatment (e.g. see Browne 1988: 55). It is this trade-off between strong and weak ties that we formally model and statistically analyze in the remainder of the article.

II. Simulation Model

Let a *policy network* consist of N interest groups with potentially common interests (but not common positions) in a set of issues, and let an *event* consist of the full debate and information transfer that occurs among these N groups when the government considers action in a relevant policy domain. For example, the policy domain might be health, the issue might be healthcare financing, and an event might be the 1994 Clinton healthcare plan debate. We assume that for a given piece of information, in a population of N interest groups, there is probability that any given interest group has the information at the beginning of an event. Our model describes the process by which this information then diffuses through the informational network that connects interest groups. If an interest group is not one of the initial groups with information, if and when it will acquire that information depends on its connections to other groups. The trick for an interest group, then, is to position itself in the network so that information will flow to it as quickly as possible.[7]

The 'collective demand for information' among lobbyists is the fraction of the network population that is interested in the information. In the lobbying context, there is clearly great variation by event in how many groups are interested in acquiring information. Some issues are more complex and general than others, and this will determine the general demand for information on that issue. More health policy groups are likely to be interested, for example, in hospital cost containment than in DNA research. We therefore assume:

Assumption 1: The collective demand for policy information varies across events.

In the simulation model, we assume that the fraction of the population of interest groups that needs information, μ, varies over events and may equal 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, or 1.[8]

We assume that each event is made up of R rounds. Given the costs of and other constraints on communicating information as described above, assume that during each round a group with information may pass that information selectively on to one other group. For any pair of groups, A and B, there may be no tie from A to B, a weak tie from A to B, or a strong tie from A to B. Given the strong tie priority rule set out above, we assume that:

Assumption 2: If A has information, it will first send that information to a strong tie, and only if no strong ties need information will it send it on to a weak tie.

In the simulation, we add the assumption that all groups have a time constraint, T, on how many ties they can form (otherwise groups would form strong ties to all other groups), such that: $T = W + \lambda S$, where $\lambda > 1$ (since strong ties are more expensive than weak ties).[9]

Lobbyists may therefore invest in a continuum of potential strategies. At one end of the continuum, lobbyists might invest their time in gaining many 'weak tie' acquaintances in a loose network of contacts who know something about the policies in which they are interested. We label this an *acquaintance strategy*. At the other end of the spectrum, lobbyists may invest their time in gaining a few valued 'strong tie' lobbying partners, political friends *in whom* they will invest more time and cultivate more trust, and *from whom* they expect to receive more information in return. We call this the *chum strategy*. We seek to model the optimal trade-off in the mixture (or the choice not to mix) between these two pure strategies.

Finally, we assume that over time interest groups learn effective strategies for obtaining information:

Assumption 3: Interest groups emulate the relatively successful networking strategies of other interest groups in the system.

This emulation process is modeled with a genetic algorithm (e.g. see Goldberg 1989; Holland and Miller 1991; Andreoni and Miller 1995; Axelrod 1997; see generally Kollman et al. 1995, 1998). The basic assumptions of the genetic algorithm are that after a fixed number of events the relatively successful strategies are spliced together to form new strategies. After this process is iterated a number of times, the population of strategies will tend to converge on a single, highly successful strategy (see Appendix 1 for a summary of the genetic algorithm as utilized in this article).

Figure 2 summarizes how we implement these assumptions in the simulation model.[10]

The key question we are asking is how the allocation of time between strong and weak ties is affected by the demand for information (μ) in a given event. Below we summarize a set of 1000 simulations, with 100 interest groups, where strong ties 'cost' five times as much as weak ties (i.e. $\lambda = 5$), groups can have up to 10 strong ties (or 50 weak ties), there are 5 rounds per event, 40,000 events,

- *Basic model parameters*. There are N groups. Each group is informed at the beginning of an event with probability δ. Each group needs information at the beginning of the round with probability μ. μ varies from event to event, and may equal 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, or 1. μ is publicly known, and is chosen randomly at the beginning of an event. Each group has a time budget, T, for establishing contacts: $T = W + \lambda S$, where $\lambda > 1$.
- *Tie investment decision*. At the beginning of an event, a group chooses how many strong and weak ties to establish, based on μ. These ties are then randomly chosen at the beginning of the event.
- *Information dissemination*. There are R rounds in an event. During each round, groups that have information may pass that information on to one other group that needs information. In each round, if a group has information, it will first check among the strong-tie groups to whom it sends information. If one or more of those groups need information and one or more weak ties needs information, it will send information to one weak tie.
- *Adaptation*. In the first event of the simulation, strategies are randomly determined. In subsequent events, more successful strategies are emulated (see Appendix 1 for description of genetic algorithm used to adapt strategies).

Figure 2. Key simulation assumptions

after every 200 of which adaptation occurs via the genetic algorithm. In each event there are 5 rounds during which information spreads. The performance of each group (used in the genetic algorithm) is measured by the proportion of the rounds in which the group was informed when it needed information. Thus, if a group needed information in event 5, and received information in round 3 of event 5, it would receive a score of 0.6.

In these simulations each group has what we call a 'network strategy string' (NSS) – a list of 10 integers between 0 and 10. The first digit in the list indicates how many strong ties the group will choose if $\mu = 0.1$, the second digit how many strong ties the group will choose if $\mu = 0.2$, the third digit how many strong ties the group will choose if $\mu = 0.3$, and so on, until the tenth digit, which indicates how many strong ties the group will choose if $\mu = 1$ (we assume that each group devotes the remainder of its time to weak ties).[11] The population of NSSs evolves through the run of a simulation, converging on NSSs that maximize the amount of information each group receives. At the beginning of each simulation, the values of the NSSs are randomly chosen from a uniform distribution. Thus, at the beginning of these simulations, the average group selects five strong ties (and 25 weak ties) for each value of μ.

As we mention above, the strength of weak ties literature asserts that strong ties tend to be more intra-clique than weak ties. In the interest group universe, one might imagine that strong ties are within coalitions, and weak ties between coalitions. A key issue, then, is whether this empirical regularity affects the model results. In the analyses below, we present the results model results under two conditions: 1) where strong ties are distributed randomly, and 2) where the 100 interest groups are partitioned into 5 cliques of 20 groups each; strong ties are still randomly allocated, but *just intra-clique*. Weak ties, in both cases, do not depend on the partitioning of cliques.

The question now is: What is the relationship between μ and the number of strong (and weak) ties each group selects at the end of these simulations? Figure 3 summarizes the average number of strong ties selected at the end of these 1000 simulations under both conditions for the partitioning of strong ties. First consider the case where strong ties are not partitioned. Figure 3 demonstrates a strong pattern – the higher the values of μ the more strong ties a group selects. For $\mu = 0.1$, the percentage of the time budget of groups invested in strong ties, averaged across all groups in the 1000 simulations, is 38%, where this number increases monotonically as μ approaches 1. At $\mu = 1$, almost all the time budget invested by a group in ties to other groups is in strong ties (95%).

This finding mirrors Boorman's (1975) argument that strong ties are more valuable in the employment search context when unemployment is high. There is a solid intuition here: as more groups need information, the probability that a group with information will pass it on to a weak tie drops precipitously. Consider a group from whom 5 other strong-tie groups and 25 weak-tie groups would like to get information. If $\mu = 0.1$, the probability that that group would pass information on to *any* weak-tie group at the beginning of an event is 59%. If $\mu = 0.5$, this probability drops to 3%, and for $\mu = 0.9$, to 0.001%! The 5 strong ties present a barrier that grows exponentially with μ. Our first result is therefore:

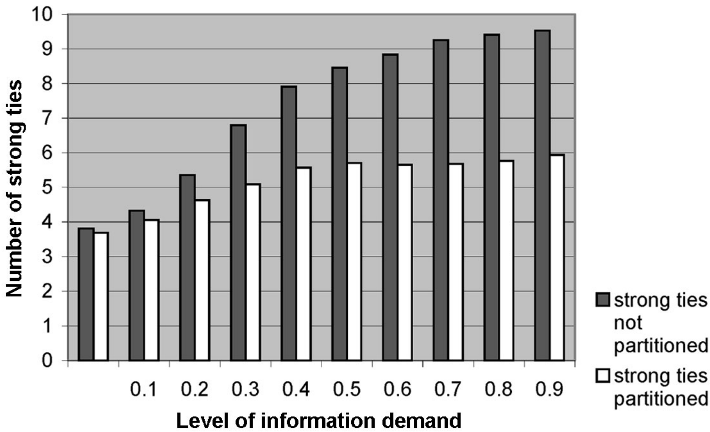

Figure 3.

Result 1: The more interest groups seeking information regarding an event, the more strong ties (and fewer weak ties) those groups will seek.

The Boorman study imposes the assumption that there is no systematic difference between the structure of the strong-tie and weak-tie network. We are interested in the optimal trade-off between strong and weak ties assuming that strong ties tend to be intra-clique and so are less likely to disseminate new information. Figure 3 shows that when strong ties are partitioned into cliques, groups do indeed systematically invest in fewer strong ties than in the condition where strong ties are not partitioned into cliques. This finding replicates Granovetter's key insight: *the intra-clique nature of strong ties reduces their value as sources of information*. But even in this extreme scenario, where strong ties are exclusively intra-clique, *the investments a lobbyist will make in strong ties increase with the level of information demand in a given event*. The intra-clique bias does have a disproportionate effect on the value of strong ties for high values of μ, so the relationship between μ and number of strong ties levels off for very high levels of μ (for values 0.5 or greater). This is likely because as the density of intra-clique ties reaches this threshold, information diffuses so quickly within the clique that an additional tie produces very little benefit. Our second result is therefore:

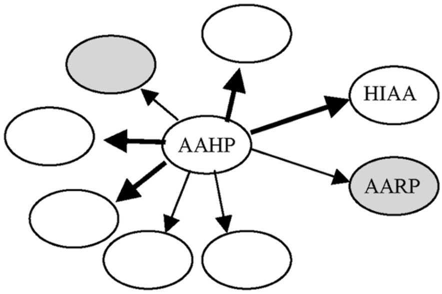

Figure 4. low information demand

Result 2: The tendency of strong ties to be intra-clique attenuates but does not reverse the importance of strong-tie contacts in a high information demand environment.

Both results 1 and 2 imply the same testable proposition: the more groups collectively demand information, the greater the advantage to having friends rather than acquaintances as contacts.

Thus, returning to the example from Figure 1. The relative value of the strong tie AAHP has to HIAA as compared to the weak tie AAHP has to AARP is contingent on the demand for information of the other actors AAHP is connected to. In Figure 4, only one other actor (a weak tie) that AAHP is connected to needs information that the AAHP has (signified by the shading). The AARP would be first or second in line to receive information that the AAHP has. In Figure 5, information demand is far higher (with 8 rather than 3 actors needing information). The value of HIAA's strong tie will drop (it is guaranteed being just one of the first four actors to receive information); as will the value of AARP's tie (it will be somewhere between the fifth and eighth actors to receive information). In a world where at critical junctures events move quickly, those at the end of the queue may never receive the information in time to use it.

III. Hypotheses and Data for the Empirical Analyses

The above model offers a simple and testable implication: the greater the collective demand for information among groups,

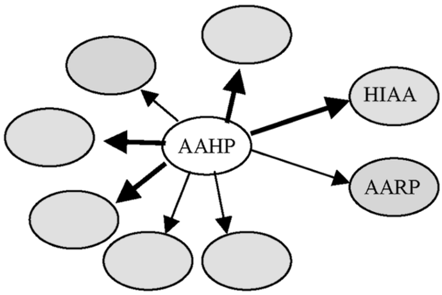

Figure 5. High information demand

measured as the relative number of groups in the population seeking a particular piece of information, the greater the tendency of groups to invest in strong ties relative to weak ties. We test this implication in two ways, with organization-level data and with ecological event-level data.

Event-Level Hypothesis

Our data encompass interactions over many lobbying events, which are occasions for lobbyists to approach the government as it is considering an official action on an issue (e.g. when a committee is marking up a bill on hospital cost containment). We expect that at the event level, the more groups that are interested in the lobbying event, the greater the average number of strong ties of the groups active during that event.[12]

Hypothesis 1A: The average number of strong ties to groups involved in a given event is positively related to the number of groups interested in that event (the level of 'collective information demand' in those events).

In the data that we use to test this relationship, the network data are effectively aggregated over many events. That is, groups do not start with new networks with each event, but can only tweak their networks over time depending on their informational needs. This should attenuate (but not eliminate) the predicted relationship.

Organization-Level Hypothesis

Hypothesis 1A implies that at the event level, groups should establish more strong ties if they are involved in a high information demand event. A typical interest group is involved in many different events, however, and at the organization level a group's strong-tie investment should be a function of the overall profile of events in which the group is involved. We therefore produce a second test of result 1 of the model at the individual group level. If the demand for information varies across events, and groups are differentially involved in those events, then we should expect a positive correlation across interest groups between the level of information demand in the set of events they are involved in and their group-level strong-tie investments. That is, groups that are disproportionately involved in events in which there is a high demand for information should have more strong ties than groups that are not.

Hypothesis 1B: The number of strong ties to a group is positively related to the average level of information demand in the profile of events in which that group is involved.[13]

Controls

The organization-level model controls for characteristics of the organization that also may affect contact-making behavior, and the event model controls for the aggregate characteristics of the set of organizations involved in each event. Our simulation model assumes that groups have a time budget in which the choice between strong and weak ties is a zero-sum trade-off. As the time budget is unobservable, there is no conceivable way to reconstruct it given our data. Because groups with a large time budget will establish more of both strong and weak ties, we enter the number of weak ties in the model as a partial proxy for a group's time budget. If we had a measure for the budget, and included that measure in the equation below, we would expect a negative relationship between the number of weak ties and the number of strong ties. In the absence of a measure for this time budget, we expect the relationship to be (spuriously) positive, since the time budget should be positively related to both. By including weak ties as a control, the impact of independent variables we include in the equation below should be interpreted as affecting the *balance* of investments in strong versus weak ties.[14]

In addition, we control for a number of group characteristics in our data set. We have several measures of the political clout of an interest group, on the assumption that groups with more political influence can gain access to the government irrespective of their relative credibility, as, for example, through campaign contributions (Bennedsen and Feldmann 1998). Groups with greater clout may therefore have the luxury to pursue weak ties, which confer little information for a high information demand lobbying event, but which confer more information on average as events come and go. To control for this, we include measures of each group's lobbying budget, and estimates of its capacity to mobilize both its members and the public as issues arise (see Table 1). We control for the group's age, assuming that older groups have had more time to establish strong contacts. Finally, we control for whether or not the group is an issue-oriented public interest group.

Data

We test the informational contact-making model in healthcare politics, where, at the time encompassed by our data, technical policy information was at a premium (Hyman 1971; Schwartz 1972; Alford 1975; Bauman 1976).[15] We employ the rich data collected by Laumann and Knoke (1987) for their book *The Organizational State*. Laumann and Knoke surveyed informants from an exhaustive list of the most prominent and influential health lobbying organizations.[16] Their sample of health lobbying organizations includes industry associations (such as the American Insurance Association and the Pharmaceutical Manufacturers' Association – now PhRMA), 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. These data document the full network of communication ties from each of these health policy organizations to each other, lobbying groups' internal organizational characteristics, and each organization's lobbying activity in 85 policy events that occurred between 1973 and 1980.

In Table 1 we summarize the dependent variables and how they were constructed, and in Table 2 the independent variables.

Table 1. Dependent Variables

Strong ties – group level	A count of the number of a group's strong ties through which it receives information. A strong tie occurs if some other group reports that it gives advice to the group as part of a 'trusted exchange of sensitive and confidential advice'.
Strong ties – event level	The average number of group-level strong ties for the groups involved in an event.

Table 2. Independent Variables

Theoretical variable: μ	
Collective demand for information – event level	The fraction of all groups that reported a moderate or high level of interest in the event, multiplying the fraction by 100 to allow for percentage-point interpretation of the coefficients.
Collective demand for information – group level	The average of the event-level information demand of the events in which the group participates.
Control variables	
Weak ties to other health lobbying groups	The number of a group's weak ties through which it receives information. A weak tie occurs if some other group 'regularly and routinely discusses national health policy matters' with the group but does not report having a strong tie with the group.
Organization budget	Recorded in 1980 dollar amounts, logged to improve maximum likelihood model convergence.
Estimated mobilization capacity	The number of times other groups name the organization as one whose influence comes from its ability to 'mobilize its members or employees to support a proposal'.
Estimated public mobilization capacity	The number of times other groups name the organization as one whose influence comes from its ability to 'mobilize general public opinion to support a proposal'.
Organization age	Recorded in years.
Public interest group	Coded 1 if the group describes its main function as a public interest group voluntary organization, 0 otherwise.

Note: In the event-level (ecological) model, the control variables are measured as the average of these organization-level control measures for all groups participating in the event.

IV. Empirical Analysis: Contact-Making in U.S. Healthcare Politics

We now examine the impact of information demand upon tie-making in two ways. First, we examine our network over time, by looking at a sequence of events in health policy. In a second analysis, we decompose the network and examine strong ties at the group level.

Results from Events-Level Analysis (Network 'Time Series')

We first assess the relationship between the information demand and lobbyist contact-making by examining a set of 85 lobbying events that occurred in the health policy domain in the 1970s. Table 3 summarizes the results of a regression of strong ties on information demand with the full set of ecological controls, and with a test of temporal autocorrelation (Model 4). Table 3 also summarizes three alternative specifications: a reduced model of strong ties on collective demand for information and weak ties (Model 1); the reduced model with a test of temporal autocorrelation of errors (Model 2); and a regression of strong ties on information demand and the full set of control variables but without the test of temporal autocorrelation (Model 3).[17]

The results summarized in Table 3 offer strong support for Hypothesis 1A: *the higher the level of information demand in an event, the more strong ties those groups involved in that event have*. This relationship is significant at $p < 0.001$, where a 1 SD increase (14.66 percentage points) in the fraction of groups interested in an event is associated with nearly 2 additional strong ties for the average group involved (the average group had 6.33 strong ties). While the significance of the budget ($p < 0.05$) parameters suggests that models 3 and 4 include the preferred specification, in the other two specifications the relationship between information demand and strong-tie investment is substantively similar and significant at $p < 0.01$ or better.

Results from Group-Level Analysis

The analysis in this section takes the group as the unit of analysis. Table 4 presents two negative binomial regressions.[18] The first includes all of the group-level independent variables listed in

Table 3. Relationship between information demand and strong-tie investments in the network: event-level analysis (Prais-Winsten Regression Estimates)

Variables	*Model 1* μ + weak ties	*Model 2* μ + weak ties AR(1)	*Model 3* μ + all controls	*Model 4* μ + all controls, *AR(1)*
Constant	−5.4129* (2.7202)	−6.0579** (2.7133)	−4.4951 (3.7191)	−4.5181 (3.7182)
Aggregate demand for information (μ) (*Test of H1*: Proportion of groups reporting moderate or strong interest in the event)	10.3966** (2.5942)	11.0192** (2.5978)	8.9339** (2.5444)	8.9596** (2.5457)
Average weak ties of groups participating in event	0.5030** (0.0520)	0.5122** (0.0516)	0.4282** (0.0672)	0.4289** (0.0672)
Average budget of groups participating in event	–	–	1.26e–07** (3.77e–08)	1.26e–07** (3.77e–08)
Average age of groups participating in event	–	–	0.0036 (0.0324)	0.0033 (0.0324)

Proportion of public interest groups participating in event	–	–	2.5513 (3.3442)	2.5390 (3.3411)
$\rho(\varepsilon_t)$ (Autocorrelation parameter)	–	0.0785	–	0.0049
Marginal effects of μ [Additional strong ties – for every group in the network – from a 1 SD increase in the aggregate demand for information]	1.52	1.62	1.31	1.31
Number of events (d.f.)	85 (82)	85 (82)	85 (79)	85 (79)
Adjusted R^2	0.5448	0.5586	0.5958	0.5963
F	51.27**	54.15**	25.77**	25.82**
Durbin-Watson	1.8521	1.9852	1.9724	1.9804

Note: ** Denotes significance at $p < 0.01$. * Denotes significance at $p \leq 0.05$. (All tests are two-tailed.)

Source: Laumann and Knoke (1987).

Dependent variable is the average number of strong ties among all groups participating in the event. (Standard errors in parentheses.)

Table 4. The demand for information and lobbyists' 'social' investment in strong ties

	Full model		*Reduced model*	
Variables	*Poisson*	*Negative binomial*	*Poisson*	*Negative binomial*
Constant	−0.4891	−0.6395	−0.5594	−0.6077
	(0.6349)	(1.3838)	(0.4767)	(0.8333)
Number of weak ties to groups	0.0177**	0.0193**	0.0134**	0.0143**
	(0.0026)	(0.0068)	(0.0022)	(0.0053)
Average demand for information (μ) across issues in which group i is involved (Hypothesis #1B)	6.5975**	6.1623*	3.8575*	3.7688^{+}
	(1.8175)	(3.1002)	(1.5752)	(2.1114)
ln(Budget)	0.0072	0.0168	0.0504^{+}	0.0533
	(0.0327)	(0.0607)	(0.0265)	(0.0429)
Estimated mobilization Capacity	−0.0985*	−0.0894	–	–
	(0.0478)	(0.0849)		
Estimated public Mobilization capacity	−0.0007	0.0061	–	–
	(0.0278)	(0.0531)		
Organization age (years)	0.0046**	0.0045	0.0060**	0.0057*
	(0.0017)	(0.0032)	(0.0014)	(0.0026)
Public interest group	−0.0723	−0.0521	–	–
	(0.1191)	(0.2314)		
Dispersion	–	0.2871**	–	0.3174**
		(0.0887)		(0.0873)
N	64	64	84	84
χ^2_{LLR}	112.05** (7)	41.76** (1)	106.82** (4)	65.04** (1)

Note: ** Denotes significance at $p < 0.01$. * Denotes significance at $p < 0.05$. $^{+}$ Denotes significance at $p < 0.10$. (All tests are two-tailed.)

Source: Laumann and Knoke (1987).

Maximum likelihood count regressions (Poisson and negative binomial); dependent variable is number of strong ties of group i. (Standard errors in parentheses.)

Table 2. The second is a reduced model that excludes the organizational attribute variables, except for the group's budget, from the first regression. For comparison, we also include the equivalent Poisson regressions (the negative binomial models are to be preferred, since in both versions of the model the level of dispersion of the dependent variable is significant at $p < 0.001$).

The group-level estimations provide support for Hypothesis 1B: *the greater the involvement of an interest group in issues in which the information demand is high, the greater that group's investment in strong ties, controlling for general propensity to establish ties (measured as the number of weak ties)*. In both the Poisson and negative binomial regressions in Table 4, the impact of information demand upon strong ties is estimated to be positive and statistically distinguishable from zero. The impact of information demand is substantively significant as well: in the full negative binomial regression of Table 4, the marginal impact of a standard deviation increase in information demand (0.04), with all other variables set to their means, is 1.6 more strong ties (the marginal effect of a 1 percentage-point increase is 0.39 ties). In other words, a 5 percentage-point increase in the aggregate demand for information is sufficient to lead the average group to invest in two additional strong ties. This effect is diminished in the reduced Model 4. In Model 4 a standard-deviation increase in information demand is associated with one additional strong tie (the marginal effect of a 1 percentage-point increase is 0.25 ties).

Another way of understanding the marginal effects of the aggregate demand for information is to assess the effects of a shift from the minimum (0.05, or 5% of groups) to the maximum (0.28) of the information demand variable. Holding all other variables at their means, this shift would be associated with nine additional strong ties for the average group. A shift from the first quartile of information demand (0.11, or 11% of groups) to the third quartile (0.22) yields an additional four strong ties for the average group.

Two other interpretations of these results merit discussion here. First, the marginal effects of information demand are consistent across estimations. Notice that the marginal effects from the group-level analysis of Table 4 are roughly comparable to the effects observed in the event-level analysis in Table 3. While this is not surprising, given that the two estimations are different cuts from the same sample, it is nevertheless added evidence for the consistency of our results across two different analyses of the data. Second, the observed level of information demand is precisely at the level where our model suggests that the marginal effects of this variable should be greatest – when μ is low (see Figure 3). Notice that approximately one in four groups seeks information about any given policy event. If our measurements of μ are accurate, this is precisely the range from Figure 3 where increases in μ have the greatest effect upon strong-tie investments.

Other Variables

As expected, the relationship between number of weak ties and strong ties is consistently estimated to be positive and significant. This is likely a spurious relationship, where both are positively related to the time budget that the organization devotes to making ties. The estimated effects from the political clout variables are statistically weak, but where significant, the effects are in the expected direction. For example, the ability to mobilize group membership is a measure of political clout, and in the organization-level regression (full model, Poisson) this measure of clout appears to reduce the need to establish strong ties. The effect of group budget is positive and significant in event-level analysis (and nearly so in the reduced organization-level Poisson model), suggesting that a large budget results in a capacity to develop the costlier strong ties.

The impact of organizational age on number of strong ties is estimated to be positive and significant at $p < 0.05$ in the reduced model. The relationship is also substantively significant: Taking marginal effects estimates from the reduced negative binomial model, every additional year of interest group age is associated with 0.037 strong ties. The mean of group age in our sample is 40.37 years, with a standard deviation of 37.1 years. Hence a 1 SD boost in interest group age is associated with an increase of approximately 1.5 strong ties (1.37). Moving from the minimum of the age variable (4 years) to the maximum (136 years) would yield an additional *four* strong ties. This may be because strong ties take extended periods to develop. Lobbyists can establish weak ties quickly – over a 'cocktail', perhaps.

V. Conclusion

As Milbrath's (1963: 260) respondent whom we quote in Section I notes, 'you get much better information from people who know you, know what your interests are, and know that they can trust you'. This quote usefully suggests that 1) interest groups gain much of their political and policy information through their social contacts, and 2) that the dissemination of information through social contacts follows general social rules. In particular, groups tend to give priority to their strong ties over their weak ties when they choose to convey new information. Given this rule, we develop a simulation model of information transfer among interest groups and find that the more demand for information about an event, the more a lobbyist will follow a 'chum strategy', forming more strong ties and fewer weak ties. Our statistical analyses of lobbying networks in healthcare politics in the United States provide empirical support for these arguments. We find empirically that groups involved in issues where the information demand is high tend to invest more time in developing strong-tie 'chums' than in weak-tie acquaintances.

The model has interesting implications for the efficiency of the network as a whole at informing its members. The network structure that would result in the fastest diffusion of information is one in which every group invested exclusively in weak ties; strong ties tend to be intra-clique and weak ties tend to be inter-clique, weak ties are more likely to transmit novel information. But because groups are more likely to communicate information to their strong-tie contacts, interest groups often invest in strong ties. As a result, the network structure diverges from the 'ideal', where the greater the aggregate interest and involvement of interest groups in an event, the greater the divergence. This prediction of a 'network failure', similar in structure to a prisoner's dilemma, raises empirical and normative questions of how these individual contact strategies affect the overall informedness of public policy. In particular, the model suggests that the greater the need for a well-reasoned and broad-based decision, the greater the tendency for a policy community to shatter into competing cliques that do not share information.

This article illustrates how the value of a particular strong or weak tie is contingent on the other ties in the system, and on the flow of information along those other ties. In contrast to an efficient market for information, where all exchanges are arm's length, the actual exchange of information among interest groups is governed by social rules. We focus on strong-tie priority, but there are a variety of other social rules endemic in social relationships that deserve study and that are described in the literatures on social networks, including social exchange (Emerson and Cook 1978), homophily (e.g. for interest group applications, see Hojnacki and Kimball 1998; Koenig and Braunninger 1998), and transitivity (e.g. see Holland and Leinhardt 1971, 1981). The common thread through these literatures is the principle of interdependent interconnectedness – that the interactions of any particular actor have ramifications that ripple through the system. It is this principle that we seek to insert into the research on how interest groups seek and receive information.

NOTES

We gratefully acknowledge helpful comments from John Brehm, Ken Kollman, and Paul Teske. We retain exclusive rights, of course, to any errors contained herein.

1. In a growing literature, scholars have examined the strategic problems of credibility in games of information transmission (Austen-Smith 1992; Austen-Smith and Wright 1992, 1994; Rasmussen 1993). In this article, we examine one of the preconditions of informational credibility: *the problem of information acquisition*.
2. The model we present here is based solely on the informational advantages that networks confer. See Krackhardt (1992) for a more general discussion of strong ties and weak ties.
3. This is in contrast to signaling models that assume that groups acquire policy information at some set price. See for instance Austen-Smith and Wright's definition of an 'information acquisition strategy' as a *probability of payment* for information (1992: 34).
4. Kerwin (1994: 201) notes the informational advantage of contacts as well, finding that 100% of the interest groups he surveyed reported that they monitored rule-making in part through communication with 'colleagues in other groups'. For 41.7% of these groups such communications occurred more than once a week, and for 93.2% at least once a month. Similarly, Golden (1998: 258) found that most of the groups she surveyed relied on issue networks to gather information on rule-making.
5. These limits, of course, vary by the type of information and the technology available to the communicator. Thus, many interest groups place a fair amount of information on the web (e.g. in the health policy area see the AMA website– www.ama-assn.org). However, much of the information of relevance in the lobbying world is unlikely to be disseminated through the web.
6. See, Mary Agnes Carey, 'Medicare + Choice Plan in Trouble as Insurers Line Up to Leave', *Congressional Quarterly Weekly Report*, 20 May, 2000, p. 1183.

7. This model diverges from Boorman's (1975) model in two important ways. First, Boorman makes highly restrictive assumptions about the structure of the network. The approach we take allows us to manipulate the structure of the network to examine the impact of the structure on our findings. Second, Boorman's model assumes that information may only be effectively passed on to one actor. This assumption makes more sense in the employment context, where only one person may fill a job, than in the lobbying context, where consumption of information is often at least partially non-rival. The mathematical 'apparatus' of Boorman's model is therefore quite different from the model presented in this article.
8. This corresponds to the parameter of the same label in Boorman's (1975) model, which represented the unemployment rate. Note that if $\mu = 0$ no information transmission occurs.
9. The assumptions regarding strong tie priority and the budget constraint, T, also follow from Boorman (1975).
10. The code for the simulations is available from the authors upon request.
11. In this model, asymmetric ties are distributed randomly. For example, if A has one strong tie, and it is to B, A gets information from B, and B does not necessarily get information from A. A more realistic assumption, but far more difficult to implement, is that ties will typically be symmetric – A and B exchange information – and that tie formation and maintenance will, in part, be based on that reciprocity.
12. Each interest group respondent was asked to indicate the nature of the group's lobbying activity and inactivity on a series of governmental health policy decisions between 1973 and 1980. For example, the group may have actively lobbied with a particular position, it may have just held a conference or seminar, or it may have held a position but did not actively lobby.
13. Hypotheses 1A and 1B are logically equivalent, but in testing them both on our data we are effectively checking the robustness of our empirical findings.
14. By way of analogy, imagine one were modeling consumption of individuals, where individuals' incomes varied, that no income was saved, and that individuals consumed only two goods: widgets and gadgets. Assume one was testing whether some individual-level variable, x, affected consumption of widgets. A regression of consumption of widgets on gadgets and x which yielded positive coefficients for both gadgets and x would simply indicate that, for a given level of income, x resulted in increased consumption of widgets and decreased consumption of gadgets.
15. The relative importance of information in health lobbying can be inferred from the 'sample' of issues in the Laumann and Knoke (1987) data set, which includes biomedical research issues such as DNA research and human experimentation, the organization of healthcare delivery issues such as HMOs and hospital cost containment, and regulation of food additives or medical devices.
16. The sample of organizations is not a probability sample drawn from a known population, but rather an exhaustive list of organizations that are consequential or highly visible in healthcare lobbying. An organization was deemed consequential if it appeared with some degree of regularity between 1973 and 1980 in newspaper articles covering healthcare politics, congressional hearings, *amicus* filings in federal court, health-lobbying registration lists, or was named by a panel of health politics experts. Laumann and Knoke used this method of non-random

random selection since there is no known universe for sampling health-lobbying organizations, and since it avoids selecting organizations on their degree of connectedness (see Laumann and Knoke 1987: 95). The survey informant was either the organization's executive director, government affairs or staff specialist. Laumann and Knoke had an 89.4% response rate from health-lobbying organizations yielding 135 observations (see Laumann and Knoke 1987: 97–101).

17. An AR(1) specification is added because the events analyzed in Table 3 are ordered sequentially, although the inter-event times are not equivalent. One difficulty with the dependent variable in Table 1 is that it is theoretically constrained to lie above 0, whereas ordinary least squares makes no such assumptions. However, the mean of this variable (21.86 strong ties per group) is 4 SD (5.14) away from zero.
18. The negative binomial regression estimator operates as follows. Let the dependent variable S_i be the number of strong ties of group i. The observed S_i are assumed to be generated by a negative binomial distribution with mean ξ and variance $\xi(1+\tau\xi)$. Letting $g_{\mathrm{NB}}(S_i)$ be the negative binomial probability distribution for S_i we have $g_{\mathrm{NB}} = Pr[S_i = k] = \Lambda(\tau^{-1}+k)/[\Lambda(\tau^{-1})k!]u^{1/\tau}(1-u)^k$, where $u = \tau^{-1}/(\tau^{-1}+\xi)$. The gradient and log-likelihood appear in Greene (2002).
19. The genesis of the genetic algorithm is in Holland (1975) and has found wide application to optimization problems. See Goldberg (1989) and Mitchell (1996) for overviews and guides. Social science applications include Axelrod (1997) and Andreoni and Miller (1995), among many others.
20. This index is raised to the third power so as to increase the rate of convergence. Thus, if strategy A performs 10% better than strategy B, it is 33% more likely to be chosen as a 'parent' than strategy B.

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Appendix 1: Genetic Algorithm

The genetic algorithm is a computational way of searching a large solution space that is (roughly) modeled on the evolutionary process.[19] The basic idea is that solutions, in the beginning, are randomly generated and then tested. The solutions then 'breed', where probability of breeding is positively related to performance. This process is iterated, and will usually lead to some convergence on a particular solution that performs better than other solutions. More precisely, it is assumed that:

(1) There is some population of problem solutions.
(2) Those solutions are multidimensional and may be represented numerically on each dimension.

(3) After some test or set of tests, new solutions are generated from the old solutions, where old solutions are spliced together to generate new solutions. The probability that a given old solution will be chosen is monotonically related to its performance in the set of tests. This testing, selection, and splicing process will usually continue over a period of time.
(4) Often, in addition to the splicing process, there is a mutation process, where, on a given dimension of a particular 'offspring' strategy, there is some probability that a value on that dimension will be randomly chosen, rather than selected from a parent.

Thus, in the simulation in this article, there is:

(1) A population of N strategies (100 in the simulations summarized).
(2) These strategies are 10 dimensional, one dimension for each value of μ. Each dimension may have $T/\lambda + 1$ values (this is the maximum number of strong ties). Thus, for example, in the simulations summarized in the article, each dimension may have a value between 0 and 10. Each NSS may have one of $10^{(T/\lambda)+1}$ values (10^{11} in the simulations summarized).
(3) The strategies are tested by measuring average informedness over S events ($S = 200$ in the article). Each event is made up of R rounds ($R = 5$ in the simulations summarized). For a given event, a group's informedness is the fraction of the rounds in which that group was informed. Thus, if a group was informed 3 out of the 5 rounds, its informedness in that event was 0.6. Only the performance of those groups that need information in a given event and do not have it at the beginning of the event is counted in assessing the performance of a group. After S rounds an index of average informedness over those rounds will be generated. This index is used in choosing the 'parents' of new strategies, where N pairs of parents will be chosen to generate N new strategies. For each pairing, the probability that a given strategy will be chosen as a parent is proportional to the average informedness of that strategy raised to the third power.[20] For a given pair, an offspring is generated by randomly choosing five dimensions from each parent. In the above simulations, this process is repeated 200 times for each simulation.
(4) There is a mutation probability (= 0.01 in the simulations summarized) where, for each dimension, a value not from the

offspring's parents might be chosen (from a uniform distribution over the range of possible values of number of strong tie choices).

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