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TESTING MULTITHEORETICAL, MULTILEVEL HYPOTHESES ABOUT ORGANIZATIONAL NETWORKS: AN ANALYTIC FRAMEWORK AND EMPIRICAL EXAMPLE

NOSHIR S. CONTRACTOR
University of Illinois at Urbana-Champaign

STANLEY WASSERMAN
Indiana University and
Visible Path Corporation

KATHERINE FAUST
University of California, Irvine

Network forms of organization, unlike hierarchies or marketplaces, are agile and are constantly adapting as new links are added and dysfunctional ones dropped. We review some of the theoretical and methodological accomplishments and challenges of contemporary research on organizational networks. We then offer an analytic framework that can be used to specify and statistically test simultaneously multilevel, multitheoretical hypotheses about the structural tendencies of organizational networks. We conclude with an empirical study illustrating some of the capabilities of this framework.

The past decade has witnessed considerable scholarly interest in conceptualizing twenty-first-century organizational forms as "network organizations" (Miles & Snow, 1995; Monge & Fulk, 1999; Nohria, 1992; Poole, 1999; Powell, 1990). The network organization, these advocates argue, will supplant bureaucracies (and their descendants, the multidivisional form and the matrix form) as the twenty-first-century organizational coin of the realm. Network forms of organization are neither vertically organized hierarchies like their bureaucratic predecessors nor unorganized marketplaces governed by supply and demand (Powell, 1990; Williamson, 1991). Rather, network organizational forms use flexible, dynamic communication linkages to connect multiple organizations and people into new entities that can create products or services. These new forms are agile and are constantly adapting as new links are added and dysfunctional ones dropped. Thus, the evolving, emerging network form *is* the organization.

The changes looming in the organizational landscape signal the need for a new generation of organizational theory and research that responds to the assumptions, aspirations, and adversities that will characterize these twenty-first-century organizational forms. While there has been a long-standing interest in the study of organizations from a social network perspective (for reviews, see Krackhardt & Brass, 1994; Mizruchi & Galaskiewicz, 1994; Monge & Eisenberg, 1987), the fundamental changes outlined above suggest that the research agenda needs to evolve from studying networks in (or between) organizations to grappling with the notion that the network *is* the organization. This nuanced yet significant change in perspective has substantial—and substantive—implications for the deployment of a comprehensive network analytic framework to specify and statistically model the structural tendencies of network forms on the basis of multiple theories and at

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multiple levels of analysis. Toward that goal, we begin by reviewing some of the theoretical and methodological accomplishments and challenges of contemporary research on organizational networks. We then offer an analytic framework that can be used to specify and statistically test *simultaneously* multilevel, multitheoretical hypotheses about the structural tendencies of organizational networks. We conclude with an empirical study that illustrates some of the capabilities of this framework.

RECONCEPTUALIZING ORGANIZATIONS AS NETWORKS

A social network consists of a set of actors and one or more relations between the actors. The network perspective is flexible in its applicability to different kinds of actors and to different kinds of relations. Actors may be any kind of meaningful social unit, including individuals, collective entities, firms, organizations, and divisions within organizations, as well as nonhuman agents, such as knowledge repositories (Carley, 2002; Contractor, 2002; Contractor & Monge, 2002). The relations may be any kind of linkage between actors, including formal role relations, affective expressions (friendship, respect), social interactions, workflows, transfers of material resources (money, goods), publishing and retrieval of knowledge, flows of nonmaterial resources (information, advice), and business alliances, to name but a few.

The social network approach to organizations is entirely fitting, since, as O'Reilly observes, "Organizations are fundamentally relational entities" (1991: 446). The focus on relations naturally leads to representation and analysis of organizations as social networks. Indeed, Nohria asserts, "All organizations are in important respects social networks and need to be addressed and analyzed as such" (1992: 4). Moreover, this claim holds whether the focus is on interacting individuals within a single organization, divisions within a firm, or networks of interacting firms. Again, Nohria notes these different levels of foci: "The premise that organizations are networks of recurring relationships applies to organizations at any level of analysis—small and large groups, subunits of organizations, entire organizations, regions, industries, national economies, and even the organization of the world system" (1992: 4).

As we enter the new millennium, the new network forms of organizing, precipitated by technological developments, are eroding the distinction between formal and emergent structural categories that traditionally have been used to characterize organizations. Contrary to traditional views, contemporary organizations are increasingly constructed out of ephemeral communication linkages, where the

> networks of relations span across the entire organization, unimpeded by preordained formal structures and fluid enough to adapt to immediate technological demands. These relations can be multiple and complex. But one characteristic they share is that they *emerge* in the organization, they are not preplanned (Krackhardt, 1994: 218).

These developments offer new challenges for future research on organizational networks both from a theoretical and a methodological standpoint.

THEORETICAL AND METHODOLOGICAL CHALLENGES

Theoretically, the increasing irrelevance of research contrasting formal and emergent structures has prompted researchers to advocate a shift in focus from examining "emergent" (i.e., informal) networks to understanding the "emergence" of organizational networks. In other words, the focus has shifted toward modeling the dynamics through which flexible organizational forms emerge. Based on a review of the empirical literature, Monge and Contractor (2001) identify nine families of theoretical mechanisms that have been used to explain the creation, maintenance, dissolution, and reconstitution of organizational networks. These are (1) theories of self-interest, (2) theories of mutual interest and collective action, (3) cognitive theories, (4) cognitive consistency theories, (5) contagion theories, (6) exchange and dependency theories, (7) homophily theories, (8) proximity theories, and (9) theories of network evolution and coevolution. The theoretical mechanisms are summarized in Table 1.

Monge and Contractor's review demonstrates four theoretical implications for studying the emergence of organizational networks. First, a wide array of social theories are amenable to

TABLE 1
Selected Social Theories and Their Theoretical Mechanisms

Theories	Theoretical Mechanisms
Self-interest theories	Individual value maximization
Social capital	Investments in opportunities
Structural holes	Control of information flow
Transaction costs	Cost minimization
Mutual self-interest and collective action theories	Joint value maximization
Public good	Inducements to contribute
Critical mass	Number of people with resources and interests
Cognitive theories	Cognitive mechanisms leading to
Semantic/knowledge networks	Shared interpretations/expertise
Cognitive social structures	Similarity in perceptual structures
Cognitive consistency theories	Choices based on consistency
Balance	Drive to avoid imbalance and restore balance
Cognitive dissonance	Drive to reduce dissonance
Contagion theories	Exposure to contact leading to
Social information processing	Social influence
Social learning	Imitation, modeling
Institutional	Mimetic behavior
Structural theory of action	Similar positions in structure and roles
Exchange and dependence theories	Exchange of valued resources
Social exchange	Equality of exchange
Resource dependence	Inequality of exchange
Network exchange	Complex calculi for balance
Homophily theories	Choices based on similarity
Social comparison	Choose comparable others
Social identity	Choose based on own group identity
Proximity theories	Choices based on proximity
Physical proximity	Influence of distance
Electronic proximity	Influence of accessibility
Network evolution and coevolution theories	Variation, selection, retention
Organizational ecology	Competition for scarce resources
Complex adaptive systems	Network density and complexity

network formulations. Second, in some cases, different theories, using similar theoretical mechanisms, offer similar explanations but at different levels of analysis. Third, different theoretical mechanisms sometimes offer complementary as well as contradictory explanations at the same level of analysis. Fourth, there is considerable variation in the depth of conceptual development and empirical research across the different theories and theoretical mechanisms. Thus, their review highlights the need for network research that is not only theoretically motivated but also cognizant of incorporating multiple theoretical mechanisms at multiple levels of analysis.

Methodologically, the shift in focus from examining emergent networks to explaining emergence has challenged network analysts to make three moves: from (1) exploratory and descriptive techniques to confirmatory and inferential techniques, (2) single-level, single-theoretical network analyses to multitheoretical, multilevel analyses, and (3) purely network explanations to hybrid models that also include attributes of the actors. These are discussed in greater detail below.

Confirmatory Network Analysis

In the past two decades there has been considerable progress in the development of descriptive network metrics. Since network data are, by definition, relational, nonindependent observations, "standard" statistical methods that assume independent units simply are not appropriate. The efforts to develop statistical models for network processes have been relatively sparse, disparate, and esoteric, thereby making them inaccessible to the larger research community (see Part V of Wasserman & Faust, 1994). For instance, there are measures that can be used to describe the level of reciprocity in a network—that is, the extent to which communication links from actor A to actor B are reciprocated, for all pairs in the network, and there are statistical tests of whether the level of reciprocity in a network is more than one would expect by chance (Wasserman & Faust, 1994: Chapter 13). However, standard statistical procedures cannot be applied to determine if the number of triangles in the network (a property of triples of actors, all of whom are tied to each other) is greater than expected, given the number of two-stars (an actor connected to two others). Testing such a hypothesis is problematic, because the triads are not independent of one another.

Multilevel Network Analysis

One of the key advantages of a network perspective is the ability to collect, collate, and study data at various levels of analysis (actor, dyadic, triadic, group, organizational, and interorganizational). However, for the purposes of analysis, most network data are either transformed to a single level of analysis (e.g., the actor or the dyadic level), which necessarily loses some of the richness in the data, or are analyzed separately at different levels of analysis, thus precluding direct comparisons of theoretical influences at different levels. For instance, social exchange theory suggests that the tendency to have a communication tie from actor A to actor B is predicated on the presence of a communication tie from actor B to actor A. However, balance theory suggests that the tendency to have a communication tie from actor A to actor B is predicated on the configuration of ties the two actors have with third actors, C through, say, Z.

While social exchange theory makes a prediction at the dyadic level, balance theory makes a prediction at the triadic level. Jones, Hesterly, and Borgatti extend this dilemma even beyond the triadic level, noting that although many organizational studies adopt a network perspective, "these studies most often focus on exchange dyads, rather than on the network's overall structure or architecture" (1997: 912). Yet, by limiting attention to dyads and ignoring the larger structural context, "these studies cannot show adequately how the network structure influences exchanges" (Jones et al., 1997: 912). This is the problem of "dyadic atomization" noted by Granovetter (1992).

Gnyawali and Madhavan (2001) propose a multilevel network model for capturing competitive dynamics phenomena. At the actor level, they propose firm network centrality and structural autonomy; at the dyadic level, they propose structural equivalence; and at the global level, they propose network density as influencing "(1) the likelihood of a firm's initiating a competitive action . . . and (2) the likelihood of a competitor responding to that action" (Gnyawali & Madhavan, 2001: 434). However, as they acknowledge, while network analysis offers independent statistical tests for theoretical predictions at each of these levels of analysis, combining and comparing effects simultaneously necessitates an analytic framework that offers multilevel hypothesis testing. In fact, it is often difficult to determine the appropriate level at which a network property applies. Two actors are structurally equivalent if they occupy identical structural positions; thus, structural equivalence might be viewed as a dyadic property, yet determining the nature and identity of the positions requires information about global properties of the network. Indeed, the opportunities and challenges of multilevel theory building extend beyond just the study of organizational networks (Klein, Tosi, & Cannella, 1999).

Hybrid Network Attribute Models

There has been a long-standing debate among structural scholars about the merits and feasibility of incorporating information about an actor's attributes (e.g., an individual's organizational affiliation in an interorganizational network) into studies examining the actor's network (Wellman, 1988). Setting aside the "Simmelian sensibility" (Wellman, 1988: 25) of the formalists, who dismiss the utility of looking at actors' attributes, the majority of network scholars embrace the idea but are deterred by the feasibility of creating hybrid models that incorporate information about actors' attributes to explain their network patterns. Although there has been considerable empirical network research that incorporates data on actors' attributes, these studies are often limited, as described previously, to one level of analysis. For instance, theories of homophily would suggest that in an interorganizational network actors with similar organizational affiliations are more likely to have communication ties with one another than with actors from other organizations. In a potentially conflicting prediction, theories of collective action would argue that actors with similar organizational affiliations are more likely to be structured in centralized networks among themselves than with actors across different organizations. Thus, theories of collective action lead to the expectation that ties will not be more likely between actors with similar characteristics. Simultaneously combining and contrasting these two predictions involving actors' attributes goes beyond the capabilities of most contemporary network analytic methods.

In summary, there is a pressing need for organizational network analyses to extend the focus from descriptive network metrics to statistical approaches. These statistical techniques need to simultaneously incorporate multiple theoretical explanations at all relevant levels of analysis—the actor, dyadic, triadic, and, possibly, even the global level. Further, techniques need to incorporate theoretical explanations that are based on information about the actors' attributes.

We now describe an analytic model that considers the genres of multitheoretical, multilevel hypotheses that might influence the structural tendencies of a network. This model has three potential benefits. First, it serves as a template to stimulate a conscious attempt to specify hypotheses grounded in multiple theories and at multiple levels. Second, it seeks to make the appropriate selection and deployment of network statistical techniques more accessible to the larger research community, rather than remaining in the hands of the network methodologists. Finally, it serves network methodologists by highlighting attention on the theoretically challenging areas where there remains a need to develop new statistical techniques.

MULTITHEORETICAL, MULTILEVEL MODELS

We adopt the position that network organizational forms need to be studied as relational systems; consequently, we now introduce a statistical vocabulary for investigating hypotheses about the relational properties of organizations as social networks. The focus is on hypotheses that are explicitly relational and, thus, make claims about the patterns or structures of organizational networks. The problem is that since these hypotheses concern interdependencies (relations) among actors, they are not testable using "standard" statistical methods that assume independent observations. To overcome this obstacle, in this section we frame these hypotheses in terms of the probabilities of *graph realizations* with specific structural tendencies. The section begins by introducing the notion of graph realization and the logic of statistical modeling of social networks using random graph models.

Graph theorists use the term *graph* to describe a network. Here we assume that the graph under consideration is random; hence, the observed network (i.e., the empirical data) is only one graph realization among (usually) many theoretical possibilities. Consider an interorganizational consortium of 17 members representing various industry and government organizations. The observed communication network (i.e., the data collected) is one realization of a graph consisting of 17 nodes and the possible ties (or edges) among them.

Theoretically, there are many possible graphs that could arise on communication ties among the 17 members. All of these are possible graph realizations. The number of possible graph realizations can be quite large. In a network of 17 individuals, each individual can have ties to 16 other individuals. Hence, the network of 17 individuals can have a total of 272 (17 times 16) ties. If the ties are dichotomous (i.e., ties to individuals are either present or absent) and the relation is directed (the graph is a *directed graph*), each of the 272 ties can be in one of two states. Hence, there are 2^{272} possible configurations of the network, or approximately 7.5885×10^{81}—that is, the number of configurations is over 7 followed by 81 zeros! The set of possible configurations of the network is referred to as the *sample space* (Wasserman & Faust, 1994).

The observed network is only one of these possible graph realizations. It is worth noting that we are interested in graphs with a fixed numbers of nodes. So, in the example above, the sample space only comprises graphs on 17 nodes. This distinguishes the focus of our research from sections of mathematical graph theory where node numbers are allowed to increase with a view to determining asymptotic results or phase transitions as networks reach a certain size.

The probability of the observed graph relates to the probability distribution across the sample space. For instance, the probability of the observed graph is vastly different in the uniform distribution of graphs (in which case it is very small indeed!) compared to certain other distributions. Hypotheses about network properties in effect pick out different types of graphs as more probable within the sample space. There is nothing unusual about this: it is exactly the same logic for statistical inference regarding individuals, the only difference being that we have a distribution of graphs, rather than a distribution of individual scores. The question of interest in statistical modeling of social networks is whether the observed graph realization exhibits certain hypothesized structural tendencies. The extent to which these tendencies are exhibited is captured by parameters, which are estimated by quantifying the effects of the hypothesized structural property on the probability of ties being present or absent in the network. These parameters describe a distribution of graphs with the hypothesized properties, in which the observed graph is the most typical representative. If a parameter is statistically significant, then the hypothesized property is statistically important for understanding the structural tendencies of the observed network.

This logic is central to random graph models and to statistical models including Markov random graph models (Frank & Strauss, 1986; Strauss & Ikeda, 1990) and the p^* family of models (Anderson, Wasserman, & Crouch, 1999; Pattison & Robins, 2002; Pattison & Wasserman, 1999; Robins, Elliott, & Pattison, 2001; Robins, Pattison, & Wasserman, 1999; Wasserman & Pattison, 1996). In many of these models, nodes are assumed to be homogeneous—that is, they do not have distinguishing labels. As a consequence, graphs of the same type may have relatively large probabilities if graphs that are *isomorphic* are considered to be equivalent.

Table 2 summarizes various genres of network hypotheses in terms of the probabilities graph realizations will exhibit the hypothesized relational property. In each case, the hypothesis is that graph realizations with the hypothesized property have larger probabilities of being observed. In other words, the probability of ties being present or absent in the graph reflects the hypothesized relational property. Consistent with the multilevel focus of the hypotheses that we investigate, these models allow conclusions both about global network properties (the probability of the graph or, more precisely, the nature of the graph distribution) and about the probability of network ties, given properties of their surrounding network (a local property).

Table 2 begins by distinguishing endogenous and exogenous variables that influence the probability of ties being present or absent in the focal network. It should be noted that the exogenous-endogenous distinction being made here is not equivalent to similar terminology used in the development of causal models in general and structural equation models in particular. Unlike their use in causal modeling, endogenous variables here are not predicted by exogenous variables. Rather, both explain structural tendencies of the network. Structural tendencies based on configurations of the focal relation itself—in this case, the communication relation—are defined as *endogenous variables*. In contrast, structural tendencies that incorporate factors other than the focal relation itself—for instance, the attributes of actors in the network—are defined as *exogenous variables*. Hence, all variables "outside" the focal communication relation are defined as exogenous variables.

Endogenous variables (rows 1 through 4 in Table 2) refer to various relational properties of the focal network itself that influence the probability ties will be present or absent in the same network. From a metatheoretical perspective, these endogenous variables capture the extent to which relational properties of the network influence its self-organization. It is important to clarify that, as in any attempt to explain self-organization, endogenous variables do not represent a tautology or circularity in argument. Instead, they suggest that the configuration of ties in the observed realization reflects an underlying structural tendency that is consistent with the hypothesized network property. Exogenous variables (rows 5 through 10 in Table 2) refer to various properties outside the focal network that influence the probability ties will be present or absent in the focal network. Hence, exogenous variables include the attributes of the actors in the network and additional network relations among the actors, as well as the same network relation at previous points in time. Within each of these two categories (i.e., endogenous and exogenous variables), the table

TABLE 2
Summary of a Multilevel, Multitheoretical Framework to Test Hypotheses About Organizational Networks
Null Hypothesis: All Ties Are Independent with Equal Probability

Independent Variable	Examples of Specific Measures	Hypotheses: Graph realizations where . . .
1. Endogenous (same network): *actor level*	Actor structural autonomy	. . . high structural autonomy has a higher probability of occurring (e.g., *theory of structural holes*)
2. Endogenous (same network): *dyadic level*	Mutuality, reciprocation	. . . high mutuality has a higher probability of occurring (e.g., *social exchange theory*)
3. Endogenous (same network): *triadic level*	Transitivity, cyclicality	. . .high cyclicality has a higher probability of occurring (e.g., *balance theory*)
4. Endogenous (same network): *global level*	Network centralization	. . . high centralization has a higher probability of occurring (e.g., *collective action theory*)
5. Exogenous (shared actor attributes): *actor level*	Age, gender, organization type, education	. . . ties between actors with similar attributes have a higher probability of occurring (e.g., *theories of homophily*)
6. Exogenous (shared actor attributes): *dyadic level*	Differential mutuality and reciprocation	. . . mutual ties between actors with similar attributes have a higher probability of occurring (e.g., *exchange theory*)
7. Exogenous (shared actor attributes): *triadic level*	Differential transitivity and cyclicality	. . . transitive (or cyclical) ties between actors with similar attributes have a higher probability of occurring (e.g., *balance theory*)
8. Exogenous (shared actor attributes): *global level*	Differential network centralization	. . . network centralization among actors with similar attributes has a higher probability of occurring (e.g., *collective action theory*)
9. Exogenous (network): *other relations*	Advice, friendship network	. . . communication ties co-occuring with ties on a second relation have a higher probability of occurring (e.g., *cognitive theories*)
10. Exogenous (network): *same relation at previous point in time*	Communication network	. . . ties between actors co-occurring with ties at preceding points in time have a higher probability of occurring (e.g., *evolutionary theories*)

offers a further subclassification based on the extent to which the probability of ties being present or absent in the network is influenced by properties at the actor, dyadic, triadic, and global levels.

In the remainder of this section, we review the influence of endogenous variables and discuss the exogenous variables at each of the actor, dyadic, triadic, and global levels. We make a concerted effort to illustrate each of these categories and subcategories by using hypotheses derived from the nine families of theoretical mechanisms for the emergence of organizational networks identified by Monge and Contractor (2001).

Endogenous Influences on Network Structural Tendencies

Actor level. The actor level refers to various actor-level network properties that influence the probability ties will be present or absent in the network. In the case of endogenous variables (row 1 in Table 2), these actor-level properties could include network metrics, such as an actor's centrality, prestige, or structural autonomy in the network. These are actor-level properties because they characterize the position of an individual actor in the network. For instance, the *theory of structural holes* (Burt, 1992) suggests that actors seek to enhance their structural autonomy by forging ties with two or more unconnected others, thus creating indirect ties between the people with whom they are linked. This hypothesis would be supported if there were greater probabilities for graph realizations in which actors had a high degree of structural autonomy. In other words, this hypothesis would be supported if the probability of ties being present or absent in the network reflected actors' tendencies to exhibit structural autonomy.

Figure 1 shows a hypothetical six-person network. If there is a tendency for actors to abide by the *theory of structural holes*, actor A is less likely (shown with a negative sign) to have a tie with actor C, because it would be redundant with the indirect tie actor A has with actor C via actor B. However, there will be a greater tendency (represented with a positive sign) for actor A to have a tie with actor D, since this would represent a nonredundant tie.

It is worth noting here, and in the discussions accompanying Figures 2 through 10, that we are describing probabilistic tendencies for ties to be present or absent. Therefore, in Figure 1, there may well be some occasions where a tie exists from A to C. However, the probability of these ties will diminish if there are ties from actor A to actor B and from actor B to actor C.

Dyadic level. The dyadic level refers to various dyadic counts that influence the probability ties will be present or absent in the network. In the case of endogenous variables (row 2 in Table 2), these dyadic-level properties could include mutuality and reciprocation. For instance, *theories of social exchange* (Blau, 1964; Homans; 1958), *network exchange* (Willer & Skvoretz, 1997), and *resource dependence* (Emerson, 1972a,b; Pfeffer & Salancik, 1978) suggest that actors (individuals or organizations) forge ties using a calculus of exchange of material or information resources. In its most elemental form, this hypothesis would be supported if there were greater probabilities for graph realizations in which pairs of actors had a high degree of reciprocated (or mutual) ties. In other words, this hypothesis would be supported if the probability of ties being present or absent in the network reflected actors' tendencies to exhibit mutuality or reciprocity.

In Figure 2, social exchange theory would suggest a positive tendency for a tie from actor F to actor A, since it would reciprocate the tie from actor A to actor F. However, social exchange theory would posit a negative tendency for a tie from actor D to actor C, since it would not reciprocate a tie from actor C to actor D.

This example also offers a simple illustration of the cross-level implication of a dyadic-level theoretical mechanism. By increasing the tendency of reciprocity at the "local" dyadic level, we observe a graph with a large proportion of reciprocated ties, with implications for global outcomes.

Triadic level. The triadic level refers to various triadic network configurations that influence the probability ties will be present or absent in the network. In the case of endogenous

FIGURE 1
Endogenous Actor Level: Structural Hole Theory

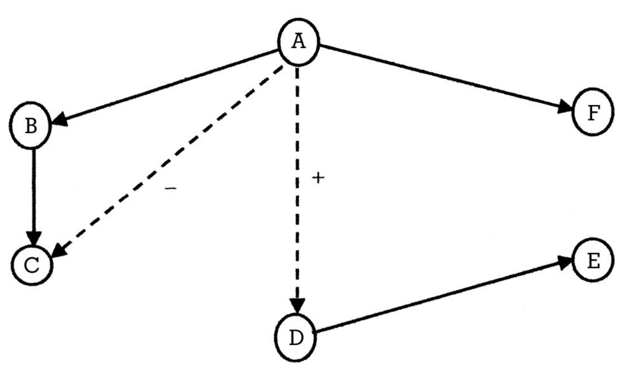
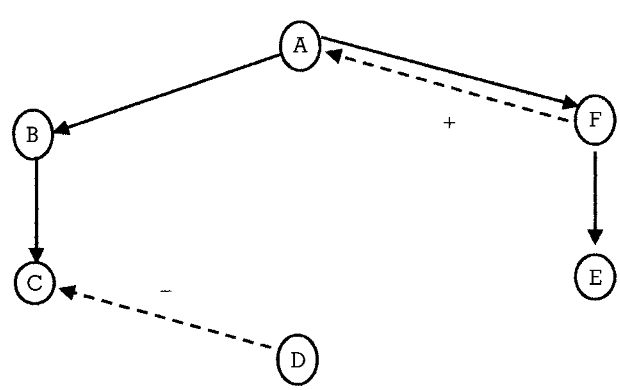


FIGURE 2
Endogenous Dyadic Level: Social Exchange Theory



variables (row 3 in Table 2), these triadic-level properties include transitivity or cyclicality. A triad is *transitive* if, when actor A has a tie to actor B and actor B has a tie to a third actor, C, actor A has a tie to actor C. Tendencies for transitivity can be interpreted in a number of ways, depending on the substance of the relation under study. If the relation is one of sentiment (such as liking or friendship), then *theories of cognitive balance* (Heider, 1958; Holland & Leinhardt, 1975, 1981) suggest a tendency toward consistency in relations. Colloquially, a friend's friend should be one's own friend, and one should like one's friend's friends. In contrast, transitivity in formal relations, such as exercise of authority, reflects a hierarchical tendency—one's boss's boss is also one's boss. Hypotheses about transitive behavior would be supported if there were greater probabilities for graph realizations in which triads of actors in the network exhibited a high degree of transitivity.

Cyclicality in triads occurs when there is a tie from actor A to actor B, a tie from actor B to actor C, and a tie from actor C to actor A, completing the cycle. Interpretation of cyclicality depends on the substance of the relation. When the tie is one of flow of resources (such as doing favors or providing information), then cyclicality can be thought of as illustrating the *theory of generalized exchange* (Bearman, 1997). Actor A does a favor for B, and B, rather than return the favor directly to A, does a favor for C, who, in turn, does a favor for A, returning A's favor to B indirectly. Hypotheses about cyclical behavior would be supported if there were greater probabilities for graph realizations in which triads of actors in the network exhibited a high degree of cyclicality.

In Figure 3, theories of balance would posit a greater tendency for actor A to have a tie to actor C, because actor A has a tie to actor B and actor B has a tie with actor C. However, theories of balance would posit less tendency for a tie from actor A to actor E, because it does not complete a triad.

Global level. The global level refers to overall network measures that influence the probability ties will be present or absent in the network. In the case of endogenous variables (row 4 in Table 2), these global properties include the network's degree of centralization. A network has a high degree of centralization when some actors in the network have a much higher degree of centrality than other actors in the network. For instance, *theories of collective action* (Coleman, 1973, 1986; Marwell & Oliver, 1993) and *public goods theories* (Fulk, Flanagin, Kalman, Monge, & Ryan, 1996; Monge et al., 1998) suggest that actors in a network are more likely to obtain a collective good if the network is centralized (Marwell, Oliver, & Prahl, 1988). This hypothesis would be supported if there were greater probabilities for graph realizations in which networks had a high degree of centralization. In other words, this hypothesis would be supported if the probability of ties being present or absent in the network reflected the network's tendencies to exhibit a high degree of centralization.

In Figure 4, theories of collective action would suggest that actor A has a greater tendency to forge a tie with actor E, since the tie enhances the relative centrality of actor E and thereby the overall network's centralization.

FIGURE 3
Endogenous Triadic Level: Balance Theory

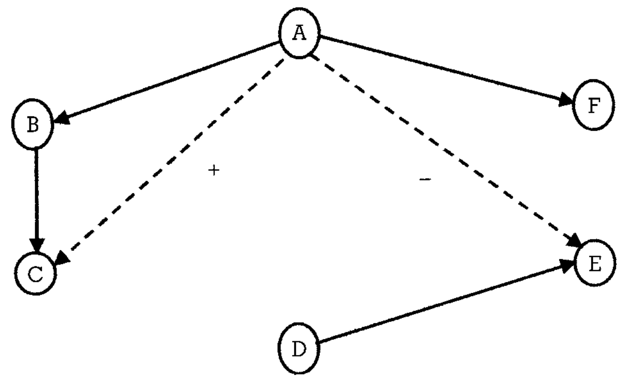
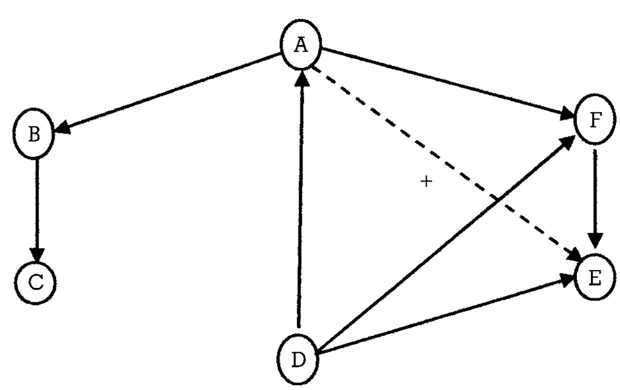


FIGURE 4
Endogenous Global Level: Collective Action Theory



Exogenous Influences on Network Structural Tendencies

In addition to the influence of actor, dyadic, triadic, and global properties of the endogenous variable (i.e., the focal network itself), exogenous variables (i.e., various properties outside the focal network) also influence the probability ties will be present or absent in the focal network. As mentioned earlier, these exogenous variables include attributes of the actors in the network (rows 5 through 8 in Table 2), as well as additional networks of relations among the actors (row 9 in Table 2) and the same network of relations at previous points in time (row 10 in Table 2). These cases are discussed below. While rows 1 through 4 consider structural tendencies for the formation of network ties between any two actors, rows 5 through 8 consider the structural tendency for *differential* network tie formation specifically among actors who also share common attributes, such as organizational affiliation. It is worth noting that, in some cases, the differential network tie formation may be privileged among actors who do *not* share common attributes—for instance, buyers and sellers. While our illustration here focuses on theories of homophily that posit ties among similar actors, theories of exchange might well posit ties among actors who differ in certain attributes.

Actor level. The actor level for exogenous variables (row 5 in Table 2) refers to various actor attributes that influence the probability ties will be present or absent in the network. These actor-level properties include such attributes as age, gender, membership in an organization, and the type of organization. For instance, *theories of homophily* suggest that individuals have ties to others with whom they share similar attributes. Homophily has been studied on the basis of similarity in age, gender, education, prestige, social class, tenure, and occupation (e.g., Coleman, 1957; Ibarra, 1992, 1993, 1995; McPherson, Smith-Lovin, & Cook 2001). Hypotheses based on homophily would be supported if there were greater probabilities for graph realizations in which actors with shared attributes were more likely to have ties with one another. In other words, these hypotheses would be supported if the probabilities of ties being present or absent in the network reflected actors' tendencies to choose others with similar attributes.

Figure 5 indicates that theories of homophily would posit a greater tendency for a tie from actor A to actor C, since they both share a common attribute (both being from government), and a lower tendency for a tie from actor A to actor E, because they do not share a common attribute (actor F being from industry).

Dyadic level. The dyadic level for exogenous variables (row 6 in Table 2) refers to various shared attributes that influence the probability ties will be present or absent in the network. These dyadic-level properties include mutuality and reciprocation (defined previously in the discussion of row 2 in Table 2). In an *extension of the theories of social exchange and resource dependence,* the argument proposed here is that there is a greater tendency for exchange ties (i.e., mutual or reciprocated ties) to occur among pairs of actors who share similar attributes. Hypotheses based on this *differential mutuality or reciprocation* would be supported if there were greater probabilities for graph realizations in which actors with shared attributes were more likely to have mutual (or reciprocated) ties with one another. In other words, these hypotheses would be supported if the probability of ties being present or absent in the network reflected actors' tendencies to reciprocate ties with other actors sharing similar attributes.

Figure 6 shows how theories of resource dependence would posit a greater tendency for mutual ties between government actors A and B

FIGURE 5
Exogenous Attribute Actor Level: Homophily Theories

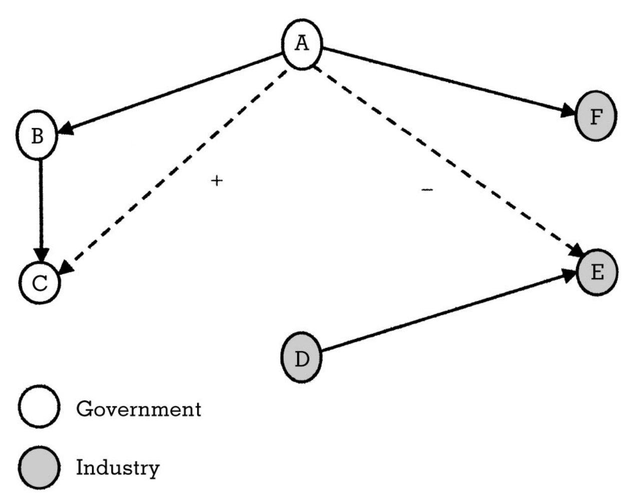


FIGURE 6
Exogenous Attribute Dyadic Level: Resource Dependence Theory

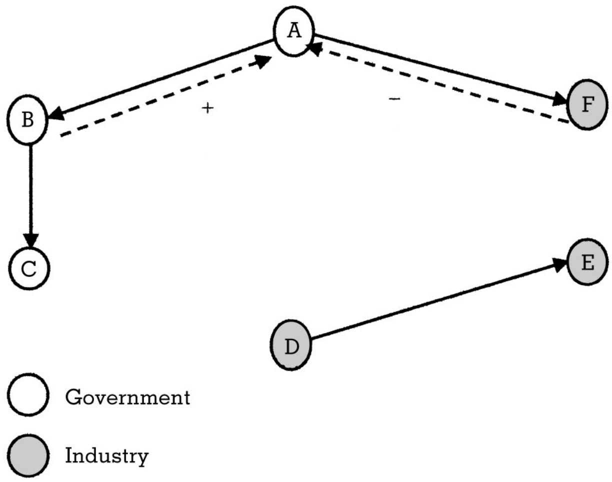
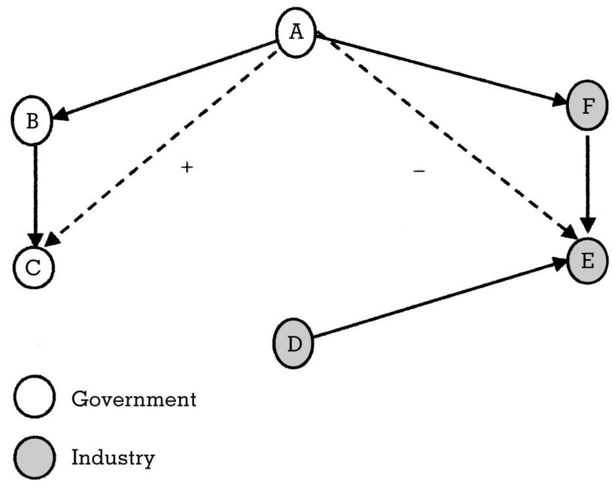


FIGURE 7
Exogenous Attribute Triadic Level: Balance Theory



and a lower tendency for mutuality between government actor A and industry actor F.

Triadic level. The triadic level for exogenous variables (row 7 in Table 2) refers to various shared triadic attributes that influence the probability ties will be present or absent in the network. These triadic-level properties include transitivity and cyclicality (defined previously in the discussion of row 3 in Table 2). In an *extension of the theories of cognitive balance and generalized exchange,* the argument proposed here is that there is a greater tendency for transitive and cyclical ties, respectively, among actors who share similar attributes. Hypotheses based on this *differential transitivity and cyclicality* would be supported if there were greater probabilities for graph realizations in which actors with shared attributes were more likely to have transitive and cyclical ties with one another. In other words, these hypotheses would be supported if the probability of ties being present or absent in the network reflected actors' tendencies to engage in transitive or cyclical relations with other actors sharing similar attributes.

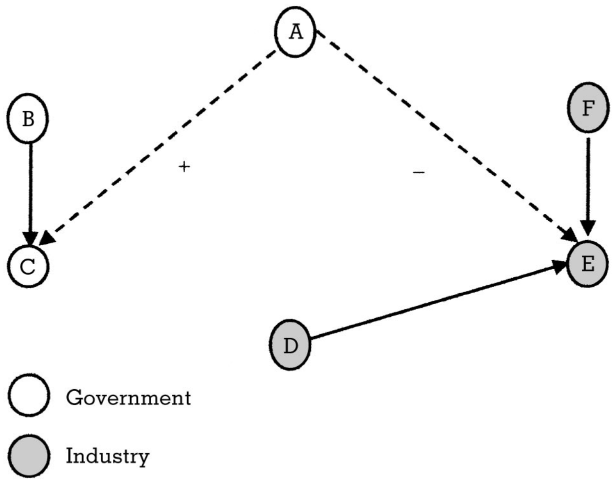
Figure 7 indicates that theories of cognitive balance would posit a greater tendency for a tie from actor A to actor C, since it completes a transitive triad among government actors. However, there is a lower tendency for a tie from actor A to actor E, since it completes a triad that includes both government and industry actors.

Global level. The global level for exogenous variables (row 8 in Table 2) refers to various shared global attributes that influence the probability ties will be present or absent in the network. These global properties include network centralization (defined previously in the discussion of row 4 in Table 2). In an *extension of the theories of collective action and public goods,* the argument proposed here is that there is a greater tendency for network centralization to occur among subgroups of actors who share similar attributes. Hypotheses based on *differential network centralization* would be supported if there were greater probabilities for graph realizations in which actors with shared attributes were more likely to have higher levels of subgroup network centralization. In other words, these hypotheses would be supported if the probability of ties being present or absent in the network reflected actors' tendencies to forge more centralized subgroup networks with other actors sharing similar attributes.

In Figure 8, theories of collective action would suggest a greater tendency for a tie from actor A to fellow government actor C, since it would enhance the centralization within government actors, but a lower tendency for a tie from actor A to industry actor E, since it would enhance centralization between government and industry actors.

Other relations in the network. In addition to attributes of the actors, additional relations

FIGURE 8
Exogenous Attribute Global Level: Collective Action Theory



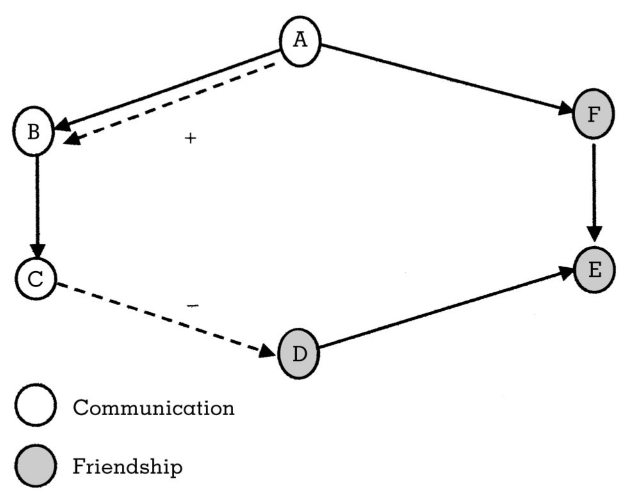
among the actors represent a second set of exogenous variables that influence the probability ties will be present or absent in the focal network (row 9 in Table 2). For instance, the *convergence theory of communication* (Richards & Seary, 1997; Rogers & Kincaid, 1981), *cognitive theories* (Carley, 1986; Carley & Krackhardt, 1996; Krackhardt, 1987a; Stohl, 1993), and *transactive memory theory* (Hollingshead, 1998; Moreland, 1999; Wegner, 1995) offer arguments that can be used to map the influence of actors' cognitive or semantic networks (Monge & Eisenberg, 1987) onto their communication networks. These theories argue that the presence or absence of a cognitive or semantic tie between these actors is associated with the presence or absence of a communication tie between the actors. Hypotheses based on the influence of exogenous networks would be supported if there were greater probabilities for graph realizations in which the actors' ties in the focal network corresponded to their ties in the exogenous networks. In other words, these hypotheses would be supported if the probability of ties being present or absent in the focal network reflected the presence or absence of ties in the exogenous networks.

It may appear that the objective sought here could be obtained far more easily by computing a simple correlation between the two relations in the network. While that is indeed the case, the lack of independence among the observations and the fact that the individual variables under study are usually dichotomous preclude the use of standard statistical techniques to assess the significance of this correlation. Techniques introduced by Hubert (Hubert 1978; Hubert & Schultz 1976) based on permutation tests (one of the solutions to the Quadratic Assignment Problem) have been used to test the significance of association between two relations in a network. While organizational network researchers have used such permutation tests extensively (Krackhardt, 1987b), the technique does not generalize to the multirelational, multilevel framework proposed here. Recently, these situations have been viewed as *multivariate* networks (Wasserman & Pattison 1999) and the relations modeled simultaneously.

Figure 9 indicates that there is a greater tendency for a friendship tie from actor A to actor B, because they communicate with one another, and a lower tendency for a friendship tie from actor C to actor D, because they do not communicate with one another.

Relations at previous points in time. Finally, the probability ties will be present or absent in the primary relation can also be influenced by the presence or absence of ties in that same relation at previous points in time (row 10 in Table 2). In their most primitive form, *theories of evolution* (McKelvey, 1997) would argue that inertia alone would predict that a tie between actors at a previous point in time would increase the tendency of the tie to be maintained

FIGURE 9
Exogenous Other Relations: Cognitive Theories

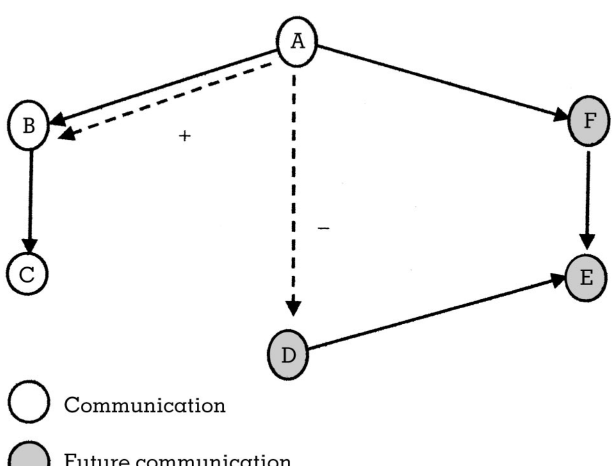


at a subsequent point in time. For instance, Gulati hypothesizes that "the higher the number of past alliances between two firms, the more likely they are to form new alliances with each other" (1995: 626). Hypotheses based on the influence of the same network at previous points in time would be supported if there were greater probabilities for graph realizations in which the actors' ties in the focal network corresponded to their ties in the preceding networks.

Figure 10 indicates that evolutionary theories would posit a greater tendency for a future tie from actor A to actor B because of an existing tie from actor A to B, and a lower tendency for a future tie from actor A to actor D because of the lack of an existing tie from actor A to actor D.

The treatment of exogenous variables described here is intentionally attenuated to reflect the lack of statistical techniques addressing the plethora of hypotheses that can be studied by considering the interactions among the exogenous variables described above. Two scenarios are worth considering. First, the influence of exogenous networks (either of different relations in the same network of actors or the same network at previous points in time) on the focal network can be moderated based on a third set of exogenous variables: the attributes of the actors. In other words, the tendency to build on preexisting ties may be different for actors with different shared attributes. An illustration of this situation is represented in Stevenson and Gilly's study of organizational problem-solving networks, where they note that "managers are more likely than non-managers to use preexisting ties when forwarding organizational problems" (1993: 103).

FIGURE 10
Exogenous Prior Relations: Evolutionary Theories



A second scenario would be the influence on the focal network of an exogenous network (which is a different relation in the same network of actors *and* at a previous point in time). This is the case when new kinds of ties might be established against the backdrop of existing relationships of a different type. For example, as Granovetter (1992) has argued, economic transactions are often "embedded" in social relations. This would suggest that economic relationships between actors might be more likely when they have a prior social relationship. While the statistical models, including the p^* family of models, have incorporated techniques to test hypotheses in the ten situations described in this section, additional efforts are being made to address the more complicated scenarios, such as the two illustrated above (Pattison & Robins, 2002; Snijders, 2001).

In summary, we have introduced an integrative analytic framework that seeks to examine the extent to which the structural tendencies of organizational networks are influenced by multitheoretical hypotheses operating at multiple levels of analysis. The exigencies of nonindependence in relational data preclude the use of standard statistical testing procedures. Hence, we introduced the notion of graph realizations and described how the hypothesized properties of networks influence the probabilities of graph realizations. In the next section we illustrate how some of these hypotheses can be tested in an empirical study.

EMPIRICAL EXAMPLE: THE CRADA NETWORK

Sample

The example here is based on a subset of data from a larger research project examining the social and organizational issues surrounding the creation of "virtual work communities" (Fulk, Lu, Monge, & Contractor, 1997). The community under study was composed of representatives from three agencies of the U.S. Army and four private corporations, who forged a Cooperative Research and Development Agreement (CRADA). The goal of this CRADA, a network organization, was the commercial production of software for improving the building design process for large institutional facilities. The four private companies were a CAD operating systems developer, a construction software firm, a software development company, and an architectural firm. The U.S. Army partners included a research laboratory, a district office, a unit of the army reserves, and members from headquarters. The software to be produced through this CRADA would offer advanced "virtual" coordination capabilities through its object-oriented technology and modular design system.[1]

CRADAs, which were first authorized by the 1986 Technology Transfer Act, enable government and industry to negotiate patent rights and royalties before entering into joint R&D projects. They were conceived as an incentive for industry, to facilitate investment in joint research by reducing the risk that the products of the research would fall into the public domain and be exploited by both domestic and international competitors. Since 1989, there has been an exponential growth in the creation of CRADAs, reaching over 2,200 by 1993. The Departments of Energy, Commerce, Agriculture, and Defense initiated a large proportion of these. CRADAs involve large, medium, and small businesses in a wide variety of industries, including computer software, materials, agricultural chemicals, biomedical research, and electronic networking.

Unlike most other CRADAs, which are dyadic arrangements involving only one partner from private industry and one from government, the CRADA studied here involved multiple private and government organizations. As a result, the private organizations needed not only to hammer out an agreement with the multiple government agencies but also to work through the difficult process of negotiating an agreement for how their own private partnership was to function and how the benefits of the alliance were to be distributed among the partners. After a complex set of negotiations, a partnership framework was developed among the business participants, and the CRADA agreement was signed in a formal ceremony. Hence, the structure and practices of this CRADA reflect many of the features of the new network forms of organizing described in the introduction.

[1] Additional information about this project can be obtained from http://impact.usc.edu/impact/JIVE/contents.htm.

Data

The network being analyzed in this example was the communication that occurred in the month prior to the signing of the CRADA agreement among the seventeen members representing the various private and government organizations. In this network a tie was directed from a member in one organization to a member in the same or another organization if the member reported communication during the month of study—a dichotomous relationship (either present or absent).

Hypotheses

We test eight hypotheses derived from four theories at three levels (dyadic, triadic, global). The first four hypotheses being tested here posit that the probabilities of graph realizations (of which the observed network is but one realization) are influenced by *endogenous* properties of the network itself at the dyadic, cyclical triadic, transitive triadic, and global levels. Exchange and dependence theories would suggest a structural tendency toward mutuality among the actors at the dyadic level (Hypothesis 1). Cognitive consistency theories would suggest a structural tendency toward transitivity and cyclicality among the actors at the triadic level (Hypotheses 2 and 3). And collective action theories would posit a structural tendency toward greater network centralization—variance in outdegrees (Hypothesis 4a)—and prestige—variance in indegrees (Hypothesis 4b).

The remaining four hypotheses examine the influence of one *exogenous* attribute of the members in the network—whether they represented a government agency or industry. These four hypotheses posit that the probabilities of graph realizations are influenced by the exogenous attribute at the actor, dyadic, transitive triadic, and global levels. Homophily theories would suggest a structural tendency for actors with the *same* attribute (belonging to government or industry) to exhibit greater communication (Hypothesis 5), mutuality (Hypothesis 6), transitivity (Hypothesis 7), and centralization/prestige (Hypothesis 8a and b) with others sharing their attribute. The hypotheses shown in Ta-

TABLE 3
Multitheoretical, Multilevel Hypotheses About the Structural Tendencies of an Interorganizational Network

Independent Variable	Hypotheses: Graph realizations where. . .
Endogenous (same network): *actor level*	
Endogenous (same network): *dyadic level*	H1: . . . actors have a high degree of reciprocated (or mutual) communication ties
Endogenous (same network): *triadic level*	H2: . . . triads of actors in the network exhibit a high degree of cyclicality
	H3: . . . triads of actors in the network exhibit a high degree of transitivity
Endogenous (same network): *global level*	H4: . . . the network has a high degree of outdegree centralization (4a) and prestige (or indegree) centralization (4b)
Exogenous (actor attributes): *actor level*	H5: . . . actors in the network who belong to the same type of organization (i.e., government or industry) are more likely to have ties with one another
Exogenous (actor attributes): *dyadic level*	H6: . . . actors in the network who belong to the same type of organization (i.e., government or industry) are more likely to have mutual (or reciprocated) communication ties
Exogenous (actor attributes): *triadic level*	H7: . . . actors in the network who belong to the same type of organization (i.e., government or industry) are more likely to be embedded in transitive ties with one another
Exogenous (actor attributes): *global level*	H8: . . . actors in the network who belong to the same type of organization (i.e., government or industry) are more likely to have higher levels of subgroup (outdegree) centralization than the overall network's centralization (8a) and higher levels of subgroup prestige (or indegree) centralization than the overall network's prestige network centralization (8b)

ble 3 are presented so that they map directly onto the framework summarized in Table 2 and described previously. As is evident, the eight hypotheses tested in this empirical illustration map directly onto seven of the ten cells described in Table 1.

As discussed below, we test these multitheoretical, multilevel hypotheses by statistically estimating the extent to which structural tendencies implied by these hypotheses influence the probabilities of observing certain realizations of the network.

p^* Statistical Models for Testing Multitheoretical, Multilevel Hypotheses

The hypotheses tested here use the p^* family of statistical models. This family was first introduced in the mid 1980s (Frank & Strauss, 1986; Strauss & Ikeda, 1990) and popularized in the late 1990s by a number of researchers (e.g., Pattison & Wasserman, 1999; Robins et al., 1999; Wasserman & Pattison, 1996).[2] In brief, these models are based on the fact that the Hammersley-Clifford theorem (Besag, 1974) provides a general probability distribution for a sociomatrix X from a specification of which pairs of tie random variables are conditionally dependent, given the values of all other random variables. These conditional dependencies express hypothesized structural tendencies in the network. Specifically, a *dependence graph* $\mathbf{D}$ with node set $N(\mathbf{D}) = \{X_{ij}: i, j \in N, i \neq j\}$ and edge set $E(\mathbf{D}) = \{(X_{ij}, X_{kl}): X_{ij}$ and $X_{kl}\}$ is assumed to be conditionally dependent, given the rest of X. We can use $\mathbf{D}$ to obtain a model for $\Pr(X = x)$, denoted p^*, in terms of parameters and substructures corresponding to cliques of $\mathbf{D}$. The model has the form

$$\Pr(X = x) = p^*(x) = (1/c)\exp\{\Sigma_{P \subseteq N(\mathbf{D})} \alpha_P z_P(x)\}$$

where

1. the summation is over all cliques P of $\mathbf{D}$ (with a *clique* of $\mathbf{D}$ defined as a nonempty subset P of $N(\mathbf{D})$ such that $|P| = 1$ or $(X_{ij}, X_{kl}) \in E(\mathbf{D})$ for all $X_{ij}, X_{kl} \in P$);

[2] A thorough history of this family can be found in the chapters on p^* in Carrington, Scott, and Wasserman (2003), especially in the Wasserman and Robins (2003) chapter. We refer readers to these chapters for further mathematical and statistical details about p^*.

2. $z_P(x) = \Pi_{Xij \in P} x_{ij}$ is the (observed) *network statistic* corresponding to the clique P of **D;** and
3. $c = \Sigma_x \exp\{\Sigma_P \alpha_P z_P(x)\}$ is a *normalizing* quantity.

The quantities $z_P(x)$ are calculated from the observed network and correspond to the hypothesized structural tendencies expressed in the dependence graph. The α_P are parameters corresponding to the cliques P of **D.** These parameters express the importance of the associated structural tendency for the probability of the graph.

One possible dependence assumption is Markov, in which $(X_{ij}, X_{kl}) \in E(\mathbf{D})$ whenever $\{i, j\} \cap \{k, l\} \neq \emptyset$. This assumption implies that the occurrence of a network tie from one node to another is conditionally dependent on the presence or absence of other ties in a *local neighborhood* of the tie. A Markovian local neighborhood for X_{ij} comprises all possible ties involving i and/or j. We primarily make a Markov dependence assumption in our models. Many other dependence assumptions are also possible, and the task of identifying appropriate dependence assumptions in any modeling venture poses a significant theoretical challenge. The multilevel, multitheoretical hypotheses that we investigate here illustrate the flexibility and generality of this approach.

Analysis and Results

The p^* family of models was used to simultaneously test the eight hypotheses. We used logistic regression to fit a series of nested models where the response variable was the presence or absence of a tie between each pair of actors. The explanatory variables were the changes in the hypothesized network statistic when that specific tie changed from a 1 to 0.[3] These variables were computed using Prepstar (see Crouch & Wasserman, 1998) and the MultiNet network analysis software programs (Seary & Richards, 2001), and then fitted using standard logistic regression techniques (see Crouch & Wasserman, 1998). This maximum pseudo-likelihood method of estimation is, at best, approximate, and in particular provides standard errors that may be too large. As such, this method provides only an approximate basis for null hypothesis statistical testing.

There have been considerable and promising recent efforts to develop Monte Carlo maximum likelihood procedures, which produce reliable standard errors more appropriate for formal statistical testing (for a review, see Wasserman & Robins, 2003). Estimation procedures for five of the simpler models hypothesized here have been implemented in SIENA (Snijders, 2001, 2002). Algorithms for the more complex models are expected to be available in the near future. Where possible, we estimated each model using Monte Carlo maximum likelihood procedures and compared the results with those obtained from the maximum pseudo-likelihood procedures. In all cases, there were modest differences in the values of the estimates, with the similarity of the estimates decreasing as the number of the parameters estimated increased. However, the estimates using the two procedures led to the same conclusions about support (or lack thereof) for the hypotheses. Again, we issue to the reader a cautionary note about making inferential decisions based on approximate techniques.

The results for the fitted models using maximum pseudo-likelihood are shown in Table 4. The first column indicates the variables included in the model. The second column indicates the number of parameters estimated in the model. The number of parameters estimated corresponds to the number of variables in the model. The third column reports the fitness of the model. The fitness value is twice the negative of the log pseudo-likelihood of the model, sometimes referred to as the pseudo-likelihood deviance. Hence, the magnitude of this value should be interpreted as a "badness of fit" measure. Models that have a lower deviance can be assumed to better predict the observed network. Pseudo-likelihood estimates are approximate; in particular, the standard errors may be too large. Although the decrease in the badness of fit values between two nested models does not approximate a chi-squared distribution (where the degrees of freedom are the difference in the number of parameters estimated in the two models), a large difference in fit may be evidence that an effect is present. As such, these values can be used as an effective heuristic guide. The fourth column reports the mean of the absolute residuals across all 272 (17 times 16)

[3] Wasserman and Pattison algebraically derive the rationale for this approach (1996: 407).

TABLE 4
Goodness of Fit for the Hypothesized Models

Model	Number of Parameters	Pseudo-likelihood Deviance −2 (log pseudo-likelihood)	Mean of the Absolute Residuals
1. Choice (intercept term − uniform distribution of ties)	1	354.39	0.459
2. Choice + mutuality (H1)	2	254.25	0.294
3. Choice + mutuality + cyclicality (H2)	3	241.97	0.281
4. Choice + mutuality + transitivity (H3)	3	228.84	0.266
5. Choice + mutuality + transitivity + cyclicality	4	228.01	0.265
6. Choice + mutuality + transitivity + choice within shared attribute (H5)	4	222.75	0.259
7. Choice + mutuality + transitivity + choice within shared attribute + mutuality with shared attribute (H6)	5	221.72	0.256
8. Choice + mutuality + transitivity + choice within shared attribute + transitivity within shared attribute (H7)	5	218.93	0.254
9. Model 6 + degree centralization (H4a) + degree prestige (H4b)	6	211.66	0.241
10. Model 6 + degree centralization + degree prestige + degree centralization within shared attribute (H8a) + degree prestige within shared attribute (H8b)	8	202.21	0.232

ties. The residuals are the difference between the observed ties and the probabilities for those ties predicted by the model. The mean of the absolute residuals, along with the pseudo-likelihood deviance, serves as a simple badness of fit measure.

The first model (Model 1) is a baseline model where the single explanatory variable, sometimes referred to as *choice,* is always valued at 1. This model estimates one parameter, for the variable choice, and reflects the null hypothesis that the probabilities for ties in the network are a constant, given by the total number of ties in the network, and there are no additional structural effects. As such, it is the equivalent of an intercept term or a grand mean in regression or ANOVA, respectively. The pseudo-likelihood deviance or badness of fit value, 354.39, reported for this model was large, indicating a poor fit. Further, the mean of the absolute residuals was quite high (0.459). Clearly, the probabilities for graph realizations were not constant and were dependent on other structural properties of the network, such as mutuality, transitivity, centralization, and so on. The effects of these hypothesized structural properties are tested in the models below.

Model 2 tests the first hypothesis that there is a greater probability for graph realizations in which actors have a high degree of mutuality or reciprocation. The two parameters estimated in this model include the parameter for the choice (the baseline) variable estimated in Model 1 and the change statistic associated with the dyadic endogenous network property of mutuality. A large decrease in the badness of fit value from Model 1 to Model 2 (354.39 − 254.25 = 100.04, d.f. = 1) indicates support for Hypothesis 1. The mean of the absolute residuals fell from 0.459 to 0.294. Consistent with social exchange theory, given the number of other possible realizations of the observed graph, there were more mutual communication ties than would be expected by chance. That is, there was a greater-than-chance probability for mutual ties in the CRADA network. Substantively, this suggests that individuals involved in this software collaboration were more likely to be engaged in mutual interactions than in some form of a linear (or possibly hierarchical) set of unidirectional interactions.

Models 3 and 4 test, individually, the second and third hypotheses, which state, respectively, that there is a greater probability for graph realizations in which triads of actors are embedded in cyclical and transitive relations. Models 3 and 4 incorporate the parameters specified in Model 2, in order to test the hypotheses about triads controlling for the influence of dyads. The large decrease in the badness of fit values from Model 2 to Model 3 (254.25 − 241.97 = 12.28, d.f. = 1) and Model 4 (254.25 − 228.84 = 25.41, d.f. = 1) lends evidence to the importance of both cyclicality and transitivity. However, the mean of the absolute residuals was higher for Model 3 with cyclicality (0.281) than it was for Model 4 with transitivity (0.266). Consistent with balance theory, these findings support the hypotheses that, given the number of other possible realizations of the observed graph, there were more transitive and cyclical structures in the CRADA communication network than would be expected by chance. Substantively, these findings suggest that individuals involved in this software collaboration had a tendency to work collectively in triads rather than to rely on unitary chain-of-command or independent dyadic links.

Model 5 tests, collectively, Hypotheses 2 and 3, regarding transitivity and cyclicality, respectively. There was a very small drop in the badness of fit measure from Model 4 (which tested Hypothesis 3, regarding transitivity) to Model 5 (228.84 − 228.01 = 0.83, d.f. = 1). Likewise, the mean of the absolute residuals fell marginally from 0.266 (for Model 4 with transitivity) to 0.265 (for Model 5 with cyclicality and transitivity). This indicates that when both transitivity and cyclicality effects are included (Model 5), little gain in fit is realized over a model containing transitivity alone (Model 4). This finding suggests that, in the CRADA network, the actors' tendency to engage in cyclical communication triads was not substantial after controlling for their tendency to engage in transitive communication triads. In other words, after taking into account the greater-than-chance probability of transitive triads in the CRADA communication network, there was no greater-than-chance probability of finding cyclical triads in the network. Substantively, this would suggest that individuals in the network did demonstrate some level of hierarchy. If actor A went to actor B and actor B went to actor C, there was a greater tendency for actor A to also seek communication with actor C (transitivity), rather than for actor C to seek actor A (cyclicality).

From a statistical standpoint, the minimal gain in fit resulted in dropping the cyclicality variable in the estimation of subsequent nested models. It is worth noting that our model did not estimate tendencies for other triadic structures, such as 2-in stars (where one actor receives a link from two other actors), 2-out stars (where an actor sends links to two other stars), or mixed stars (where an actor receives a link from one star and sends a link to another star). A strictly hierarchical model should include those effects. However, we chose not to include them because we did not identify a sufficiently strong theoretical argument for their inclusion. Technically, even if these parameters were estimated, we would expect to retain the triadic effects we report here.

Models 6, 7, and 8 test Hypotheses 5, 6, and 7, which state, respectively, that there is a greater probability for graph realizations in which actors in the network who belong to the same type of organization (government or industry) are more likely to have ties with one another, that these ties are mutual, and that these ties are transitive. Model 6 results in an appreciable gain in fit over earlier models, suggesting individuals were more likely to report ties to other individuals in their own organizational type than to individuals in the other organizational type. The mean of the absolute residuals dropped further, to 0.259. In other words, after controlling for the previously tested hypotheses (ceteris paribus), there was still a greater-than-chance probability that actors would have communication ties with others within their own organizational type (government or industry). This provides support for theories of homophily. It should be noted that this model posits that the densities of ties within organizations are the same. That is, the model does not posit a different propensity for actors within government agencies to form ties among themselves as compared to actors within industry to form ties among themselves.

Given only a minor decrease in fit from Model 6 to Model 7 (222.75 − 221.72 = 1.03, d.f. = 1) and Model 8 (222.75 − 218.93 = 3.82, d.f. = 1), little evidence exists for differential mutuality or differential transitivity effects over and above differential choice. The mean of the absolute residuals also dropped marginally, from 0.259 to 0.256. Substantively, this suggests that individuals involved in this software collaboration were not more likely to be engaged in mutual interactions with individuals in their own type of organization compared to individuals from the other type of organization. Further, it suggests that the tendency of individuals to interact in transitive triads was no more pronounced within organizations of their own type (be it government or industry) than it was in the other type. Here again, the mean of the absolute residuals dropped minimally, from 0.256 to 0.254. In other words, ceteris paribus, there was not a greater-than-chance probability for actors in one organizational type to forge mutual ties or transitive ties involving other actors from the same organizational type. The lack of support for the hypothesized differential effects for mutuality and transitivity suggests that individuals were not "ganging up" in dyads or triads within their respective government or industry sectors. Given the goal of the CRADA to collaborate across these boundaries, this may be interpreted as a promising sign. From a statistical standpoint, the lack of improvement in fit implies that the exogenous variables associated with mutuality and transitivity should be dropped from subsequent nested models.

Model 9 tests Hypotheses 4a and 4b, which state that there is a greater probability for graph realizations in which the network has a high degree of centralization and prestige, respectively. The substantial improvement in the fit of Model 9 over previous models indicates support for Hypothesis 4. The mean of the absolute residuals dropped substantially, to 0.241. In other words, ceteris paribus, there was a greater-than-chance probability for actors to forge ties that would enhance the overall centralization of the network. Substantively, this means that, consistent with theories of collective action, the CRADA communication network exhibited a strong structural tendency toward centralization. We acknowledge that adding centralization and prestige parameters to the model goes beyond Markov dependence assumptions. Models that incorporate non-Markov dependence assumptions can lead to estimation problems. This is an active area of research (see Carrington et al., 2004).

Finally, Model 10 tests Hypothesis 8, which states that there is a greater probability for graph realizations in which actors in the network who belong to the same type of organization (government or industry) are more likely to have higher levels of network centralization than the overall network's centralization. Here again, the substantial improvement in the fit of Model 10 over Model 9 (211.66 − 202.21 = 9.45, d.f. = 1) suggests a strong effect of differential centralization on the probability for graph realizations. Further, the mean of the absolute residuals dropped from 0.241 (for Model 9) to 0.232. However, before substantively interpreting this finding and concluding that this indicates support for Hypothesis 8, it is important to examine the individual parameter values associated with the variables fitted in Model 10.

While Table 4 reports global measures of fit for each of the ten models, Table 5 reports the parameter estimates and the associated tests of significance for the best-fitting model (Model 10). The first column lists the variables included in Model 10. The second column is the parameter estimate for the corresponding explanatory variable. A large positive value of a parameter suggests the presence of the associated network structural component, while a large negative value suggests its absence. One can also interpret the parameters in terms of log odds. Thus, for a unit increase in the explanatory variable, the odds ratio that the response equals 1 (i.e., a tie is present) changes by a factor of $\exp(\theta_1)$. (The magnitude of this effect depends on a number of possibilities. For instance, there can only be one possibility for mutuality, but an arc might be involved in several triads so that what appears as a modest transitivity effect may actually be substantial.)

The third column indicates the Wald statistic, which is defined as the {(parameter estimate)/Standard Error(parameter estimate)}^{2}. It should be noted that the pseudo-likelihood estimates of the standard errors used to compute the Wald Statistic are approximate. The fourth column in Table 5 indicates the extent to which each variable contributes to a change in the odds ratio of

TABLE 5
Parameters for the Best-Fitting Model (Model 10)

Variable	B	Wald Statistic	Exp(B)
Choice (intercept term)	−5.61	54.99	
Mutuality (H1)	2.11	32.21	8.25
Transitivity (H2)	.26	24.72	1.30
Choice within shared attribute (H5)	2.48	15.37	11.94
Degree centralization (H4a)	2.84	8.67	17.12
Degree prestige (H4b)	2.33	6.46	10.28
Centralization within shared attribute (H8a)	−5.50	4.53	0.004
Prestige within shared attribute (H8b)	−4.35	2.75	0.01

a tie being present. Consider Hypothesis 1, where, in the second column, the mutuality parameter is estimated to be 2.11. The fourth column indicates that if there is a tie from actor B to actor A, the odds of a mutually reciprocated tie from actor A to actor B will increase by a factor of exp(2.11), which is 8.25. Likewise, according to Hypothesis 2, if actor A is connected to actor C and actor C is connected to actor B, the odds of a tie from actor A to actor B (which would complete a transitive triad) increases by a modest factor of 1.30. Further, considering Hypothesis 3, if actor A and actor B both represent the same organization, the likelihood of a communication tie between them increases by a factor of exp(2.48), which is 11.94. In contrast, considering Hypothesis 8, since the parameter for centralization within a shared attribute (i.e., organization type) is -5.50, the odds of a tie that contributes to a more centralized network among government or industry organizations are substantially decreased by a factor of exp(-5.50), which is 0.004. This is a strong effect, albeit not in the direction hypothesized. Hence, despite the substantial improvement of fit in Model 10 (reported in Table 4), the negative coefficient associated with this variable indicates a significant effect in the direction opposite that proposed by Hypothesis 8.

These results indicate that there is a lower-than-chance probability that actors would forge ties that would enhance the centralization of the network involving other actors within their own type of organization. Given that the goal of the CRADA was to mobilize a collective agreement across government and industry organizations, this finding is (in retrospect) plausible. It indicates a structural tendency to downplay centralization within organizational type (government or industry). This finding, taken in conjunction with a tendency to centralize in the overall CRADA network (Model 9, Hypothesis 4), would suggest that individuals' propensity for collective action across organizational types superceded any parochial attempts to centralize within their own organizational type.

The positive overall centralization/prestige parameters and the negative subgroup centralization/prestige parameters are best considered together. The overall parameters counteract the subgroup parameters in circumstances when the node has many ties to actors outside the subgroup. One interpretation, then, is that actors are more likely to seek ties to popular actors within their organization if those actors have cross-organization ties. That is, actors who are more popular within their organization tend to be boundary spanners. However, from a statistical standpoint, the subgroup negative parameters could also reflect the fact that the variance in outdegrees (indicating centralization) is smaller within subsets of similar organizations, simply because the actors are fewer in number.

In summary, the results of this empirical illustration suggest that there were structural tendencies in the CRADA network to reciprocate communication ties (Hypothesis 1, see Figure 2), engage in transitive communication triads (Hypothesis 2, see Figure 3), foster a centralized overall network (Hypothesis 4, see Figure 4), and communicate more with individuals in organizations of their own type, be it government or industry (Hypothesis 5, see Figure 5). Further, contrary to Hypothesis 8, there was a structural tendency to eschew centralization within the network comprising members of their own organizational type. The remaining three hypotheses were not supported. In addition to its substantive implications, this empirical example offers a modest illustration of how the framework for testing multitheoretical, multilevel hypotheses introduced in the previous section can be used to explain the emergence of an interorganizational network. Specifically, Model 10 nested variables at the dyadic, triadic, and global levels that were simultaneously estimated.

CONCLUSION

The advent of digital technologies has ushered in a radical reconceptualization of our conventional notions of organizing (Contractor, 2002; Contractor & Monge, 2003). New network forms of organizing are supplanting hierarchies and markets that dominated the better part of the twentieth-century "workscape." While network researchers have made substantial progress in examining networks in organizations, they are less well prepared to understand organizing as networks. The characteristics of twenty-first-century network organizational forms challenge us to extend our efforts from examining emergent networks to a more theoretically and methodologically sophisticated approach to explaining the emergence of networks.

Building on recent efforts to identify the multiple theoretical mechanisms that contribute to the emergence of organizational networks, we have proposed, and illustrated empirically, an analytic framework that has the potential to test multitheoretical, multilevel hypotheses about the structural tendencies of networks. The framework, by its very organization, also reveals the substantial theoretical and methodological limitations in current research on organizational networks. More important, the framework brings into focus the specific areas where new network methodologies need to respond to theoretical concerns and new theoretical issues can leverage some of the methodological advances.

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Noshir S. Contractor (nosh@uiuc.edu) is a professor in the Department of Speech Communication at the University of Illinois at Urbana Champaign and has appointments in Psychology, Library & Information Science, and the Center for Advanced Study. He received his Ph.D. from the University of Southern California. His research investigates factors that lead to the formation, maintenance, and dissolution of dynamically linked knowledge networks.

Stanley Wasserman (stanwass@indiana.edu) is the Rudy Professor of Sociology, Psychology, and Statistics and has appointments in the Departments of Sociology, Psychological and Brain Sciences, and Statistics at Indiana University. He is also chief scientist of Visible Path Corporation. He received his Ph.D. in statistics from Harvard University. His research centers on applied statistics.

Katherine Faust (kfaust@uci.edu) is on the faculty in the Sociology Department and the Institute for Mathematical Behavioral Sciences at the University of California, Irvine. She received her Ph.D. from the University of California, Irvine. Her research focuses on methods for comparative social structural analysis and relationships between population processes and social network structure.