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Networks and Flows in Organizational Communication

Communication networks are the patterns of contact that are created by the flow of messages among communicators through time and space. The concept of message should be understood here in its broadest sense to refer to data, information, knowledge, images, symbols, and any other symbolic forms that can move from one point in a network to another or can be cocreated by network members. These networks take many forms in contemporary organizations, including personal contact networks, flows of information within and between groups, strategic alliances among firms, and global network organizations, to name but a few. This book offers a new multitheoretical, multilevel perspective that integrates the theoretical mechanisms that theorists and researchers have proposed to explain the creation, maintenance, dissolution, and re-creation of these diverse and complex intra- and interorganizational networks (Monge & Contractor, 2001). This focus provides an important new alternative to earlier reviews of empirical literature, organized on the basis of antecedents and outcomes (Monge & Eisenberg, 1987) or research themes within organizational behavior (Krackhardt & Brass, 1994).

Although examining the emergence of communication networks is in itself an intellectually intriguing enterprise, the inexorable dynamics of globalization provide an even more compelling impetus for communication researchers and practitioners (Held, McGrew, Goldblatt, & Perraton, 1999). This chapter begins by underscoring the rationale for studying the emergence of communication networks and flows in a global world. The chapter also situates the contributions of this book in previous communication perspectives on formal and emergent communication networks in organizations as well as current philosophical perspectives on the study of emergence in structures.

Communication Networks and Flows in a Global World

Communication networks and the organizational forms of the twenty-first century are undergoing rapid and dramatic changes (Fulk & DeSanctis, 1999). What is unfolding before our collective gaze is being driven by spectacular advances and convergences in computer and communication technology and by the collective economic, political, societal, cultural, and communicative processes collectively known as globalization (Grossberg, Wartella, & Whitney, 1998; Monge, 1998; Robertson, 1992; Stohl, 2001; Waters, 1995). While many of the changes brought about by globalization are beneficial to humankind, others are clearly detrimental (Scholte, 2000). Key to the changing organizational landscape is the emergence of network forms of organization (Monge, 1995) as an integral part of the coevolution of the new "network society" (Castells, 1996). These organizational and social forms, which are neither classical markets nor traditional hierarchies (Powell, 1990), nor both (Piore & Sabel, 1984), are built around material and symbolic flows that link people and objects both locally and globally without regard for traditional national, institutional, or organizational boundaries.

The emphasis here is on the flow as well as the form. In fact, Appadurai (1990) theorizes globalization as a series of five flows that he calls "scapes": ethnoscape, technoscape, financescape, mediascape, and ideoscape. These represent the movements of peoples, technologies, finance capital, entertainment, and ideology/politics through global networks. Thus, capital, material, labor, messages, and symbols circulate through suppliers, producers, customers, strategic partners, governing agencies, and affiliates to form what Hall (1990) calls the "global postmodern culture" (p. 29), one that is simultaneously global and local. Built on the basis of flexible, dynamic, ephemeral relations, these network flows constitute the bulk of organizational activity (Monge & Fulk, 1999). Thus, global organizations are processes, not places.

Globalization processes are fundamentally altering our perceptions of time and space. Harvey (1989) points to *space-time compression* where both time and space collapse on each other as instantaneous communication obliterates the time it takes for messages to traverse space. Scholte (2000) discusses a fundamental change in the social geography caused when people inhabit supraterritorial spaces that transcend specific locales. Giddens (1984) articulates *space-time distanciation*, a process by which social relations, or in our case, organizational communication relations, are stretched across space and time, making them more abstract and remote.

Historically, organizations were organized by place, that is, by locale, and "when" was associated with "where." Organizations were established at specific locations, and events tended to occur in the particular locations where organizations existed. As early communication technology enabled people to communicate at a distance, organizations came to be organized by time (Beniger, 1986). Today, at the dawn of the new millennium, communication technology makes it possible for people to experience the same event at the same time anywhere in the world (O'Hara-Devereaux & Johansen, 1994). Distance no long matters, and time shrinks space. Communication and computer technologies have merged to generate "virtual organizations" so that people at a distance can work as if they were in the same space at the same time (DeSanctis & Monge, 1999). As virtual organizational forms proliferate, the virtual will become "real," in that it will be seen as the natural and accepted way to organize (DeSanctis & Monge, 1999).

Castells (1996) points to the emergence of "timeless time," a phenomenon that is created by hypertext and other new multimedia features, like hyperlinks, message permutations, and image manipulations, that destroy what was historically perceived as the natural sequence and time ordering of events (p. 462). These communication forms alter the way organizations, people, and the rest of the world are experienced. As Castells says, "All messages of all kinds become enclosed in the medium, because the medium has become so comprehensive, so diversified, so malleable, that it absorbs in the same multimedia text the whole of human experience, past, present, and future" (p. 373). These dramatic changes in time, space, and virtual experiences are likely to intensify in the coming decades as communication technologies continue to converge. These are processes we need to understand.

Granovetter (1985, 1992) chastised organizational scholars for failing to see organizations as *embedded* in the network of larger social processes, which they influence and which also influence them, particularly those that generate trust and discourage malfeasance. But as important as Granovetter's arguments have been, they tell only one side of the story. In contrast, Giddens

(1984, 1991, 2000) applies the concept of embeddedness to the processes of globalization. He and a number of other scholars have argued that people and organizations around the globe have traditionally been focused on their local networks rather than global contexts. People tend to be more embedded in home, neighborhood, community, and organizational networks in their hometowns, states, and countries than they are in distant connections around the globe. But, Giddens argues, the processes of globalization are changing this. Specifically, they are leading to *disembedding*, the process by which traditional network ties are broken. Equally important, globalization leads people to establish new ties at a distance through a process of *reembedding*, thus restructuring the world and shifting the focus from the local to the global. In some cases, others argue, these new ties at a distance can restructure and strengthen local diasporas (Tsgarousianou, Tambini, & Bryan, 1998). For organizations, too, disembedding is important because it generates restructuring processes, new networks and connections with distant organizational communities around the world. Communication plays a central role in these embedding and disembedding processes as it provides the information, knowledge, and motivation that enable people to envision alternative relations. How these processes work will be central to our understanding of twenty-first-century organizations.

Another aspect of globalization is *reflexivity*, a "deepening of the self" that provides opportunities for new forms of personal relations and participation in new kinds of communication networks (Lash & Urry, 1994, p. 31). As communication technology conveys news, information, and entertainment about organizational and societal processes around the globe, people become more informed about the world, themselves, and their place in the larger scheme of things. These identity-altering experiences include processes of *individuation*, whereby people come to rely less on traditional norms, values, and institutions and more on their own knowledge of things (Giddens, 1991; Lash & Urry, 1994). This leads to individualized patterns of consumption and mass customization of products, both important challenges for future organizations. It also changes the nature of work expectations and experiences, as well as affiliations within a wide range of social, political, religious, and recreational organizations. Thus, over the next decades we are likely to see substantial global transformations in the ways in which people view themselves, in how they relate to organizations, and in what they are willing to tolerate (Held, McGrew, Goldblatt, & Perraton, 1999).

One early manifestation of these changes is the development of "e-lancers," that is, electronically connected freelancers, people who work together on a temporary basis to produce goods and services (Malone &

Laubacher, 1998). This new breed of worker brokers their services on the open market, see themselves as transients, and have little if any loyalty or commitment to the organizations for which they work. Instead, their loyalty is invested in their craft. Indeed, Internet Web sites like guru.com thrive by connecting e-lancers with each other and with contract projects.

Another manifestation of these global transformations is the emergence of the disposable workforce, "people who have several years of skills development and tenure with a firm who lose their jobs through no fault of their own and cannot find comparable employment elsewhere" (Conrad & Poole, 1997, p. 582). From a network perspective, these are people who have had their organizational ties severed, who are floating unconnected in the workforce, and who must establish new connections in order to survive economically. These are people who have been disembedded by their workday world and who seek reembedding. Both of these examples are a long way from the world of long-term tenured university professors or the Japanese corporate model of lifelong employment.

If the phenomenon we take as our stock in trade, organizational communication, is itself undergoing radical transformation, then we too must change our ways of studying it. And to be effective, the ways in which we change must reflect the transformations that we seek to understand. Since the nature of organizations is radically changing in the twenty-first century we will need to abandon former notions of what constitutes organizations and explore new possibilities—among them, networks of flows and connections, perhaps even rhizomes (Eisenberg, Monge, Poole, et al., 2000)—irrespective of traditional names, charters, boundaries, or walls. We must transcend our disciplinary parochialism in favor of incorporating insights from other perspectives not normally included in our analytic frameworks, including economics, philosophy, political science, new forms of systems thinking like coevolutionary, complexity, and self-organizing systems theories, and many others.

Finally, we must recognize that globalization is producing as many if not more negative outcomes than positive ones. We must incorporate in our work explicit attention to problems generated by globalization, including the displacement of labor, the exploitation of child workers, the migration of workforces, the degradation of the environment, and many other important problems. With all this and much more ahead of us, the twenty-first century should be a most interesting and challenging time to study communication networks and flows within and among organizations. The following section situates the arguments of this book within the context of previous communication research on formal and emergent networks.

Formal Versus Emergent Networks

Historically, organizational communication scholars have made important theoretical and empirical distinctions between formal and emergent networks. Theoretically, the notion of "emergent network" was a designation that originally differentiated informal, naturally occurring networks from formal, imposed, or "mandated" networks (Aldrich, 1976), the latter of which represented the legitimate authority of the organization and were typically reflected by the organizational chart. The formal networks were presumed to also represent the channels of communication through which orders were transmitted downward and information was transmitted upward (Weber, 1947). Early organizational theorists were aware that the formal organizational structure failed to capture many of the important aspects of communication in organizations and discussed the importance of informal communication and the grapevine (Barnard, 1938; Follett, 1924). Several scholars developed ways to study the grapevine and informal networks such as Davis's (1953) Episodic Communication in Channels of Organizations (ECCO) analysis, a technique for tracing the person-to-person diffusion of rumors and the flow of other information in an organization.

Fukuyama (1999) argues that social and organizational structure spans a continuum that ranges from formal to informal. He says, "No one would deny that social order is often created hierarchically. But it is useful to see that order can emerge from a spectrum of sources that extends from hierarchical and centralized types of authority, to the completely decentralized and spontaneous interactions of individuals" (p. 146). Researchers have provided considerable evidence over the years for the coexistence of the two networks. For example, using a variant of ECCO analysis, Stevenson and Gilly (1991) found that managers tended to forward problems to personal contacts rather than to formally designated problem solvers, thus bypassing the formal network. Similarly, Albrecht and Ropp (1984) discovered that "workers were more likely to report talking about new ideas with those colleagues with whom they also discussed work and personal matters, rather than necessarily following prescribed channels based upon hierarchical role relationships" (p. 3). Stevenson (1990) argued that the influence of formal organizational structure on the emergent structure could be best understood on the basis of a status differential model. In a study of a public transit agency, he found evidence that the social distance across the hierarchy reduced the level of communication between higher- and lower-level employees, with middle-level employees serving as a buffer.

An important rationale for studying emergent communication networks has evolved out of the inconclusive findings relating formal organizational structure to organizational behavior (Johnson, 1992, 1993; also see McPhee & Poole, 2001). Jablin's (1987) review of the empirical research on formal organizational structures pointed to the inconclusive nature of studies involving structural variables such as hierarchy, size, differentiation, and formalization. More recently, a series of meta-analytic studies have concluded that the relationships between formal structure, organizational effectiveness (Doty, Glick, & Huber, 1993; Huber, Miller, & Glick, 1990), and technology (Miller, Glick, Wang, & Huber, 1991) are largely an artifact of methodological designs. The fact that formal structural variables have failed to provide much explanatory power has led several scholars to question the utility of further research on formal structures. Rather, they have argued that it is preferable to study emergent structures because they better contribute to our understanding of organizational behavior (Bacharach & Lawler, 1980; Krackhardt & Hanson, 1993; Krikorian, Seibold, & Goode, 1997; Roberts & O'Reilly, 1978; Roethlisberger & Dickson, 1939).

A creative alternative to abandoning formal networks in favor of studying emergent ones is to find new ways to examine both. The problems with formal structures have prompted some scholars to develop network measures that capture in emergent networks the key concepts used to describe formal organizational structure. For example, Krackhardt (1994) has developed four measures of informal structure—connectedness, hierarchy, efficiency, and least-upper-boundedness (unity-of-command)—that map onto theories of an organization's formal organizational structure.

Further, the increased use of new computer-mediated communication systems has spawned research that uses formal organizational structure as a benchmark against which to compare emergent communication networks, for example, those that emerge in an electronic medium. Several interesting, though somewhat conflicting, findings have been generated. In a two-year study of more than eight hundred members of an R&D organization, Eveland and Bikson (1987) found that electronic mail served to augment, and in some cases complement, formal structures. Similarly, Bizot, Smith, and Hill (1991) found that electronic communication patterns corresponded closely to the formal organizational structures in a traditionally hierarchical R&D organization. However, Rice (1994a) found that the electronic communication structures initially mirrored formal organizational structures, but these similarities diminished over time. Hinds and Kiesler (1995) explored the relationship between formal and informal networks in a telecommunications company. They found that communication technologies were increasingly used as a tool for lateral communication across formal organizational boundaries; this finding was most pronounced for technical workers. Lievrouw and Carley (1991) argued that new communication technologies might usher in a new era of "telescience" by offering alternatives to the traditional organizational structures in universities and industry.

The literature comparing face-to-face or mediated emergent communication structures to formal structures generally demonstrates a *pro-emergent bias*, that is, the theory and empirical evidence focus on the advantages of informal communication to individuals and organizations. However, Kadushin and Brimm (1990) challenged the assumption that three types of emergent networks, (1) the shadow networks (the "real" way things get done), (2) the social interaction networks, and (3) the career networks (the venue for so-called networking) always serve to augment the limitations of the organization's formal network. Instead, they argued that these three informal networks frequently work at cross-purposes, thereby restricting rather than promoting the organization's interests. In a study of senior executives in a large international high technology company, they found that by saying, "Please network, but don't you dare bypass authority," organizations create what Bateson (1972) called a *double bind*, a choice situation where each alternative conflicts with the others. They argued that "an important first step is to recognize the incompatibilities between emergent network structures and corporate authority structures and to move this inconsistency from the realm of double bind to the domain of paradox" (Kadushin & Brimm, 1990, p. 15).

Clearly, scholars continue to be interested in the study of the differences between formal and emergent networks in organizations. Ironically, however, the distinction between formal and informal structures in organizations has diminished significantly in recent years and may become increasingly irrelevant in coming decades. The reasons for this convergence center on shifts in organizational structure and management philosophy. Prominent among these are changes to more team-based forms of organizing, the adoption of matrix forms of organizational structure (Burns & Wholey, 1993), and shifts to network forms of organizing (Miles & Snow, 1986, 1992, 1995; Monge, 1995). At the core of these changes has been the explosion of lateral forms of communication (Galbraith, 1977, 1995) made possible by new information technologies that facilitate considerable point-to-point and broadcast communication without regard for traditional hierarchy (Fulk & DeSanctis, 1999).

These developments have eroded the distinction between prior structural categories used to characterize organizations, specifically, between

formal and informal and/or between formal and emergent. Contrary to traditional views, contemporary organizations are increasingly constructed out of emergent communication linkages, linkages that are ephemeral in that they are formed, maintained, broken, and reformed with considerable ease (Palmer, Friedland, & Singh, 1986). As Krackhardt (1994) says, "An inherent principle of the interactive form is that 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" (p. 218, italics in the original). The networks that emerge by these processes and the organizations they create are called network organizational forms.

The Emergence of Structure from Chaos

The concept of emergence represents a complex and intricate set of beliefs about how order appears out of randomness in nature and society. As such, it has attracted considerable interest in the physical and social sciences as well as philosophy (Dyson, 1997; Gell-Mann, 1994; Holland, 1995, 1998). In the context of organizations, McKelvey (1997) defines emergence as "any order, structure, or pattern appearing in complex random events that cannot be attributed to some specific prepensive purposeful activity or decision by some identifiable official or unofficial component entity" (p. 359).

Emergence typically refers to a set of arguments that higher-level phenomena appear to exhibit properties that are not revealed at lower levels. Clearly, notions of level and by implication, the notion of multilevel systems, are an integral part of the concept of emergence. Kontopoulos (1994) argues that differences in interlevel orderings reflect the nature of different types of emergent structures. As shown in figure 1.1, levels may be nested or nonnested. Nesting implies that lower levels are at least partially included in higher levels. Nested structures may be fully nested as in the case of hierarchies, or partially nested, as in the case of heterarchies, also called "tangled composite structures" (p. 55, see also Hofstadter, 1979; McCulloch, 1945, 1965).

Tangledness refers to the fact that relations between levels lead to overlapping structures. Tangledness typically produces considerably more autonomy and complexity at each level than the nonoverlapping relations found in hierarchies. For example, based on the well-worn notion of a "unitary chain of command," people in organizational hierarchies report to one

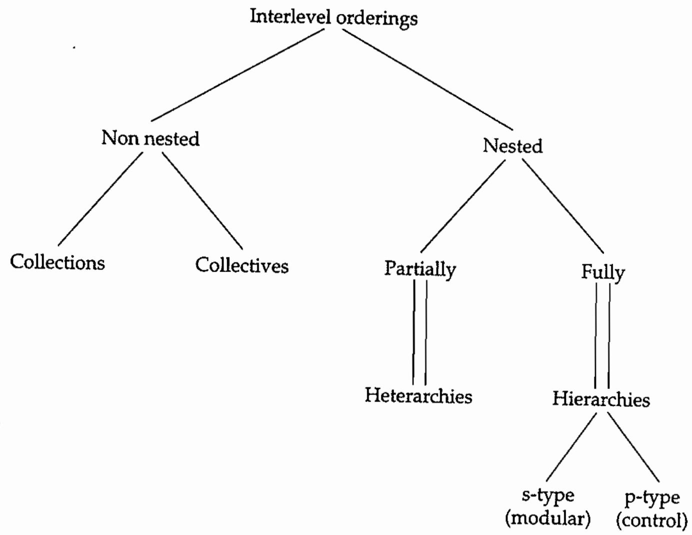


Figure 1.1
Interlevel ordering. Redrawn from K. M. Kontopoulos, *The Logics of Social Structure*. Copyright 1993 by Cambridge University Press. Used by permission of Cambridge University Press.

and only one boss, each of whom also reports to one and only one boss throughout the organization, which makes for clear-cut and unambiguous lines of authority. People in heterarchies, such as the "matrix" form of organization, typically report to multiple bosses, who also report to several bosses. This tangled composite form of structure is considerably more complex and autonomous than the simple, fully nested hierarchy. Finally, two types of hierarchies are differentiated. The first is the p-type hierarchy (named after Howard Pattee who formulated early principles of hierarchy) that operates on the basis of strong control principles from the top down. The second is the s-type (named after Herbert Simon, who pioneered the logics of emergent structures), which operates on the basis of a weaker principle of modularity from the bottom up (Kontopoulos, 1994, p. 54–55).

The notion of emergence also raises questions regarding which levels determine other levels. Microdetermination occurs when the lower level parts influence the behavior of the higher levels. Macrodetermination occurs when the higher levels determine the behavior of the lower level parts. Of course, other possibilities exist. Each level could determine the other in equal or differential amounts. Or, neither level could determine the other, in which case, each might be determined by externalities, which are other processes outside of the structure and its parts, which impact one or more levels of the structure. And, finally, we must permit the possibility of each level causing itself via feedback loops over time and via self-organizing processes. As shown in figure 1.2 heterarchies permit all of these forms of influence. In fact, adequate accounts of the emergence of networks are likely to require some degree of all of them.

Holland (1997) argues that one major theme runs through the various notions of emergence: "In each case there is a procedure for freely generating possibilities, coupled to a set of constraints that limit those possibilities" (p. 122). One example is neural networks: In this case, Holland says, "We have the possible ranges of behavior of individual neurons (firing rates) constrained by their connections to other neurons" (pp. 122–123, see also Cilliers, 1998). Holland extends this view by arguing that all emergent so-

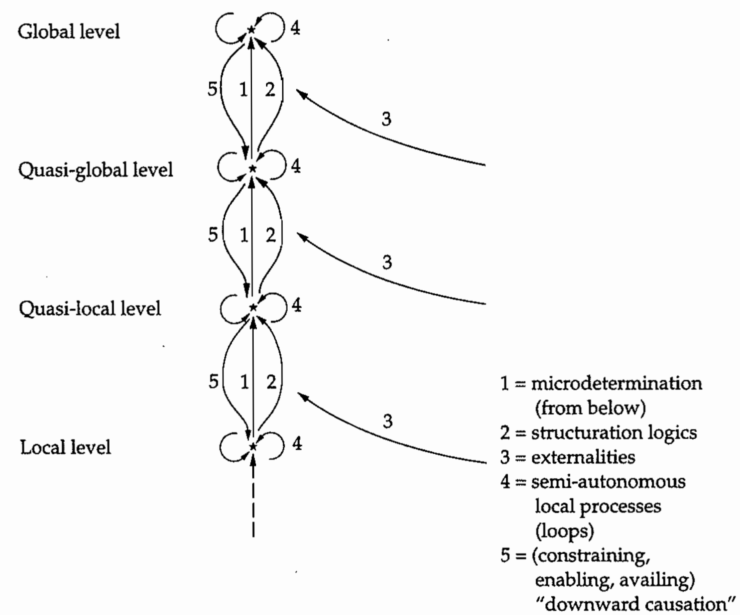


Figure 1.2
The general form of heterarchical level structure. Redrawn from K. M. Kontopoulos, *The Logics of Social Structure*. Copyright 1993 by Cambridge University Press. Used by permission of Cambridge University Press.

cial behavior can be accounted for by a general algorithm in which the interactions between agents is determined by the inputs to each and the set of rules that constrain possible reactions. He calls this algorithm "constrained generating procedures." We will have more to say about this strategy in chapter 3.

Emergence implies the idea of incorporation. As Kontopoulos (1994) says,

> A dominant, higher, emergent structure appears, subsuming fully or partially various previous modes of organization. This new structure re-organizes the possibility space, the resources and the processes, sets a new boundary for the emergent structure on the basis of which new laws and properties may appear, and ecologically asserts its new-found unity. This amounts to what Pattee and Polayni have called a new closure property that operates as a new law of organization, the logic of the emergent structure. (p. 39)

Kontopolous (1993) identifies five different epistemic positions on emergence. These views comprise alternative ways of conceiving of structural emergence. The five consist of three forms of emergence that can be arrayed on a continuum that is anchored on one end by "reductionism" or upward determinism and at the other by "holism" or downward determinism. Philosophers have debated these two polar positions since the early Greeks. It is the three intermediary positions that have emerged during the last half of the twentieth century as alternatives to the two traditional positions.

The first position is *reductionism*, in which all of the elemental parts of a system are aggregated into higher-level structures. An aphorism that captures the essence of reductionism states that "the whole is equal to the sum of its parts." Emergence refers to the fact that the collection shows properties not shown by the individual elements. The collective phenomena show "'synchronized aggregation,' that is, formation of higher collective quasi-entities exhibiting novel properties and new stabilities" (Kontopolous, 1994, p. 26). Reductionism also implies that higher levels of structure are completely determined by the lower levels. (Reductionism also refers to the epistemic belief that all observable phenomena, and therefore all knowledge, ultimately can be explained by the laws of physics, that is, reduced to the behavior of elementary particles. Thus, society can be reduced to psychology; psychology can be reduced to biology, biology to chemistry and chemistry to physics. This view has been thoroughly discredited. See Holland, 1998.)

The second view is *construction or compositional emergence*. This epistemic strategy contains a partial microdeterminism but also includes a focus on

"relational-interactional and contextual-ecological variables" (p. 12). This is a form of microdeterminism in which the parts and their interactions comprise the structure of the larger system. Holland (1995, 1998) argues that the interaction of a large number of agents following a small number of rules can generate highly complex macrostructures. Hofstadter's (1979) description of the behavior of ant colonies provides one classic example. The behavior of individual ants follows about a dozen rules, yet the structure and behavior of the entire colony is highly complex (Wilson, 1971). Thus, the emergent structure depends in important ways on the relationships that exist among the parts as well as the context of external variables.

Heterarchy is the third conception of emergence. Heterarchies are "tangled composite structures" that have multiple overlapping, relations across levels. To use McKelvey's (1997) terms, heterarchies represent "multiple orders" (p. 355) that are determined by multiple other levels. Rather than being determined solely from the bottom up as in compositional models, or from the top down, as in hierarchies, heterarchical levels codetermine each other. Heterarchies operate on the basis of "partial determination from below, partial determination from above, partial focal-level determination, (and) residual global indeterminacy. . . . This is possible by virtue of the fact that heterarchies involve multiple access, multiple linkages, and multiple determinations" (Kontopoulos, 1994, p. 55). McKelvey (1997) points out that this multiple determination makes heterarchies more complex than hierarchies, and therefore, these multiple orders may be difficult to trace. To illustrate this problem, he provides the example of a division manager who wishes to introduce structural "reengineering" processes into a firm. Resistance to the change can stem from subordinates or superiors, thus crossing three levels, and making identification of emergence more difficult than in a simple top down hierarchy or bottom up reductionism.

The fourth view of emergence is hierarchy. As shown in figure 1.1, hierarchies are largely (fully) nested structures, which means that higher levels include lower levels. In hierarchies, the microparts are partially overdetermined by the higher levels. Everyone is familiar with traditional organizational authority hierarchies, where each person reports to one and only one boss. All bosses have authority over all bosses below them in the hierarchy, thus subsuming their authority. The top boss has authority over all. Hierarchy is the dominant form of civil, religious, and other forms of bureaucracy. In organizational networks, hierarchies frequently represent the formal organizational structure.

The anchor on the continuum is holism, sometimes also called transcendence, which constitutes a strong downward determination of the microparts by the macrosystem. Holism is sometimes summarized by the aphorism that "the whole is greater than the sum of its parts." This view emphasizes the totality of the structure, the autonomy of higher levels of structure from lower levels, and the macrodetermination of the parts of the structure by the total structure. In network analysis, holism would emphasize that the overall organizational structure is independent of the particular people who comprise the network. It would also focus on the ways in which the network structure imposes constraints on the behaviors of individuals in the network.

Emergence and Time

Emergence can be viewed from two perspectives with regard to time. *Synchronous* emergence refers to the fact that at any given point in time it is possible to examine both the parts of the network and the entire cross-level structure and see properties such as stability and modularity at one level that do not exist at other levels. Synchronous emergence could show both the parts and their associated network configurations as well as the entire network restraining the behavior of the parts. *Diachronic* emergence refers to the fact that the behavior of the system over time generates properties at one or more levels that did not exist at prior points in time. Diachronic emergence provides much more interesting views of the dynamics of network emergence because it reveals a much greater portion of the emergent process than the synchronic perspective (see Monge & Kalman, 1996, for a further discussion of sequentiality, simultaneity, and synchronicity).

This section has introduced, in the abstract, key concepts and epistemic perspectives associated with the notion of emergence. In order to relate these abstractions to the emergence of organizational networks, the next two sections review the genesis of network forms in organizational contexts as well as the perspectives that have been used historically to study the emergence of structure in organizations. Following that review, we will examine several families of multilevel theories and theoretical mechanisms that can be used to understand the implications of emergent structure.

Network and Organizational Forms

Communication network patterns that recur in multiple settings are called *network forms*. An early theoretical paper by Bavelas (1948), based on Lewin's (1936) psychological field theory, identified a number of small group com-

munication network forms in organizations, including the chain, circle, wheel, and "comcon" (*com*pletely *con*nected), and theorized about how the different forms processed information. These network forms varied in the degree to which they were centralized, with the wheel being the most centralized, since all links centered on one individual, and the comcon the least centralized, since everyone was connected to everyone else and thus had the same number of links.

This theoretical article and an imaginative experimental design created by Leavitt (1951) generated hundreds of published articles over some twenty-five years. The primary focus of these efforts was the impact of information processing via the different network forms on productivity and satisfaction (see Shaw, 1964, for a review of this literature). Two prominent findings emerged from this research. First, centralized organizations were more efficient for routine tasks while decentralized networks were more efficient for tasks that required creativity and collaborative problem solving. Second, people in decentralized organizations were more satisfied with the work processes than people in centralized organizations, with the exception in the latter case that the central person in centralized networks was extremely satisfied. Unfortunately, little further theoretical development accompanied this plethora of empirical research. As a result, this line of inquiry has essentially died; almost no articles have been published on small group network forms in organizations during the past twenty years.

Organizational structures, including communication networks that share common features or patterns across a large number of organizations, are called *organizational forms* (McKelvey, 1982). Weber (1947) argued that bureaucracy was the universal organizational form. Three principle theoretical mechanisms that created bureaucracy were rationalization, differentiation, and integration. Rationalization occurred by specifying legitimating instructions that produced standard operating procedures, thus leaving little opportunity for individual autonomy. Rationalizing the network meant specifying who could say what to whom, often summarized by the injunction that commands should flow downward and information upward in the bureaucracy. Differentiation was the process of breaking work up into its various components. This often led to job specialization particularly as production processes proliferated and increased in size and complexity. As work became differentiated, the various parts needed to be coordinated, and thus processes of integration came into operation. Weber argued that bureaucracy differentiated along vertical organizational lines and primarily integrated that way as well. Bureaucracy allowed little room for lateral, cross-level, or cross-boundary communication networks, that is, informal or emergent networks, a feature for which it has been frequently criticized (Galbraith, 1977; Heckscher, 1994).

Miles and Snow (1986, 1992) identified four major organizational forms that have developed over the past century. These are: (1) the traditional functional form, which emerged during the early part of the century, (2) the divisional (or multidivisional) form, which was begun by Alfred P. Sloan at General Motors in the 1940s (see Chandler, 1977), (3) the matrix form, which evolved during the 1960s and 1970s, and (4) the network form, which has emerged over the past decade. Miles and Snow (1992) argue that each of these forms contains its own operating logic, or in terms of this book, its own theoretical mechanism.

The functional form uses a logic of "centrally coordinated specialization" (p. 58), which enables it to efficiently produce a limited set of standardized goods or services for a stable, relatively unchanging market. The divisional form operates by a logic of "divisional autonomy with centrally controlled performance evaluation and resource allocation" (p. 60). Divisions produce separate products or focus on separate markets but are collectively accountable to centralized authority through their communication networks. The ability to develop new divisions enables the multidivisional form to pursue new opportunities in changing markets. The matrix form combines the operating logic of functional and multidivisional forms, using the functional form to produce standardized goods and services and the shared resources of the multidivisional form to explore new opportunities via project groups or teams. The network form uses flexible, dynamic communication linkages to connect and reconnect multiple organizations into new entities that can create products or services.

Three Historical Perspectives on Emergence of Structure in Organizations

Communication network analysis falls within the intellectual lineage of structural analysis, which has had a long and distinguished history. In sociology, Herbert Spencer (1982) and Emile Durkheim (1989/1964) are often credited with introducing structural concepts into sociological thinking. In anthropology, Radcliff-Brown (1959) incorporated structural-functionalist ideas into his watershed analysis of cultures. And in linguistics, structural thinking can be traced to the pioneering work of de Saussure (1916/1966). Most structural analyses of organizations and communication

can be located in one of three traditions: (1) positional, (2) relational, and (3) cultural.

The *positional* tradition is rooted in the classical work of Max Weber (1947), Talcott Parsons (1951), and George Homans (1958). Organizational structure is viewed as a pattern of relations among positions. Sets of organizational roles are associated with positions and specify designated behaviors and obligatory relations incumbent on the people who assume the positions. The positions and attached roles constitute the relatively stable and enduring structure of the organization independent of the people who fulfill the roles. This tradition leads to the view that positions and roles determine who communicates with whom, and consequently, the communication structure of the organization. White, Boorman, and Breiger (1976) and Burt (1982) have developed the most significant recent positional theories applicable to organizational communication under the rubric of structural equivalence. This theory argues that people maintain attitudes, values, and beliefs consistent with their organizational positions irrespective of the amount of communication that they have with others in their organizational networks. The positional tradition has been criticized for its inability to take into account the active part individuals play in creating and shaping organizational structure (Coleman, 1973; Nadel, 1957; White, Boorman, & Breiger, 1976).

The *relational* tradition focuses primarily on the direct communication that establishes and maintains communication linkages. Taken collectively, these linkages create an emergent communication structure that connects different people and groups in the organization irrespective of their formal positions or roles. Rooted in systems theory (Bateson, 1972; Buckley, 1967; and Watzlavick, Beavin, & Jackson, 1966), the relational tradition emphasizes the dynamic, constantly changing, enacted nature of structure created by repetitive patterns of person-to-person message flow. Rogers and Kincaid (1981) claim that it is the dominant tradition for studying communication in organizations.

The *cultural* tradition examines symbols, meanings, and interpretations of messages transmitted though communication networks. As part of the resurgence of interest in organizational culture (Frost, Moore, Louis, Lundberg, & Martin, 1985), much of the work has been based on Giddens's (1976, 1984) writings on structuration, which attempt to account for both the creative and constraining aspects of social structure. These studies are characterized by an explicit concern for the continual production and reproduction of meaning through communication, examining simultaneously how meanings emerge from interaction and how they act to constrain subsequent interaction. The cultural tradition has spawned recent work on semantic networks (Monge & Eisenberg, 1987) described later in this book. These three traditions are discussed in greater detail in Monge and Eisenberg (1987).

Although interesting and useful, these network traditions focus attention at a metatheoretical level and fail to specify the *theoretical mechanisms*, such as self-interest, contagion, and exchange, which describe how people, groups, and organizations forge, maintain, and dissolve linkages. As such, the three network traditions demonstrate an unfortunate bias toward the consequences of network structures on attitudes and behavior rather than generating a better understanding of how and why people create, maintain, dissolve, and reconstitute network linkages. Further, while a number of scholars over the past decade have called for greater explication of network theory (e.g., Rogers, 1987; Salancik, 1995; Wellman, 1988), almost none have provided it. Finally, while several reviewers have identified theories that are applicable to network research within and between organizations (Galaskiewicz, 1985; Grandori & Soda, 1995; Mizruchi & Galaskiewicz, 1994; Smith, Carroll, & Ashford, 1995), few have systematically explored the theories and their theoretical mechanisms (Monge & Contractor, 2001).

This book addresses these issues in four ways. First, it provides a new theoretical framework that incorporates multiple theoretical mechanisms to generate network configurations. Second, it offers agent-based models of rule following behavior that incorporate theoretical mechanisms for generating complex adaptive networks. Third, it shows how computational modeling, and in particular the *Blanche* computer simulation environment, can be useful for exploring the evolutionary dynamics of networks. Finally, it reviews new developments in network analysis that permit direct estimation of network parameters of multitheoretical, multilevel models. This facilitates empirical exploration of multitheoretical explanations of the dynamics of communication networks.

In the next section we present a brief overview of the theoretical framework. In the following section we offer a synopsis of the different families of theories that provides the basis for the multitheoretical, multilevel model.

Overview of the Theoretical Framework

Chapter 2 describes the new framework, which we call the multitheoretical, multilevel model (MTML). We argue that alternative social science theories make differential predictions about communication networks. Some of the theoretical mechanisms are unique, even complementary. Others are

duplicative, at least in part. Still others compete, offering contradictory explanations. None of the theories, on their own, provide definitive, exhaustive explanations of network phenomena. The MTML framework identifies network properties such as mutuality and density and shows how these properties correspond to theoretical mechanisms in social theories. We argue that utilizing multiple theories should improve our explanations of network evolution as well as significantly increase the amount of variance accounted for by these theoretical mechanisms.

Since networks are inherently multilevel, the MTML framework identifies network properties that exist at individual, dyad, clique, and network levels. Further, it expands this perspective to include the same network at earlier points in time as well as other networks to which it might be related, both contemporaneously and historically. Finally, the framework permits incorporation of attributes of the nodes at all relevant levels. This provides a much more general framework for examining the evolution of communication networks than existing alternatives.

Chapter 3 presents an agent-based, rule-guided model of complex networks. When agents follow rules complex structures emerge. This process need not be planned in advance; it can be self-organizing. The key that ties agent-based models to the MTML framework is to make the rules correspond to the generative mechanisms of social theories. We argue and show that models built on the different theoretical mechanisms inherent in different theories lead to different emergent structures. Since some of these are complementary and others are overlapping in their explanatory value, we argue that a multitheoretical perspective will improve our explanations and our explained variance.

Chapter 4 focuses on the role of computational modeling in network research. We introduce *Blanche*, a program specifically designed to model the emergence of communication networks. We also discuss the role that computer simulations can play in exploring the dynamics and evolution of communication networks. Computational models enable us to incorporate theoretical mechanisms from social theories as the rules that agents follow. As agents follow different rules, different structures evolve over time.

Overview of the Families of Theories

The second part of the book focuses on the role of theory and theoretical mechanisms in explaining the emergence and evolution of communication networks. This review demonstrates that a wide array of theories can be used to develop network formulations. In some cases different theories, some using similar theoretical mechanisms, offer similar explanations but at different levels of analysis. The five epistemic perspectives on the emergence of structure from chaos, reviewed earlier, provide a useful context in which to integrate the heterarchical ordering of multitheoretical explanations. The review also underscores the considerable variation in the depth of conceptual development and empirical research across the different theories and theoretical mechanisms. Since the book focuses on theoretical mechanisms, many other interesting network articles that have little or no bearing on these issues have not been included. The theories and their theoretical mechanisms are summarized in table 1.1. These families are briefly summarized in the following paragraphs.

Chapter 5 presents theories of self-interest and theories of collective action. *Theories of self-interest* focus on how people make choices that favor their personal preferences and desires. Two primary theories in this area are the theory of social capital and transaction cost economics. Distinct from human capital, which describes individual personal characteristics, social capital focuses on the properties of the communication networks in which people are embedded. Structural holes in the network provide people opportunities to invest their information, communication, and other social resources in the expectation of reaping profits. Transaction cost economics examines the information and communication costs involved in market and organizational transactions as well as ways in which to minimize these costs. Network forms of organization provide an alternative to markets and hierarchy, focusing instead on embeddedness in complex networks. Information flows are essential in determining to whom a firm should link and joint value maximization offers an alternative principle to minimizing transaction costs.

Theories of mutual interest and collective action examine how coordinated activity produces outcomes unattainable by individual action. One theory that exemplifies this perspective is public goods theory, which examines the communication strategies that enable organizers to induce members of a collective to contribute their resources to the realization of a public good. Mutual self-interest often conflicts with the individual self-interests of the members of a collective and sometimes leads to free riding and other social and communication dilemmas. Network relations are often essential to the provision and maintenance of the good.

Chapter 6 discusses contagion and cognition theories. *Contagion theories* address questions pertaining to the spread of ideas, messages, attitudes, and beliefs through some form of direct contact. Contagion theories are based on a disease metaphor, where exposure to communication messages

Table 1.1
Selected Social Theories and Their Theoretical Mechanisms

Theory	*Theoretical Mechanism*
Theories of Self-Interest	Individual value maximization
Social Capital	Investments in opportunities
Structural Holes	Control of information flow
Transaction Costs	Cost minimization
Mutual Self-Interest & Collective Action	Joint value maximization
Public Good Theory	Inducements to contribute
Critical Mass Theory	Number of people with resources & interests
Cognitive Theories	Cognitive mechanisms leading to
Semantic/knowledge Networks	Shared interpretations
Cognitive Social Structures	Similarity in perceptual structures
Cognitive Consistency	Avoid imbalance & restore balance
Balance Theory	Reduce dissonance
Cognitive Dissonance	
Contagion Theories	Exposure to contact leading to
Social Information Processing	Social influence
Social Learning Theory	Imitation, modeling
Institutional Theory	Mimetic behavior
Structural Theory of Action	Similar positions in structure and roles
Exchange and Dependency	Exchange of valued resources
Social Exchange Theory	Equality of exchange
Resource Dependency	Inequality of exchange
Network Exchange	Complex calculi for balance
Homophily & Proximity	Choices based on similarity
Social Comparison Theory	Choose comparable others
Social Identity	Choose based on own group identity
Physical Proximity	Influence of distance
Electronic Proximity	Influence of accessibility
Theories of Network Evolution	Variation, Selection, Retention
Organizational Ecology	Competition for scarce resources
NK(C)	Network density and complexity

leads to "contamination." Inoculation theory provides strategies that can be used to prevent contamination. Two competing contagion mechanisms have received considerable attention in the research literature. Contagion by cohesion implies that people are influenced by direct contact with others in their communication networks. Contagion by structural equivalence suggests that those who have similar structural patterns of relationships within the network are more likely to influence one another. Social information processing (social influence) theory suggests that the attitudes and beliefs of people become similar to those of the others in their communication networks. Social learning theory and institutional theory posit that mimetic processes lead to contagion, whereby people and institutions imitate the practices of those in their relevant networks.

Cognitive theories explore the role that meaning, knowledge, and perceptions play in communication networks. *Semantic networks* are created on the basis of shared message content and similarity in interpretation and understanding. A complementary perspective views interorganizational networks as *structures of knowledge*. Creating interorganizational alliances requires building extensive knowledge networks among prospective partners and maintaining them among current partners. These knowledge networks are the mechanisms though which organizations share both explicit and tacit knowledge. *Cognitive communication structures* represent the perceptions that people have about their communication networks, that is, about who in their networks talk to whom. These individual cognitive communication networks can be aggregated to provide a collective or consensual view of the entire network. Cognitive consistency theory examines the extent to which the attitudes, beliefs, opinions, and values of network members are governed by a drive toward consistency. The theory suggests that network members tend toward cognitive similarity as a function of the cognitive balance in their networks rather than alternative mechanisms such as contagion.

Transactive memory systems consist of knowledge networks in which people assume responsibility for mastery among various aspects of a larger knowledge domain. In this way the collective is more knowledgeable than any component. Knowledge repositories linked to the larger knowledge network facilitate knowledge storage and processing. While knowledge flow is essential to an effective knowledge network, communication dilemmas sometimes lead people to withhold potentially useful information.

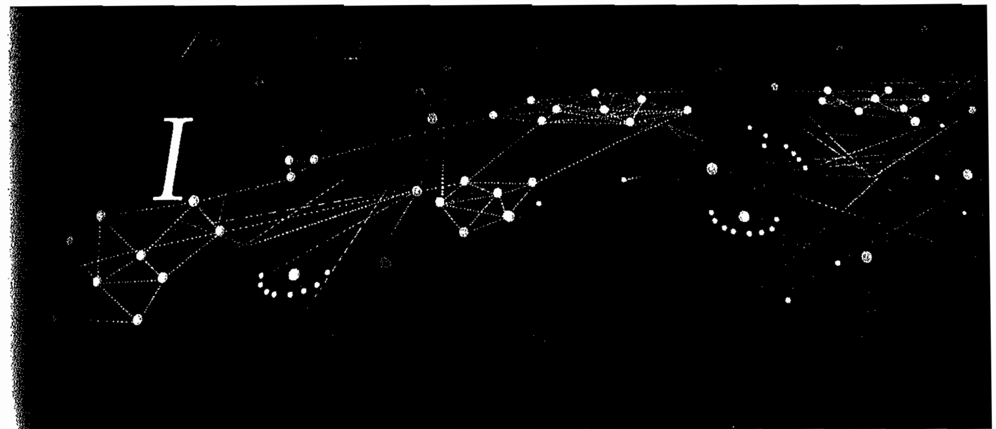
Chapter 7 focuses on *exchange and dependency theories*. These theories seek to explain the emergence of communication networks on the basis of the distribution of information and material resources across the members of a network. People seek what they need from others while giving what others also seek. The exchange form of this family of theories is based largely on equality, assuming that giving and getting generally balances out across the network. The dependency form emphasizes inequality and focuses on how those who are resource rich in the network tend to dominate those who are resource poor. Consequently, power, control, trust, and ethical behavior are central issues to both theories. Exchange and dependency theories

have both been used to examine the flow of information and the power dependencies that develop under interlocking corporate boards of directors. Exchange theory also partially accounts for the emergence of network forms of organization.

Chapter 8 discusses *homophily and proximity theories*. These account for network emergence on the basis of the similarity of network members' traits as well as their similarity of place. Traits represent a variety of personal and demographic characteristics such as age, gender, race, and professional interests. Social comparison theory suggests that people feel discomfort when they compare themselves to others who are different because they have a natural desire to affiliate with those who are like themselves. Of course, this ignores the old adage that opposites attract, which would argue for a heterophily mechanism. Proximity theories argue that people communicate most frequently with those to whom they are physically closest. The theory of electronic propinquity extends this to the realm of e-mail, telephones, and other forms of electronic communication.

Chapter 9 explores *coevolutionary theory*. Traditional evolutionary theory is based on mechanisms of variation, selection, retention, and struggle or competition. Random and planned variations in organizational traits occur, which are selected and retained on the basis of their contribution to organizational fitness and survival. Coevolutionary theory articulates how communities of organizational populations linked by intra- and interpopulation networks compete and cooperate with each other for scarce resources. In order to survive, firms must adapt to the constantly changing environmental niches in which they find themselves while also attempting to influence the ways in which their environments change.

The tenth and final chapter of the book integrates the four major contributions of the book. We begin with a review of the essential arguments advanced in this book in terms of the MTML framework and the theories discussed in chapters 5 through 9. We then discuss recent developments in "small world" research. This is an interesting and surprisingly common property where networks display considerable local connectedness while also having a low degree of separation with the other nodes in the network. Next, we discuss an agenda for future research on the emergence and evolution of organizational communication networks. We offer a number of suggestions for areas that need exploration and for the confluence of analytic strategies that could significantly advance our knowledge of network processes and novel forms of organizing in the twenty-first century. Finally, we conclude by exploring the implications of networks and flows for the globalizing world of the twenty-first century.



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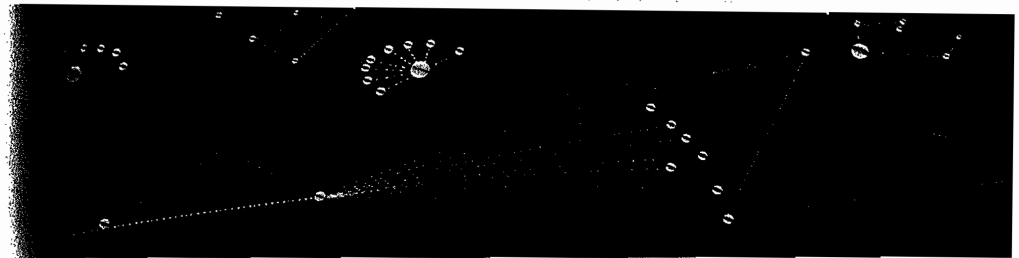
The Multitheoretical, Multilevel Framework



2

Network Concepts, Measures, and the Multitheoretical, Multilevel Analytic Framework

This chapter begins with an overview of network analysis concepts and measures. Those readers who are new to the area, or who are familiar with the social theories described in this book but not with network analysis itself, should find a careful reading of the first section of this chapter to be essential in understanding the remainder of the chapter and book. Network analysis has become a fairly technical topic, and there are a number of concepts, measures, and analytic strategies that require careful explication.

This section of the chapter should provide sufficient background in network analysis to enable an informed reading of the network literature. We hasten to emphasize, however, that it is only a brief introduction. Hence, like all other introductory materials, an attempt is made to trade-off conceptual rigor with simplicity. An extensive literature exists on network analysis, including several fine texts and a number of excellent review chapters. Those who wish to explore further the network analysis material presented in the first third of this chapter should consult the sources in the references that we have identified under "Relations in a World of Attributes." Those who are more familiar with network analysis will find the first section of this chapter less important. A quick skim should provide ample insight into our selection and use of concepts and definitions.

The second section introduces the MTML framework. It shows how various network properties at different levels of analysis can represent the generative mechanisms from different social theories. It also shows how combining theories can provide broader explanations of emergent networks than each theory can alone. As a part of that framework we introduce the statistical ideas pertaining to realizations of a graph and discuss p^* analytic strategies and the PSPAR computer program that can be used to analyze relevant data. This section concludes with an extended presentation of the MTML model, which broadly classifies variables into endogenous and exogenous factors, each with multiple levels. Examples are provided for each of the ten classes of hypotheses generated by this framework.

Network Analysis

The concept of network is extremely general and broad, one that can be applied to many phenomena in the world. At its core, network analysis consists of applying a set of relations to an identified set of entities. Road networks tie together various locales by the relationship, "can travel to," while electrical networks link different power sources and outlets with the relationship, "provides power to." In the context of organizational communication, network analysts often identify the entities as people who belong to one or more organizations and to which are applied one or more communication relations, such as "provides information to," "gets information from," "knows about," and "communicates with." It is also common to use work groups, divisions, and entire organizations as the set of entities and to explore a variety of relations such as "collaborates with," "subcontracts with," and "joint ventures with." As we will discuss later in the book, the entities could also be nonhuman agents such as knowledge repositories, avatars, and so on.

Relations in a World of Attributes

Relations are central to network analysis because they define the nature of the communication connections between people, groups, and organizations. This focus stands in sharp contrast to other areas of the social sciences, which have tended to study "attributes," the characteristics of people, groups, and organizations rather than the relations between them. Relations possess a number of important properties, including strength, symmetry, transitivity, reciprocity, and multiplexity. A large literature exists that describes these properties and other fundamentals of network analysis, including network concepts, measures, methods, and applications (see, for example, Haythornthwaite, 1996; Marsden, 1990; Monge, 1987; Monge & Contractor, 1988; Scott, 1988, 2000; Stohl, 1995; Wasserman & Faust, 1994; Wigand, 1988). Tables 2.1, 2.2, and 2.3 from Brass (1995a) summarize major network concepts. These tables describe measures of network ties, measures assigned to individuals, and measures used to describe entire networks. The measures described in this chapter and several additional metrics can be computed using network analysis software programs such as UCINET 6 (Borgatti, Everett, & Freeman, 2002), MultiNet (Richards & Seary, 2000), and Pajek (Batagelj & Mrvar, 2002). Since the focus of this book is on theory and research, we provide only a brief overview of some of the more widely used network measures and analytic techniques rather than extensive coverage.

Network Linkages

Network linkages are created when one or more communication relations are applied to a set of people, groups, or organizations. For example, in

Table 2.1
Typical Social Network Measures of Ties (Brass, 1995a)

Measure	*Definition*	*Example*
Indirect Links	Path between two actors is mediated by one or more others	A is linked to B, B is linked to C; thus A is indirectly linked to C through B
Frequency	How many times, or how often the link occurs	A talks to B 10 times per week
Stability	Existence of link over time	A has been friends with B for 5 years
Multiplexity	Extent to which two actors are linked together by more than one relationship	A and B are friends, they seek out each other for advice, and work together
Strength	Amount of time, emotional intensity, intimacy, or reciprocal services (frequency or multiplexity often used as measure of strength of tie)	A and B are close friends, or spend much time together
Direction	Extent to which link is from one actor to another	Work flows from A to B, but not from B to A
Symmetry (reciprocity)	Extent to which relationship is bidirectional	A asks B for advice, and B asks A for advice

Table 2.2
***Typical Social Network Measures Assigned to Individual Actors* (Brass, 1995a)**

Measure	*Definition*
Degree	Number of direct links with other actors
In-degree	Number of directional links to the actor from other actors (in-coming links)
Out-degree	Number of directional links from the actor to other actors (out-going links)
Range (Diversity)	Number of links to different others (others are defined as different to the extent that they are not themselves linked to each other, or represent different groups or statuses)
Closeness	Extent to which an actor is close to, or can easily reach all the other actors in the network. Usually measured by averaging the path distances (direct and indirect links) to all others. A direct link is counted as 1, indirect links receive proportionately less weight.
Betweenness	Extent to which an actor mediates, or falls between any other two actors on the shortest path between those actors. Usually averaged across all possible pairs in the network.
Centrality	Extent to which an actor is central to a network. Various measures (including degree, closeness, and betweenness) have been used as indicators of centrality. Some measures of centrality weight an actor's links to others by centrality of those others.
Prestige	Based on asymmetric relationships, prestigious actors are the object rather than the source of relations. Measures similar to centrality are calculated by accounting for the direction of the relationship (i.e., in-degree).
Roles	
Star	An actor who is highly central to the network
Liaison	An actor who has links to two or more groups that would otherwise not be linked, but is not a member of either group
Bridge	An actor who is a member of two or more groups
Gatekeeper	An actor who mediates or controls the flow (is the single link) between one part of the network and another
Isolate	An actor who has no links, or relatively few links to others

organizational contexts Farace, Monge, and Russell (1977) identified three distinct important communication networks in terms of production, maintenance, and innovation relations. Other kinds of communication linkages are possible. For example, Badaracco (1991) distinguished two types of knowledge, which he called migratory and embedded, each associated with

Table 2.3
***Typical Social Network Measures Used to Describe Networks* (Brass, 1995a)**

Measure	*Definition*
Size	Number of actors in the network
Inclusiveness	Total number of actors in a network minus the number of isolated actors (not connected to any other actors). Also measured as the ratio of connected actors to the total number of actors.
Component	Largest connected subset of network nodes and links. All nodes in the component are connected (either direct or indirect links) and no nodes have links to nodes outside the component.
Connectivity (Reachability)	Extent to which actors in the network are linked to one another by direct or indirect ties. Sometimes measured by the maximum, or average, path distance between any two actors in the network.
Connectedness	Ratio of pairs of nodes that are mutually reachable to total number of pairs of nodes
Density	Ratio of the number of actual links to the number of possible links in the network
Centralization	Difference between the centrality scores of the most central actor and those of all other actors in a network is calculated, and used to form ratio of the actual sum of the differences to the maximum sum of the differences
Symmetry	Ratio of number of symmetric to asymmetric links (or to total number of links) in a network
Transitivity	Three actors (A, B, C) are transitive if whenever A is linked to B and B is linked to C, then C is linked to A. Transitivity is the number of transitive triples divided by the number of potential transitive triples (number of paths of length 2).

a different type of linkage. Migratory knowledge is information that exists in forms that are easily moved from one location, person, group, or firm to another. Migratory knowledge tends to be contained in books, designs, machines, blueprints, computer programs, and individual minds, all of which encapsulate the knowledge that went into its creation. Embedded knowledge is more difficult to transfer. It "resides primarily in specialized relationships among individuals and groups and in the particular norms, attitudes, information flows, and ways of making decisions that shape their dealings with each other" (p. 79). Craftsmanship, unique talents and skills, accumulated know-how, and group expertise and synergy are all difficult to transfer from one place to another and particularly difficult to transfer across organizational or even divisional boundaries.

The two types of network linkages Badaracco (1991) identified were the product link, associated with migratory knowledge, and the knowledge link, associated with embedded knowledge. In the interfirm context, a product link is an arrangement whereby a company relies on "an outside ally to manufacture part of its product line or to build complex components that the company had previously made for itself" (p. 11). Knowledge links are alliances whereby companies seek "to learn or jointly create new knowledge and capabilities" (p. 12). These "alliances are organizational arrangements and operating policies through which separate organizations share administrative authority, form social links, and accept joint ownership, and in which looser, more open-ended contractual arrangements replace highly specific, arm's length contracts" (Badaracco, 1991, p. 4).

Research on interorganizational linkages began more than forty years ago with the work of Levine and White (1961) and Litwak and Hylton (1962), which spawned a quarter century of interest on the exchange of goods and material resources (see, e.g., Mitchell, 1973; Warren, 1967). More recent work has focused on communication, information, and knowledge linkages (Gulati, 1995; Powell, Koput, & Smith-Doerr, 1996; Tsai, 2001). Eisenberg et al. (1985) developed a two-dimensional typology of interorganizational linkages based on linkage content and linkage level. The content dimension separated (1) material content from (2) symbolic or informational content. The level dimension distinguished three forms of exchange. Eisenberg et al. (1985) state that

> an *institutional* linkage occurs when information or materials are exchanged between organizations without the involvement of specific organizational roles or personalities (e.g., routine data transfers between banks). A *representative* linkage occurs when a role occupant who officially represents an organization within the system has contact with a representative of another organization (e.g., an interagency committee to formulate joint policies). The emphasis here is on the official nature of the transaction and the representative capacities of the individuals. Finally, a *personal* linkage occurs when an individual from one organization exchanges information or material with an individual in another organization, but in a nonrepresentative or private capacity (i.e., via friendship or "old school" ties). (p. 237, italics in the original)

Network Concepts and Measures

Network analysis is an analytic technique that enables researchers to represent relational data and explore the nature and properties of those relations. The entities mentioned earlier in this chapter—for instance, people, work groups, and organizations—are typically represented as nodes or points in a network analysis, with one node assigned to each entity.

The *relations*, such as "communicates with" or "provides data to," are represented as lines connecting the various nodes. These lines are typically called links, ties, or arcs. Links are typically assigned properties that are believed to be inherent to the relations. Two important properties are *directionality* and *strength*. Relations can be either directional or nondirectional. Directional links are those that go from one point to another. That is, they have an origin and a destination. Nondirectional links are those that do not have a direction, representing instead a shared partnership. The relation "supplies parts to" is a directional tie since the parts go from one organization, the supplier, to another organization, the receiver. The relation "is strategically allied with" is a nondirectional relation, since it ties together two firms without a direction between the two.

The second property is *strength*, which indicates the quantity of the relation. The strength of a tie could be "dichotomous" or "valued." A dichotomous tie simply indicates whether the relation is present or absent. Thus, the dichotomous relation "communicates with" simply indicates whether two people, work groups, or organizations communicate with each other without any indication of how much communication occurs. A valued link represents the intensity or frequency of the link. Thus, the strength of the same relation, "communicates with" represented as a valued link could indicate the amount of time people spend communicating with each other, for instance, less than five minutes per week, an hour a week, several hours a week, and so on. Alternatively, it could represent the frequency with which they communicate, for example, once a month, once a week, daily, or their satisfaction with that communication on a numerical scale.

Researchers can examine one or more relations on the same set of nodes. When relations are studied one at a time, they are called *uniplex* relations. Two or more relations studied together are considered *multiplex*. Historically, most network research, including much of the work reviewed in this book, has examined uniplex relations, but there is no theoretical or analytic reason why researchers must limit themselves to single relations.

Indeed, Wasserman and Faust (1994) have argued that network research could be significantly improved if it moved from uniplex to multiplex analysis.

Representing Networks

It is customary in network analysis to organize network data in square data matrices (the same number of rows and columns) that are sometimes called *sociomatrices*. The columns and rows of the matrices are typically assigned the names or numbers of the nodes in the analysis, that is, the people, work groups, or organizations. The cells of the matrices contain entries that represent the relations between all possible pairs of nodes. If the relations are dichotomous, the entries are 1 and 0, with the one representing the presence of the relation and the zero representing its absence. A sociomatrix of 1s and 0s representing binary relations is called an *adjacency* matrix. If the relation is valued, then numbers are entered into the matrix to represent the strength (the frequency, duration, or amount) of the relation between each pair of nodes in the network. It is common to think of these matrices as "who to whom" matrices with the rows representing the "who" and the columns representing the "whom." Thus, it is possible to "read" a matrix from left to right by selecting a row representing "who," moving to a particular cell to find the nature of the relationship that exists, and then moving to the top of the column to read "with whom" it occurs. In a nondirectional network, the value associated with the tie from node A to node B is the same as the value associated with the tie from node B to node A. Hence, these matrices are symmetric, with values above the diagonal being a mirror reflection of values below the diagonal. Directional networks, however, are almost always asymmetric.

Another way to represent network data is via *graphs*. Each participant in the network is assigned a numbered or labeled point. Lines between points represent relations. If relations are directional, arrowheads are placed at the front of the line indicating the direction of the relation. Graphs with directional relations are called *digraphs*. If the relations are dichotomous, a line represents the relation while the absence of a line represents the absence of the relation. If the relations are valued, numbers can be placed on each line to represent the frequency, duration, or other quantity of the relation. These are called *valued graphs*.

In some cases the rows and columns used to represent a network may not be the same entities. For instance, the rows may represent individuals

and the columns may represent different knowledge repositories. These would then be represented in rectangular (rather than square) matrices. Such networks are sometimes referred to as *bimodal* or *affiliation* networks.

In summary, networks represent relational ties among a set of nodes. The nodes may be individuals, groups, organizations, or any other well-defined set of entities. The relations can be communication, affect, shared interpretations, or transfer of tangible or symbolic resources. Relations can be directional or nondirectional, binary or valued, and uniplex or multiplex. These networks can be represented as matrices or graphs.

Measuring Network Properties

In addition to representing the network as graphs and matrices, analysts have also developed a suite of metrics to calculate various properties of the network. These properties can be computed at various levels of analysis. Wasserman and Faust (1994) suggest that there are five distinct levels. The *individual actor* level is the level of the participants represented by the nodes or points in the network, whether individuals, groups, or organizations. At this level analysis would focus on such things as the number of contacts each participant has or the number of others who indicate contact with them. The *dyad* level examines pairs of network members together with their relations. At this level researchers might ask the extent to which ties are reciprocated between each pair in the network. The *triad* level examines three nodes at a time, focusing perhaps on the level of balance among all triads in the network. The fourth level is the *subgroup*. At this level analysts frequently want to identify who belongs to subgroups and who does not. The final *global* level is the network as a whole. Here the focus might be on the proportion of possible ties that actually exist in the network.

Individual Level of Analysis

Degree, indegree, and outdegree

For any given node, the number of directional ties emanating from it is called the node's *outdegree*. Similarly, the number of ties directed to that node, in other words, terminating there, is called the node's *indegree*. The number of nondirectional ties associated with a node is simply called *degree*. The interpretation of the degree metrics depends on the nature of the networks being examined. In a directional communication network, a node's outdegree could be interpreted as "expansiveness," while the node's indegree would signal its "popularity." Some researchers have used degree as one indicator of the node's social capital or centrality. It might seem reasonable to interpret a high degree of centrality as a positive and desirable feature of the network, but it could also be justifiably interpreted as signaling a strain such as communication overload or a constraint on the node's ability to function effectively. Nodes that have a degree of zero are referred to as *isolates;* that is, they have no ties to others in the network.

Betweenness

While degree metrics gauge the extent to which a node is directly connected to all other nodes in the network, *betweenness* measures the extent to which a node is directly connected only to those other nodes that are not directly connected to each other. That is, it measures the extent to which a node serves as an intermediary "between" other nodes in the network. Betweenness measures can be computed either by accounting for the direction of ties or simply the presence of these ties. In a communication network, a node with a high betweenness score is often interpreted as deriving power by controlling or brokering the flow of information as well as managing the interpretation of that information. Clearly, the removal or departure of a node with a high betweenness measure would eliminate the indirect connections among many other nodes in the network. As such it offers an alternative conceptualization of centrality in the network. Nodes that serve as an intermediary between *groups* of people that are not directly connected to other groups (rather than unconnected individuals) are sometimes referred to as *liaisons* or *bridges*.

Closeness

While degree metrics gauge the extent to which nodes are directly connected to all other nodes in the network, and betweenness measures indirect connections, *closeness* measures the extent to which nodes are directly or indirectly connected to all other nodes in the network. Hence a node can have a high closeness score even if the node has a low degree score, but is connected to nodes that either have high degree scores or are, in turn, connected

to other nodes that have high degree scores. Closeness is therefore interpreted as a useful measure to assess a node's ability to efficiently access information directly or indirectly "through the grapevine." In that sense, it offers a third conceptualization of an individual's centrality in the network. It also serves to measure the reach of a node's indirect network.

Padgett and Ansell's (1993) analysis of the marital and business ties among sixteen families in fifteenth-century Florence, Italy, offers an interesting illustration of the differences in degree, closeness, and betweenness measures of centrality. Padgett's data reveal that in the marital network, the Lambersteschi and the Peruzzi families were approximately equally likely to forge marital ties with other families. Hence their degree centrality in the marital network was about the same. However, the Peruzzi family had a substantially higher betweenness centrality measure than the Lambersteschi family. This suggests that members of the Peruzzi family married into other families who in turn did not marry members of one another. Another sharp contrast, involving the Medici and Ridolfi families, can be found in the business network. While the Medicis had only a marginally higher degree of closeness than the Ridolfis, their betweenness centrality was five times as large. That is, while the Medicis and the Ridolfis were equally connected via direct and indirect business ties to the remaining Florentine families, the Medicis were much more likely to engage in direct business ties with families that were not themselves involved in direct business relationships. These contrasts offer some useful explanations and understandings of the role these families played in fifteenth-century Florence.

Structural holes

Burt (1992) developed a series of measures that describe the extent to which an individual fills *structural holes* in the network. These measures examine various properties of the "ego-centered" network, that is, the subset of the overall network that exists among the partners in an individual's network. Using the egocentric network, Burt computes a measure of the individual's *effective network size*. It is based on the premise that ties among a person's network partners attenuate the effective size of that individual's network. The maximum effective size of a network occurs when an individual's communication partners are not connected to one another. However, it is reduced by the average number of ties that each of the partners have with other partners in an individual's network. Burt (1992) argues that *efficiency* is an index of the extent to which individuals have maximized the effective size of their egocentric networks. An individual's *structural constraint* is the extent to which an individual has strong ties with partners who in turn have strong ties with other partners of the individual. Finally, an individual's *hierarchical constraint* measures the extent that a single partner in the network is the source of that individual's structural constraint.

This section has provided conceptual definitions and some illustrations of network properties that can be measured for each individual or node in the network. That is, we can obtain measures for each individual's degree, betweenness, closeness, effective size, efficiency, structural constraint, and hierarchical constraint in the network. Next we describe measures that can be computed between pairs of individuals.

Dyadic (or Link or Tie) Level of Analysis

Wasserman and Faust (1994) note that the directional ties between any two individuals in a network can be characterized as symmetric, asymmetric, or null. Ties are symmetric if individuals have ties to each other. They are asymmetric if only one individual has a link to the other. They are null if neither has ties to each another. *Mutuality* or *reciprocity* is defined as the extent to which ties between two individuals are symmetric. For binary relations, mutuality can be present or absent, depending on whether symmetric links exist between two individuals. For valued relations, mutuality measures the similarity between the values of the links between two individuals. While mutuality measures the extent to which two individuals are directly connected to one another, it is possible to also measure the extent to which two individuals are either indirectly connected through the network (distance and geodesics) or share similar patterns of interactions with others in the network (structural equivalence). These two metrics are discussed next.

Distance and geodesics

For any pair of nodes, two types of links can exist: direct and indirect. *Direct links* are connections between any pair of nodes that involve only those two nodes. *Indirect links* occur between any two nodes by virtue of their connections with other nodes. A direct link between two nodes is said to be a

one-step connection. The smallest indirect connection is two-step, which ties together three nodes with two direct links. Here, the first node is directly connected with the second node, the second is directly connected with the third, which leads the first and third nodes to be indirectly connected to each other with a two-step linkage or two *degrees of separation*. Two nodes can have both direct and indirect connections. To complete the example just given, the first and third nodes could also have a direct link, in which case these two nodes would have a direct link to each other as well as an indirect link through the second node.

Higher levels of indirect links exist within many networks such as three-step connections, which tie together four nodes, four-step links, which tie together five nodes, and so on. It is this measure that is referenced in the "small world" hypothesis that any two individuals on the planet are separated on the average by six degrees of separation (Milgram, 1967). The notion of multiple-step linkages, called *n-step links* where *n* represents the number of links, naturally leads to the idea of *chains* or *paths* within the network. There are many applications of these in organizational contexts. Wasserman and Faust (1994) provide the example of dissemination of information among employees in organizations. "An important consideration is whether information originating with one employee could eventually reach all other employees, and if so, how many lines it must traverse in order to get there. One might also consider whether there are multiple routes that a message might take to go from one employee to another, and whether some of these paths are more or less efficient" (p. 105).

There are a number of network concepts that describe how to get from one point to another in a network. One of the most important of these is the *distance* between two points. The distance, typically represented by the symbol *d*, is the number of links between two nodes. The shortest distance between two points is called a *geodesic*. The largest distance is called the *diameter*.

In summary, the indirect links between two individuals provide at least two useful measures at the dyadic level. First, *reachability* is the shortest path (or the geodesic) that connects two individuals in a network. Reachability has a minimum value of one if two individuals are directly connected, a value of two if they are one-step removed, and so on. Reachability has an infinite (or undetermined) value if it is not possible for one individual to directly, or indirectly, reach the other individual.

Second, *redundancy* measures the number of alternative shortest paths (or geodesics) that connect two individuals indirectly. A high redundancy score would indicate a greater likelihood that information will flow from one individual to another via one of the multiple indirect paths.

Structural equivalence

While mutuality is a measure based on the direct links between two individuals, and reachability and redundancy are based on the indirect links between two individuals, there are additional measures of *structural equivalence* that are based on the similarity of interaction patterns between two individuals. In its strictest form, two individuals have a high degree of structural equivalence if they are tied to—and not tied to—the same other individuals in the network. A more general measure of structural equivalence, sometimes called regular equivalence, measures the extent to which two individuals have ties to similar other individuals in the network though not necessarily the same others. Similar other individuals can be defined a priori based on attributes such as profession. So, for instance, two doctors may have a high degree of regular equivalence if they both have ties to nurses, even if they are not the same nurses. However, more commonly, "similar other individuals" is defined based on their patterns of interaction in the network.

Triadic Level of Analysis

Properties of the network can also be measured for individuals in the network taken three at a time. *Transitivity* and *cyclicality* measure the extent to which every set of three actors, say, A, B, and C, in the network demonstrates certain structural patterns. If A directs a link to B and B directs a link to C, the network triad is *transitive* if A also directs a tie to C. For instance, if a group of three organizations is in a transitive relation, then if A makes a donation to B, B will make a donation to C, *and* A will also donate to C.

A network triad is *cyclical* when A directs a tie to B, B ties to C, and C in turn links to A, thereby completing the cycle. Transitivity and cyclicality are identical if the network involves nondirectional links. In essence they both assess the extent to which, for instance, we are friends with friends of our friends.

Subgroup Level of Analysis

Components and cliques

A graph or network is *connected* if it is possible to get from one point to all other points in the graph, that is, if every point is reachable from every other point. This typically happens only in relatively small networks. More likely, the graph is unconnected or *disconnected*, meaning that it is not possible to get to all points in the graph from the other points. This implies that there are subsets of points in the network that are connected to one other, called *subgraphs*; it also implies that the subgraphs are not connected to each other. These connected subgraphs of the network are called *components* of the network. A *strong component* is composed of all individuals who have direct or indirect ties to all other individuals in the component. A *weak component* is composed of individuals who are connected to all other individuals in the subgraph irrespective of the directionality of the link.

The criteria to define these components are somewhat flexible. Substantively, components index the extent to which clearly identifiable and distinct cliques exist within the network. Although the term *clique* has a very specific definition in network methodology, it was used here in the preceding sentence in its more colloquial sense. In network theory, a *clique* is defined as a maximally complete subgraph, that is, the maximum number of individuals in the network who are all directly connected to one another, but are not all directly connected to any additional individuals in the network. One or more individuals can be member(s) of more than one clique. Again, more relaxed criteria are also used to identify cliques. An *n-clique* includes the maximum number of individuals in the network who are all directly or indirectly connected to one another via no more than n links. Further, they are not directly (or indirectly) connected via n or fewer links to any other additional individual in the network. Clearly, a 1-clique (that is, where n=1) is equivalent to the strict definition of cliques. A 2-clique or a 3-clique is a less conservative definition thereby allowing more members to be included in the clique.

While n-cliques relax the requirement of a *direct* link to all members in the clique, *k-plex* relaxes the requirement of a direct link to *all* members in the network. A k-plex therefore includes the maximum number of individuals in the network who are directly connected with, at least, all but k of the individuals in the group. Further, they are not all directly connected to any other additional individual in the network. Clearly, a 1-plex group is identical to a clique, comprising individuals who are directly connected to all but one of the members in the group (that is, themselves), while a 2-plex comprises a group of individuals who are each connected directly to all but two in the group (that is, themselves and one other member).

Positions

While components and cliques help measure the extent to which subgroups of individuals in a network are cohesively connected, there are other measures which index the extent to which individuals in the network engage in similar structural interactions (or are structurally equivalent), and thereby enact similar roles or positions. While components and cliques help identify subgroups of individuals who are relationally tied to one another, role analyses identify groups of individuals who occupy similar positions. The distinction between the two sets of measures reflects the traditional intellectual distinctions between the relational and positional approaches described in chapter 1.

Global Network Level of Analysis

Density is a concept that refers to the extensiveness or completeness of the relations in the network. Another frequently used term for density is *connectedness*. Density is measured as the ratio of total links to possible links, that is, the percentage of possible relations that actually exist. Networks with few linkages are called *sparse* or sparsely connected networks; networks with many links are said to be *dense* or highly connected.

Network centralization is an umbrella concept that examines the variation in individuals' centralities within a network. Individuals' centrality scores were defined in a previous section discussing network measures at the individual level of analysis. In general, a network is centralized if a few individuals (perhaps, just one) have considerably higher centrality scores than others in the network. A network is decentralized if the members in the network have roughly the same centrality scores. This implies that people are not more (or less) central than others. Consequently, network centralization indexes the variability among the individuals' centrality. Degree network centralization measures the extent to which some individuals have a much higher degree centrality score than others.

Betweenness and closeness network centralization provide corresponding indices based on individuals' betweenness and closeness centrality scores.

The Multitheoretical, Multilevel (MTML) Analytic Framework

Representing networks as matrices or graphs and measuring properties of the network serve useful descriptive purposes. However, *explaining* the emergence of networks requires an analytic framework that enables inferences to be made on the basis of theories and statistical tests. Consequently, this section introduces the MTML framework and p^* statistical network techniques, an integrated theoretical and analytic framework that provides an appropriate basis for studying multiple substantive theories across several analytic levels on the basis of valid statistical inference techniques (Contractor, Wasserman, & Faust, 2001).

The problem of explaining network emergence explored in this book challenges network analysts to make four key moves: (1) from single theoretical to multitheoretical analyses, (2) from single level to multilevel analyses, (3) from purely network explanations to hybrid models that also account for attributes of the individual nodes, and (4) from descriptive or exploratory techniques to inferential or confirmatory ones. These four issues are discussed in greater detail in the following subsections.

Multitheoretical Analyses

First, our review of the vast network research literature (Monge & Contractor, 2001) led us to realize that relatively few network studies utilize theories as the basis for formulating research hypotheses, and those that do use only single theories. As such, they tend to account for relatively small amounts of network variance. This, of course, contributes to our knowledge of communication networks, but not nearly to the extent that most would like. This observation led us to develop the MTML perspective as a way to help compare and integrate diverse theories and to increase the explanatory power of research efforts.

Alternative social theories make differential predictions about communication networks. Some of the theoretical mechanisms are unique, even complementary. Others are duplicative, at least in part. Still others compete, offering contradictory explanations. None of the theories, on their own, provide definitive, exhaustive explanations of network phenomena. The MTML framework identifies theoretical mechanisms in social theories and shows how they correspond to network properties such as mutuality and density. We argue that utilizing multiple theories should improve our explanations of network evolution as well as significantly increase the amount of variance accounted for by these theoretical mechanisms.

Multilevel Analyses

Second, one of the key advantages of a network perspective is the ability to collect and collate data at various levels of analysis (person, dyad, triad, group, organizational, and interorganizational). However, for the purposes of analyses most network data are either transformed to a single level of analysis (e.g., the individual or the dyadic level) that 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 likelihood of a communication tie from person A to person B is predicated on the presence of a communication tie from person B to person A. However, balance theory suggests that the likelihood of a communication tie from person A to person B is predicated on the configuration of ties the two people have with third individuals, C through, say, person 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 (1997, p. 912) 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." 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, p. 912). This is the problem of *dyadic atomization* noted by Granovetter (1992). 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 hypotheses testing. The MTML framework combined with the p^* analytic techniques provides these capabilities.

Incorporating Attributes

Third, a long-standing debate among structural scholars has centered on the merits and feasibility of incorporating information about attributes of nodes into network studies. Typical examples are gender or an individual's organizational affiliation in interorganizational networks. While formalists tend to dismiss the utility of looking at attributes, the majority of network scholars embrace the idea (Wellman, 1988). Unfortunately, even those who would like to create hybrid models that incorporate attribute information to explain network patterns are sometimes deterred by the difficulty of doing it in a statistically defensible manner.

Further, while some empirical network research exists that incorporates data on individual attributes, these studies are often limited to one level of analysis, as described previously. For instance, theories of homophily would suggest that in an interorganizational network, people with similar organizational affiliations are more likely to have communication ties with one another than with people who have different organizational affiliations. In a potentially conflicting prediction, theories of collective action would argue that individuals with similar organizational affiliations are more likely to be structured in centralized networks among themselves rather than with individuals from different organizations. Simultaneously combining and contrasting these two predictions involving individuals' attributes goes beyond the capabilities of most contemporary network analytic methods.

Valid Statistical Inference

In the past two decades scholars have made considerable progress in the development of descriptive network metrics. Since network data are relational, they constitute, by definition, nonindependent observations. Consequently, "standard" statistical methods that assume independent units such as regression analysis and ANOVA are not appropriate. The efforts to develop statistical estimation of network properties have been relatively sparse, unconnected, and esoteric, thereby making them relatively inaccessible to the larger research community and inapplicable for integration across multiple levels of analysis. 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 person A to person B also exist from person B to person A. However, network analysts have been less successful in formulating statistically defensible and computationally accessible tests that can determine if the degree of reciprocity in a network is statistically significant.

In summary, there is a pressing need for a multitheoretical, multilevel approach to organizational network analysis. Further, this framework needs to include the capability to incorporate theoretical explanations that are based on information about attributes and other external characteristics outside the bounds of the properties of the focal network. Finally, valid statistical inferential techniques need to simultaneously incorporate multiple theoretical explanations at the individual, dyad, triad, and global levels of analyses.

The following section describes the p^* statistical analytical techniques for network analysis. This framework 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 provides an omnibus assessment of the complementary and contradictory influences of these multiple theories. Finally, it focuses attention on areas where opportunities remain to develop new theoretical explanations. This discussion provides the context in which it is possible to develop the genres of multitheoretical, multilevel hypotheses that influence the structural tendencies of a network. We turn to that task after describing the logic of p^* analysis.

Realizations of Graphs and Networks in p* *Analysis*

Statistically, every observed network, that is, every network data set, can be viewed as one "realization" of a network or graph. A *realization* is one particular configuration of ties in a network out of the set of possible configurations. These possible configurations are anchored at one end by a completely connected network where everyone is tied to everyone else. It is anchored at the other end by a completely empty network, one in which no one is tied to anyone else in the network. Obviously, many different realizations exist between these two poles. For example, in one realization of a three-person network, person A might be connected to persons B and C, but B and C might not be connected to each other. In an alternative realization, A might not be connected to B or C, who are themselves connected to each other.

Consider an interorganizational consortium of 17 members representing various industry and government organizations that we will examine in detail later in this chapter. The observed communication relations in the data constitute only one realization of a graph consisting of 17 people and the possible ties among them. Theoretically, there are many other graph realizations that could have arisen based on the communication ties among the 17 members. Further, it should be apparent that as the number of nodes in a network gets larger, the number of possible network realizations increases dramatically. The statistical question of interest is why the observed realization occurred out of the rather large set of other possible graph realizations.

The answer to this question resides in whether the observed graph realization exhibits certain hypothesized structural features, such as reciprocation, balance, and density. If these features exist, they increase the likelihood of some realizations and decrease the likelihood of others. The presence of these structural features are captured by estimating parameters that quantify the effects of the hypothesized structural property on the probability of ties being present or absent in the network. These estimates indicate whether graph realizations that contain the theoretically hypothesized property have significantly higher probabilities of being observed. If so, then the hypothesized property is statistically important for understanding the structural configuration of the observed network. This logic is central to random graph models, including Markov random graph models (Frank & Strauss, 1986; Strauss & Ikeda, 1990) and the p^* family of models (Anderson, Wasserman, & Crouch, 1999; Pattison & Wasserman, 1999; Robins, Pattison, & Wasserman, 1999; Wasserman & Pattison, 1996).

Recall our discussion in the preceding paragraphs that a network of 17 individuals can have a very large, but finite, number of realizations or configurations. At one end of the continuum is a network of 17 individuals with no directed communication links between them. At the other end of the continuum is a network of 17 individuals, all of whom have direct communicative links to one another, a completely connected network. Along this continuum there is a very large number of possible configurations. In a network of 17 individuals, each individual can have links to 16 other individuals. Hence the network of 17 individuals can have a total of 272 (17 times 16) links. If the network is a binary network (that is, links to individuals are either present or absent), each of the 272 links can be in one of two states, either present or absent. Hence there are 2^{272} possible configurations of the network or approximately 7.5885 X 10^{81}, that is, the number of configurations is over 7 followed by 81 zeros! The number of possible configurations of the network is referred to as the *sample space* (Wasserman & Faust, 1997).

Our general goal is to see if certain structural characteristics of the observed network are more, less, or just as likely to occur by chance among the various possible configurations within the sample space. These structural characteristics could be, for instance, the number of links in the observed network, the number of reciprocated links in the observed network, the number of transitive triads in the observed network, or the overall network centralization of the observed network. In order to assess tendencies for these structural characteristics in the observed network, we must begin by making some assumptions regarding the probability of finding each of the 2^{272} possible realizations within the sample space. To do so we make a simple—and as we shall argue later, somewhat simplistic—assumption, that each of the links in the network has a 50-50 chance of being observed. In our 17-person example with 272 links that are equally likely to be present or absent, each of the possible 2^{272} configurations is also equally likely to be observed. That is, each realization of the 2^{272} possible network configurations has a $½^{272}$ probability of being observed. Our assumption here implies that the various realizations follow a "uniform probability distribution," where each alternative is equally likely to occur.

Since we assumed that each link has a 50-50 chance of occurring, it also follows that in a large proportion of the 2^{272} configurations of the network the individuals will chose about half (or 8) of the 16 other individuals in the network. These would be distinct configurations because the individuals could choose different sets of 8 other individuals in each of these network realizations. We could then conclude, based on our assumption of a uniform probability distribution, that if the observed network were equally likely to occur as any of the 2^{272} possible configurations of the network, the "expected" number of links for each actor in the observed network would be 8, which is half of 16. That is, the expected number of links present in the observed network would be 136 (17 times 8). Further, if the observed network had considerably more or less than 136 links present, we would be able to assess the likelihood (or the probability) that such a configuration is likely to occur within the sample space of all possible configurations. By doing so, we will be able to statistically determine the probability that the observed network has a structural tendency for a larger or smaller number of links than one would expect purely on the basis of chance.

An important consideration in determining if the theoretically hypothesized property has a significantly higher probability of being observed is to ensure that this probability is not an artifact of other properties of the network itself. For instance, consider 2 networks of 17 individuals each. Assume that the first network has many more communication links present than in the second network. Further, suppose we observe that the first network exhibits a much higher degree of reciprocity (a larger number of mutual links) than in the second network. This observation alone does not warrant a claim that the first network has a greater structural tendency toward reciprocity. The higher reciprocity in the first network may well be an artifact of the greater

number of links in that network. That is, if there were more links in a network, one would expect higher reciprocity purely on the basis of chance. Hence, in order to determine if the first network exhibits a greater tendency toward reciprocity, statistical techniques need to be applied that *condition* on the number of links in the network (see Wasserman & Faust, 1997).

More generally, these techniques facilitate testing for higher-level structural characteristics, such as reciprocity, after conditioning for lower level structural characteristics, such as the number of links chosen by each individual. For instance, one can statistically test for a structural tendency toward transitivity in the network, after conditioning for lower level structural effects such as the number of links chosen by individuals in the network, as well as the number of reciprocated links in the networks. By doing so, it is possible to ensure that the structural tendency for transitivity observed in the network is not simply an artifact of the number of ties or the number of reciprocated ties in the network.

The statistical "conditioning" just described works on the basis of a fairly simple logic. Suppose that in our example of 17 individuals, we were interested in assessing whether the observed network exhibited a structural tendency toward reciprocity (or mutuality). In statistical terms, we want to assess the probability that reciprocity in the observed network is more, less, or just as likely to be found from the sample space of all possible network configurations of 17 individuals. Since, as noted previously, the reciprocity in the observed network may to some extent be an artifact of the number of links in the observed network, we would need to condition for this artifact.

This conditioning is done quite simply by reducing the sample space to include only those realizations of the graph that have exactly the same number of links as was found in the observed network. If, in the observed network, each individual had on average ties to only 3 other individuals, the total number of links present in the network would be 51 (17 times 3). In order to determine if there were a structural tendency toward reciprocity in this observed network, one would compare it to a subset of the 2^{272} network realizations that also had only 51 links. That is, the sample space used to test the structural tendency toward reciprocity would include only those network realizations where the number of links is the same as the number of links present in the observed network (51, in this example). By doing so, one is in effect comparing the degree of reciprocity in the observed network to the family of networks that have exactly the same number of links. For this reduced sample space, estimates of the reciprocity that is most likely to occur can be made. This "expected" reciprocity can then be compared to the observed reciprocity. If the observed reciprocity is much larger or smaller than the expected reciprocity one can justifiably claim that the observed network exhibits a statistical tendency toward reciprocity. Hence the process of "conditioning" is tantamount to reducing the number of possible configurations (or the sample space) to which the observed network is compared. In statistical terms, it implies that the observed network is being compared to the expected value based on a conditional probability distribution. This procedure follows the general logic of statistical inference in which systematic or expected variation is compared to a known distribution. The extent to which the observed component exceeds the expected indicates whether the observed is statistically significant at a selected probability level. As mentioned earlier, the logic of conditioning can be used to assess higher order structural tendencies such as network centralization after conditioning for lower level structural tendencies such as the number of choices made by an individual, the degree of reciprocity, the tendency toward transitivity. As such it lays the framework for multilevel statistical tests for structural tendencies in the network.

The discussion so far has been based on an overly simple premise that must now be revisited. We have assumed that, in the sample space of all possible network realizations, a link between two individuals has a 50–50 chance of being either present or absent. We then described how the structural tendency in the observed network could be compared to what would be expected from this uniform distribution of all possible network realizations. Wasserman and Faust (1997) note that this assumption can be usefully described in terms of coin tosses. In order to determine one possible network realization, suppose we used the toss of a coin to determine if a link were present between the first and the second individual in the network. Let us suppose heads counts as the presence of a link and tails counts as the absence of a link. We could toss this coin 272 times and use each result to assign the presence (or absence) of a link between each pair of individuals in the network. The 272 coin tosses will generate one possible realization of the network of 17 individuals. If we repeated this exercise of 272 coin tosses and recorded the outcome each time, we would generate a large number of possible network realizations. Assuming the coin is not "biased" toward heads or tails, each coin toss has an equal, 50-50, chance of coming up heads or tails. Further the likelihood of each coin toss is totally independent of any of the preceding coin tosses. That is, each link from one individual to another is assumed to have a 50-50 chance of occurring and each link is independent of every other link between any pair of individuals. This

is equivalent to the assumption of a *uniform probability distribution* for the realization of various network configurations.

Suppose we replace the coin with a "biased" coin—one that comes up heads 60 percent of the time, and tails 40 percent. If we repeat the above exercise we can generate a very large number of network realizations but in this case there is an unequal 60-40 chance of a link from one individual to another. Further, as in the previous case, the link from one individual to another is independent of the links from any individual to any other individual. This assumption is equivalent to what is described in statistical terms as a family of *Bernoulli distributions* that is defined by the parameters n and p. Parameter n is the number of trials, or in this case the number of possible links among the individuals, 272. The p parameter is the probability of a "success" for each trial, in this case, 60 percent for the presence rather than the absence of a link between each pair of individuals.

Extending this exercise further, suppose we were to consider a scenario where each coin toss was not independent of preceding coin tosses. This is a scenario hard to conceive in practice but one that is entirely plausible when considering networks of individuals. That is, the presence of a tie from individual A to individual B is not independent of a tie from individual B to A, individual B to C and/or individual C to A, or even in some circumstances individuals D and E. Indeed, these may be exactly the sorts of structural tendencies that we are interested in examining.

The "conditioning" process outlined is in fact one way of assessing these structural tendencies. It does so by assessing the propensity toward these structural effects based on a uniform probability distribution—after conditioning by shrinking the sample space for the plausible lower order effects, such as number of choices, degree of reciprocity, and so on. An alternative interpretation is that we assess the degree of reciprocity in an observed network using a *conditional uniform distribution* that includes all possible network realizations that have the same number of links as the observed networks. Likewise, we assess the degree of transitivity in the observed network using a conditional uniform distribution that includes all possible network realizations that have the same number of links as well as the same number of mutual and asymmetric links as the observed network.

If one assumes a uniform probability distribution, the probability of a specific realization of the network can be considered as a product of the independent probabilities of ties being present between every pair of individuals in the network. Hence, the probability of a particular network realization is analogous to a traditional contingency table such as one classifying people on the basis of gender and managerial position. In this case, the rows of the contingency table might be divided into males and females and the columns into managers and nonmanagers, where the expected value for a particular cell such as female managers can be computed as the product of the probability of being in the female row times the probability of being in the manager column. Typically, a researcher would assess a tendency for the observed number of female managers to be higher, lower, or equal to what would be expected, based on the proportion of females and managers in the sample.

In similar fashion it is possible to assess the likelihood for links or higher order structural characteristics in the network to be higher, lower, or equal to what would be expected based on the proportion of links sent and received by individuals in the network. For categorical or ordinal data, which is typical of network linkages studied by most social scientists, these effects can usually be estimated using *log linear analysis*. In a simple form of this analysis, the likelihood or expected probability of ties in the network is the product of the independent probabilities of the number of ties sent by individual A and the number of ties sent by individual B. However, a straightforward mathematical transformation, the logarithm of this likelihood, called simply the *log likelihood*, can be computed as the sum of the logarithms of the independent probabilities. This logarithmic transformation of a product of probabilities to a linear sum of probabilities is what gives this technique the name log-linear analysis. Converting the probability, which ranges from 0 to 1, to its logarithmic value widens its range from $-\infty$ to $+\infty$ enabling it to better capture the variations among the explanatory structural characteristics of the network that can theoretically occur over that range. To keep the statistical estimation analytically tractable, rather than computing the probability of a tie, techniques are used to estimate the odds of a tie. The odds are defined as the ratio of the probability of a tie being present to the tie being absent. The logarithm transformation of the odds is called a *logit*. Wasserman and his colleagues (e.g., Anderson, Wasserman, & Crouch, 1999; Wasserman & Pattison, 1996) have shown that a specific family of p^* logit network models can be appropriately estimated using *logistic regression*. Details on how to compute p^* network analyses with the PSPAR computer program are illustrated using an example at the end of this chapter.

The Multitheoretical, Multilevel Model

The brief statistical overview of the challenges and opportunities for the analysis of networks demonstrates the increasing plausibility to empirically assess

the structural tendencies of networks informed by multiple theories at multiple levels. Table 2.4 provides a summary of a multitheoretical, multilevel (MTML) framework to test hypotheses about organizational networks. The table describes ten classes of network hypotheses. Each represents a different set of relational properties that can influence the probabilities of graph realizations. In each case, the hypothesis is that graph realizations with the hypothesized property have larger probabilities of being observed than those that do not have the hypothesized property.

The table is organized by endogenous and exogenous variables that influence the probability of ties being present or absent in the focal network. *Endogenous variables* (rows 1 through 4) are relational properties inherent in the focal network that influence the realization of that network. *Exogenous variables* (rows 5 through 10) refer to various properties outside the focal network that influence the probability of ties being present or absent in the focal network, that is, its realization.

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 its use in causal modeling, endogenous variables here are not predicted by exogenous variables. Here, both explain structural tendencies of the network. *Endogenous variables* are characteristics of the relations within the network that are themselves used to explain the structural tendencies of that relation. *Exogenous variables* are characteristics of the network, other than the relation itself, that are used to explain the structural tendencies. Exogenous variables include the attributes of the people or other nodes in the network, other relations within the network, as well as the same relation in the network in the previous points in time. The following two sections review the influence of endogenous and exogenous predictors in structuring network realizations at each of the individual, dyadic, triadic, and global levels. Each of the ten classes of hypotheses is illustrated with one of the theoretical mechanisms for emergence of communication networks discussed more fully in the remaining chapters of the book.

Endogenous Network Variables

Table 2.4 contains three columns. The first identifies endogenous (rows 1–4) and exogenous (rows 5–8) predictor variables at the four levels of analysis and in relation to other networks (rows 9 and 10). The second column provides examples of specific network measures for each of the ten classes

Table 2.4

Summary of the Multitheoretical, Multilevel Framework to Test Hypotheses About Organizational Networks (Variable of Interest: Probability of the Realization of a Graph)

Independent Variable	*Examples of Specific Measures*	*Hypotheses*
1. Endogenous (same network): *Actor level*	Individual network metrics such as choice actor centrality, structural autonomy	Graph realizations that have higher values of actor level measures (e.g., centrality, structural autonomy) have larger probabilities of occurring (e.g., *theory of social capital, structural holes*)
2. Endogenous (same network): *Dyad level*	Mutuality, reciprocation	Graph realizations that have more mutuality or reciprocation (i.e., a tie from i to j and a tie from j to i) have larger probabilities of occurring (e.g., *exchange theory*)
3. Endogenous (same network): *Triad level*	Transitivity, cyclicality	Graph realizations that have more cyclicality (i.e., a tie from j to k, k to i, and i to j) or more transitivity (i.e., a tie from i to k, k to j, and i to j) have larger probabilities of occurring (e.g., *balance theory*)
4. Endogenous (same network): *Global level*	Network density, centralization	Graph realizations that have more network centralization have larger probabilities of occurring (e.g., *collective* action theory)
5. Exogenous: Actor attributes (*actor level*)	Age, gender, organization type, education	Graph realizations where there are ties between actors with similar attributes (age, gender, org type, education) have larger probabilities of occurring (e.g., *theories of homophily*)
6. Exogenous: Actor attributes (*dyad level*)	Differential mutuality and reciprocation	Graph realizations where there is a greater likelihood of mutual (or reciprocated) ties between actors with similar attributes have larger probabilities of occurring (e.g., *exchange theory*)
7. Exogenous: Actor attributes (*triad level*)	Differential transitivity and cyclicality	Graph realizations where there is a greater likelihood of transitive (or cyclical) ties between actors with similar attributes have larger probabilities of occurring (e.g., *balance theory*)
8. Exogenous: Actor attributes (*global level*)	Differential network density, centralization	Graph realizations where there is a greater likelihood of network centralization among subgroups with similar attributes have larger probabilities of occurring (e.g., *collective action theory*)
9. Exogenous: Network (*other relations*)	Advice, friendship network	Graph realizations where, say, communication ties between actors co-occur with their ties on a second relation (e.g., advice or friendship) have larger probabilities of occurring (e.g. *cognitive theories*).
10. Exogenous: Network (*same network at previous point in time*)	Communication network	Graph realizations where the ties between actors at one point in time co-occur with ties at preceding points in time have larger probabilities of occurring (e.g., *evolutionary theories*)

of hypotheses. The final column provides typical network hypotheses. Rows 1 through 4 present the four levels of endogenous relational properties of the focal network that influence the realization of the network.

Figures 2.1 through 2.10 accompany the discussions of each of the ten rows in table 2.4. Each of these figures shows a simple hypothetical network of people, departments, organizations, and so on, represented by circles that are linked to one another by lines. The solid lines represent links that are observed in the network. The dotted lines represent the likelihood for an additional link to exist in the network based on predictions made by a specific theoretical mechanism. The positive or negative sign used to label these dotted lines indicates whether the theory would predict a higher or lower likelihood for this additional link to be present. While the theory might predict several additional ties in the hypothetical network, for simplicity the figures illustrate the likelihood of only one additional tie that is more likely to be present and one additional tie that is less likely to be present.

THE INDIVIDUAL LEVEL

The *endogenous* individual level (sometimes also called the nodal or actor level) refers to network properties of the entities that comprise the network. The individual level can be people, groups or even entire organizations in the case of an interoganizational network. Column 2 of row 1 shows endogenous, nodal level properties, measured at the individual level as discussed earlier in the chapter. These include degree, betweenness, and closeness centrality, as well as measures such as effective size, efficiency, structural autonomy, and hierarchical constraint. These endogenous network properties are different from the exogenous attributes of individual nodes such as age, gender, and affiliation in that the former are viewed as inherent in the network , that is, defined by the node's relations, and the latter are viewed as attributes that are external to, and independent of, the network. (The external measures will be discussed shortly.) For instance, the theory of structural holes (Burt, 1992) suggests that individuals 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 link. Hence, as illustrated in figure 2.1, the theory of structural holes would suggest a lower probability for a tie between the actor at the top-center and the actor at the lower left corner because the former is already indirectly connected with the latter via an indirect link. However, the theory would suggest a

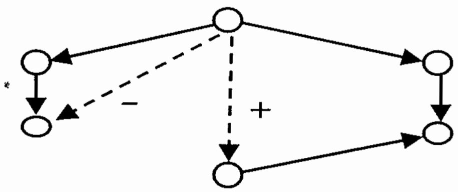


Figure 2.1
Endogenous actor level: Theory of structural holes

higher probability of a tie from the actor at the top and center to the actor at the bottom and center because the former is not otherwise indirectly connected to the latter. As indicated in row 1, column 3 and illustrated in figure 2.1, this hypothesis claims that there are greater probabilities for the realization of a particular network configuration in those situations in which individuals or organizations have a high degree of structural autonomy.

The dyadic level

The endogenous *dyad* level (also called the link or tie level) refers to various network measures that characterize the ties between nodes in the network (row 2). These dyadic level properties include mutuality and reciprocation. For instance, theories of social exchange (Blau, 1964; Homans; 1958, 1974), network exchange (Willer & Skvoretz, 1997), and resource dependency (Emerson, 1962, 1972a, 1972b; Pfeffer & Salancik, 1978) suggest that individuals and organizations forge ties by exchanging material or information resources. In its most elemental form, this hypothesis claims that the probabilities for the realization of a graph are higher in networks that have a high degree of reciprocated or mutual ties (see figure 2.2). As illus-

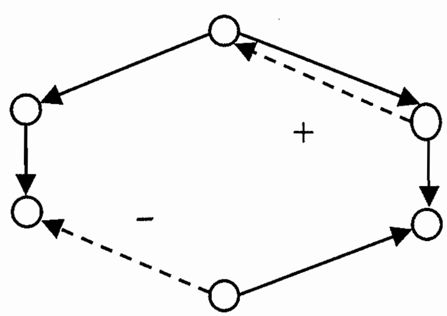


Figure 2.2
Endogenous dyad level: Theory of social exchange

trated in figure 2.2, the theory of social exchange would suggest a higher probability of a tie from the actor at the top right corner of the network to the actor at the top-center because a tie already exists between these two leading from the actor at the top-center to the actor at the top right corner, thus reciprocating the contact. In contrast, there is a lower likelihood of a tie from the actor at the bottom-center of the network to the actor toward the bottom left of the network because the left-center node does not have any ties with the bottom center node.

The triad level

The endogenous triadic level refers to measures defined on the set of possible three-node combinations in the network. In the case of endogenous variables (row 3), these triadic level network properties include transitivity and cyclicality. As defined previously, a triad is transitive if person A has a tie to person B, B has a tie to a third person C, and A also has a tie to C. 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) suggest a tendency toward consistency in relations. Colloquially, friends of friends should be one's own friends, that is, people typically like their friends' friends. In contrast, transitivity in formal relations, such as exercise of authority, reflects a hierarchical tendency in the network—one's boss's boss is also one's boss. Hypotheses about transitive behavior should be supported in network realizations that contain triads that exhibit a high degree of transitivity (see figure 2.3).

Cyclicality in triads occurs when there is a link from persons A to B, a link from B to C, and a link from C to A, completing the cycle. Interpreta-

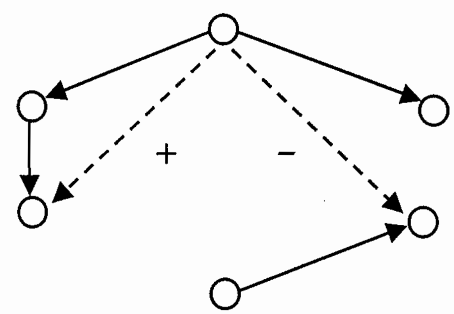


Figure 2.3
Endogenous triad level: Balance theory

tion 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 is a network property that can be thought of as illustrating the theory of generalized exchange (Bearman, 1997). Node A does a favor for B, and B, rather than returning the favor directly to A does a favor for node C, who in turn does a favor for A, thereby returning A's favor to B indirectly.

As shown in figure 2.3, balance theory suggests the likelihood of a tie from the actor at the top-center of the network to the actor at the lower left of the network. This is expected because this tie would complete a transitive triad involving the actor at the top-center of the network and the two actors on the left side of the network. However, there is a lower likelihood of a tie from the actor at the top-center of the network to the actor at the bottom right of the network because this tie would not facilitate the completion of a transitive triad. It is also worth noting that while balance theory, as indicated in figure 2.3, suggests a positive likelihood of a tie from the actor at the top-center of the network to the lower left part of the network, the theory of structural holes, as indicated in figure 2.1, suggested a lower likelihood of a tie from the actor at the top-center of the network to the actor at the lower left of the network. Taken together, these observations underscore how the MTML framework can be used to examine simultaneously two different theoretical mechanisms that may provide contradictory explanations for the likelihood of network ties.

The global level

The global level (row 4) refers to properties of the entire network that influence the probability of the realization of a specific observed network. As column 2 of row 4 shows, endogenous global properties include the network's density and its degree of centralization. The degree of centralization of the entire network depends on the extent to which a subset of people in the network has a much higher degree of centrality than the rest of the other people. This type of configuration concentrates message flow or other network activities on those nodes rather than distributing it more evenly to all the nodes. For instance, theories of collective action (Coleman, 1973, 1986; Marwell & Oliver, 1993) and public goods (Fulk, Flanagin, Kalman, Monge, & Ryan, 1996; Samuelson, 1954) suggest that people or organizations 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 the realization of networks that have a high degree of centralization (see figure 2.4).

The theory of collective action illustrated in figure 2.4 predicts a higher probability of a tie from the actor at the top-center to the actor at the lower right of the network. This occurs because the actor at the lower right of the network is a central actor and adding a link from the actor at the top-center to the actor at the lower right would enhance the network centralization of the network. However, the theory of collective action would also suggest a lower probability of a tie from the actor at the top-center of the network to the actor at the bottom-center because this tie would not increase the overall network centralization.

Exogenous Variables

Exogenous variables are elements outside the focal relation within the network that influence the probability of ties being present or absent in the focal network. As mentioned earlier, these exogenous variables derive from attributes of the nodes (rows 5 through 8), as well as properties of other relations among the network of nodes (row 9), and the same network of relations at previous points in time (row 10). These cases are discussed in the following paragraphs.

The individual level

The individual level of exogenous variables (row 5) refers to individual or organizational attributes that influence the probability of ties being present or absent in the observed network. These individual level attributes include

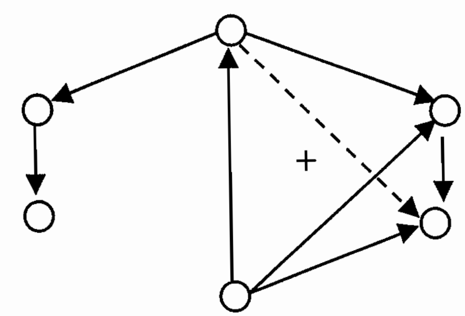


Figure 2.4
Endogenous global level:
Theories of collective action

such things as age, gender, and membership in an organization, or the type of organization. Exogenous nodal properties are different from endogenous nodal properties (row 1) in that the former are externally specified attributes of the entities that comprise the network, such as age, education, organizational affiliation, while the latter are derived from properties of the network itself, such as an individual's popularity or an organization's centrality. For instance, theories of homophily suggest that individuals seek to forge links 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., Carley, 1991; Coleman, 1957; Ibarra, 1992, 1993a, 1993b, 1995). As column 3 of row 5 shows, hypotheses based on homophily would be supported if the probabilities of ties being present or absent in the network reflected the propensity of nodes to link to others with similar attributes. In the case of the 17-member interorganizational consortium discussed earlier, the attribute of interest may be the type of organization—government or industry—in which an individual is employed (see figure 2.5).

Homophily theory suggests the greater likelihood of a tie from the actor of the top-center of the network in figure 2.5 to the lower left of the network because the two actors share a similar attribute—both represent government organizations. In contrast, the theory of homophily predicts the lower likelihood of a tie from the actor of the top-center to the actor toward the lower right of the network because the former represents a government organization while the latter represents the industry.

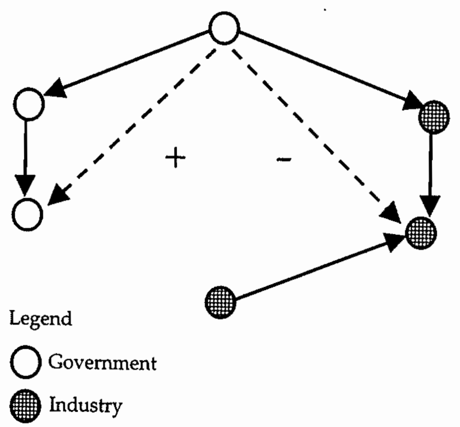


Figure 2.5
Exogenous attribute actor level:
Theories of homophily

The dyadic level

The influence of exogenous variables at the dyadic level (row 6) refers to the influence of shared exogenous attributes on dyadic properties of the network. Typical dyadic level properties include mutuality and reciprocation. As discussed previously, the endogenous influence of the focal network at the dyadic level (row 2) leads to a greater likelihood that the link from one individual to another in a network will be reciprocated. The exogenous influence described here is the "differential" (positive or negative) influence of individual's exogenous attributes on the likelihood that these links will be reciprocated. For instance, social exchange theory suggests that any two individuals are more likely to engage in interactions where they are exchanging or reciprocating resources. However, in some cases it makes sense to argue that there is an even greater (in this case, positive differential) likelihood for this reciprocation to occur between individuals who share common attributes such as gender or organizational affiliation. Thus, an extension of social exchange and resource dependence theories suggests that exchange ties, that is, mutual or reciprocated ties, are more likely to occur among people who share similar attributes. This additional likelihood is referred to as a *differential* effect. Hypotheses based on this *differential mutuality or reciprocation* would be supported if there were greater probabilities for the realization of graphs in which attributes are shared by pairs of nodes. In other words, these hypotheses would be supported if the probabilities of ties being present or absent in the network would reflect nodes' tendencies to reciprocate ties with others who share similar attributes (see figure 2.6).

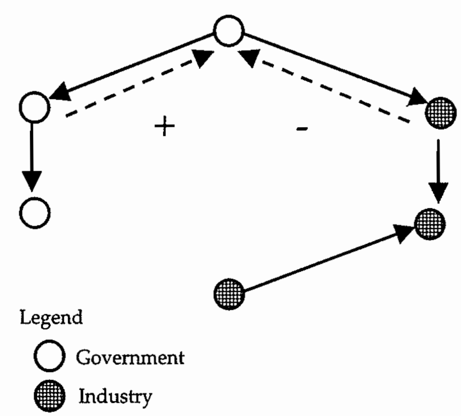


Figure 2.6
Exogenous attribute dyad level:
Resource dependency theory

Social exchange theory extended in conjunction with homophily theory specifies that there should be a greater likelihood of a tie from the actor at the upper left to the actor at the top-center of the network. This tie would reciprocate a tie from the actor at the top-center to the actor on the left of the network, and in addition both actors share the same attribute, namely representing a government organization. However, the same logic would suggest a lower probability for a tie from the actor at the upper right to the actor at the top-center of the network because even though this would reciprocate a tie from the actor at the top-center to the actor at the top-right, the two actors do not share a similar attribute. The actor at the top-center of the network represents a government organization while the actor at the upper right represents industry.

The triadic level

The triadic level for exogenous variables (row 7) refers to the influence of shared exogenous attributes on triadic properties of the network. The triadic level properties of the network include transitivity and cyclicality (defined previously in the discussion of row 3). As with the prior level, the shared exogenous attributes of the individuals in the network, differentially (positively or negatively) influence the propensity for the network to be transitive or cyclical. Theories of cognitive balance and generalized exchange can be extended to cover situations in which transitive and cyclical ties are even more likely to exist among actors who share similar attributes. Hypotheses based on this *differential transitivity and cyclicality* would be supported if there were greater probabilities for the realization of graphs in which actors with shared attributes are more likely to have transitive and cyclical ties with one another (see figure 2.7).

Balance theory can be examined in conjunction with homophily, as shown in figure 2.7. This combination suggests that there is a greater likelihood of a tie from the actor at the top-center to an actor at the lower left of the network because this tie would complete a transitive triad among three actors who share the same attribute, all representing government organizations. On the other hand, the same logic would suggest a lower probability of a tie from the actor at the top-center of the network to the actor at the lower right-hand because this tie would complete a transitive triad between three actors who do not share a similar attribute. The actor at the top-center of the network represents a government organization, while the other two actors in the triad represent private industry.

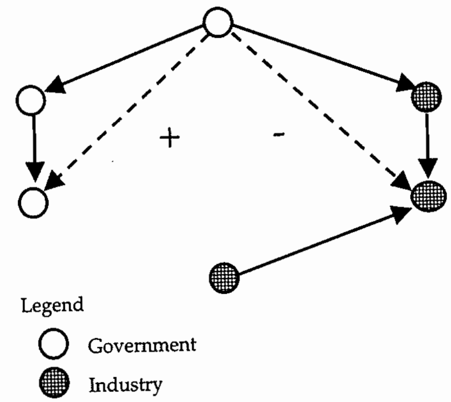


Figure 2.7
Exogenous attribute triad level: Balance theory

Note that the probabilities for additional ties indicated in figure 2.7 are identical to those reported in figure 2.5 and later in this section in figure 2.8. This illustrates how multilevel models might offer complementary explanations for the structural tendency of the network. In this case, theories of homophily at the exogenous attribute actor level (illustrated in figure 2.5), theories of balance at the exogenous triad level (figure 2.7), and theories of collective action at the exogenous global level (figure 2.8) complement one another's explanation for a higher probability of a network that includes a tie from the actor at the top and center to the actor at the lower left-hand corner; further, they complement one another in indicating a lower probability of a network that includes a tie from the actor at the top and center to the actor at the lower right-hand corner of the network.

The global level

The global level for exogenous variables (row 8) refers to the influence of shared exogenous attributes of the individuals on the global properties of the network. These global properties include network density and centralization (where some nodes in the network are much more central than others). The discussion of endogenous influences on the global properties of the network (row 4) noted that the configuration of links in the network may exhibit structural tendencies toward greater network centralization. That is, individuals may have a propensity to selectively forge ties with others in the network, thereby making some individuals more central than others. While these explanations seek to explain the global structural tendency toward centralization of the network based on the endogenous network itself, one can also examine the global properties of the network based on the influence of shared exogenous attributes of the individuals in the network. In an extension of the theories of collection action and public goods, the argument proposed here is that there is a greater likelihood for network centralization to occur among actors who share similar attributes such as organizational affiliation than among individuals who do not share these attributes. Hypotheses based on this *differential* network centralization would be supported if there were greater probabilities for the realization of graphs in which actors with shared attributes are more likely to have higher levels of subgroup network centralization. In other words, these hypotheses would be supported if the probabilities of ties being present or absent in the network would reflect actors' tendencies to forge more centralized subgroup networks with other actors who share similar attributes (see figure 2.8). In this figure, theories of collective action in conjunction with homophily predict that the government organization at the top-center of the network is more likely to forge a tie with the government organization at the lower left side because this link would further the centralized position of the latter within the network of government agencies. However, the government entity at the top-center of the network is not more likely to link with the industry representative at the lower right because this tie would not enhance the centralized position of the latter within the network of industry representatives.

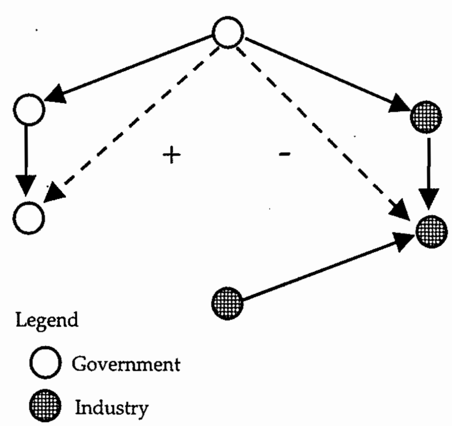


Figure 2.8
Exogenous attribute global level: Theories of collective action

Exogenous other relations

In addition to the exogenous influences of attributes of the network nodes, additional *relations* among nodes represent a second set of exogenous variables that may influence the probability of ties being present or absent in the focal network (see row 9). For instance, the convergence theory of communication (Richards & Seary, 1997; Rogers & Kincaid, 1981; Woelfel & Fink, 1980), cognitive theories (Carley, 1986, 1991; Carley & Krackhardt, 1996; Krackhardt, 1987a), and the theory of transactive memory systems (Hollingshead, 1998a, b, c; 2000) offer arguments that can be used to predict the influence of cognitive or semantic networks (Monge & Eisenberg, 1987) on their communication networks. These theories argue that the presence or absence of a cognitive or semantic tie between people is associated with the presence or absence of a communication tie between them. Hypotheses based on the influence of exogenous networks would be supported if there were greater probabilities for the realization of graphs in which the individuals' ties in the focal network corresponded to their ties in the exogenous networks. In other words, these hypotheses would be supported if the presence or absence of ties in the exogenous networks increased the probabilities of ties being present or absent in the focal network (see figure 2.9). This figure indicates that a person or organization at the top-center of the network is more likely to have a friendship relation with a person or organization at the top left side of the network because they already have a communication tie. However, the entity at the lower left of

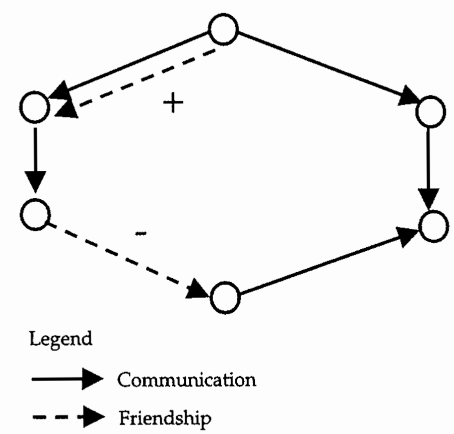


Figure 2.9
Exogenous other relations: Cognitive theories

the network is less likely to have a friendship tie with the entity at the bottom-center because they do not communicate.

It may appear that the objective sought here could be far more easily obtained by computing a simple correlation between the two relations in the network. In fact, Krackhardt (1987b) used techniques introduced by Hubert and Schultz (1976) to develop the Quadratic Assignment Procedure (QAP), which tests the significance of association between two networks. Several organizational communication researchers (e.g., Stohl, 1993) have used QAP, but in its present form the technique does not generalize to the multilevel framework proposed here.

Exogenous prior relations

Finally, the probability of ties being present or absent in the focal network can also be influenced by the presence or absence of ties in that same network at previous points in time (row 10). At its most primitive form, theories of evolution (McKelvey, 1997) would argue that inertia alone would predict that a tie between people at a previous point in time would increase the likelihood of the tie being maintained at subsequent points in time. For instance, Gulati (1995) hypothesized that "the higher the number of past alliances between two firms, the more likely they are to form new alliances with each other" (p. 626). Hypotheses based on the influence of the same network at previous points in time would be supported if there were greater probabilities for the realization of graphs in which links in the focal network

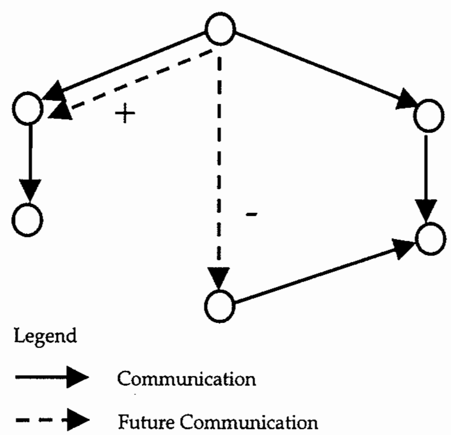


Figure 2.10
Exogenous prior relations:
Evolutionary theories

corresponded to links in the preceding networks (see figure 2.10). This graph shows that there is a greater likelihood of future communication between the actor at the top-center of the network and one at the upper left of the network because they currently communicate. However, there is a lower likelihood of future communication between the actor at the top-center of the network and the actor at the bottom-center because they have not had a prior communication tie.

The treatment of exogenous variables described in this book does not address the interactions among the exogenous variables just described. The reason for this is that current statistical techniques cannot as yet address these issues. Two scenarios are worth considering. First, the influence of exogenous networks (either of different relations on 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 (1993) 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" (p. 103). A second instance would be the influence on the focal network by an exogenous network (which is a different relation on the same network of people) *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 (1985, 1992) has argued, economic transactions are often "embedded" in social relations. This would suggest that economic relationships between people or organizations might be more likely when they have a prior social relationship. While the statistical models, including Markov random graph models and the p^* family of models, have developed techniques to test hypotheses in the ten cells described in this section, additional efforts are being made to address more complicated interaction scenarios, such as the two illustrated earlier.

Summary

This section has introduced the MTML 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, this section introduced the notion of graph realizations and described how the hypothesized properties of networks influence the probabilities of realizing a specific network configuration. These properties were broadly classified as endogenous, which means they belong to the focal relation in the network itself, and exogenous, including attributes of the actors and relations distinct from the focal relation in the network. The properties in each of these two categories were further classified on the basis of their level: actor, dyad, triad, and global. For each subcategory, theoretically motivated hypotheses were used to illustrate the influence of that property on the structural tendency of the network. Figure 2.11 presents a schematic of the overall MTML model.

A Multitheoretical, Multilevel p* *Network Analysis Example*

This final section of the chapter introduces an example to illustrate the concepts in the preceding sections of this chapter. Specifically, it tests eight hypotheses deduced from three theories at two levels. It tests these hypotheses by statistically estimating the extent to which structural tendencies implied by these hypotheses influence the probabilities of observing certain realizations of the network.

The data used in this example was collected from 17 individuals representing 7 organizations who were preparing to sign a cooperative research and development agreement (CRADA). The CRADA was established to commercialize production of software for improving the building design process for large institutional facilities. The 17 individuals were representatives from four agencies of the U.S. Army and four private corporations. The U.S. Army partners included a research laboratory, a district office, a unit of the army reserves, and members from the headquarters. The four private companies were a CAD operating systems developer, a construction software firm, a software development company, and an architectural firm.

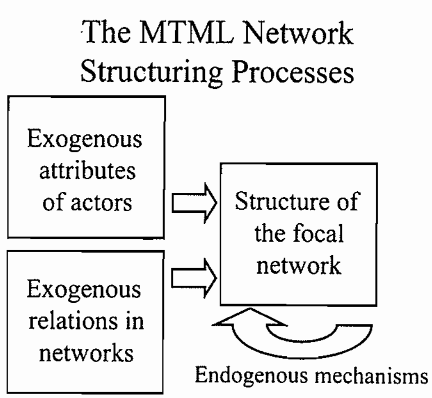


Figure 2.11
The MTML network structuring process

The organizations they represented were blocked into two types: Block 1 comprised 9 individuals representing private sector companies, and Block 2 comprised 8 individuals representing government agencies. The individuals provided these data while they were in the process of negotiating the CRADA. The data represent the amount of communication reported by each of the individuals in the time period immediately prior to the signing of their strategic alliance agreement. The data were dichotomized for use in this analysis.

Theoretical Rationale for the Hypotheses

The goal of this example is to test hypotheses about the extent to which the CRADA network demonstrates a structural tendency toward mutuality, transitivity, and cyclicality. According to *exchange and dependency theories* (discussed in greater detail in chapter 7) individuals are more likely to forge network ties with others if there are resources (material or informational) they need from others and if there are resources that they can offer those others. That is, the impetus for a network tie is the possibility of exchanging resources that make the two individuals dependent on one another. Earlier in this chapter, this structural tendency was defined as *mutuality*. In the present example, according to theories of exchange and dependency, two individuals who are involved in this collaboration to develop software are more likely to have mutual communication ties, which will enable them to exchange resources.

While theories of exchange and dependency posit structural tendencies at the dyadic level, theories of cognitive consistency (discussed in greater detail in chapter 6) examine structural tendencies at the triadic level. According to consistency theories, individuals are more likely to be friends with friends of their friends. That is, the impetus for a network tie from A to C is positively influenced by the presence of a tie from A to another individual, say B, and the tie from B to C. Earlier in this chapter we defined this structural property between A, B, and C as *transitivity*. Consistency theories can also be used to support a related claim: that a network tie from A to B and a network tie from B to C will increase the likelihood of a tie from C to A. This "closing the loop" impetus reveals a structural property that we described earlier as *cyclicality*.

Of course, hypotheses regarding structural tendencies at the dyadic level and the triadic level can only be assessed if individuals choose others in the network—a structural tendency toward *choice* at the individual level. On the basis of these relatively simple previews of theoretical arguments to be expanded in later chapters of the books, the following five hypotheses were tested.

H1: The network demonstrates a structural tendency toward choice (that is, to choose other actors).

H2: The network demonstrates a structural tendency toward choice and mutuality.

H3: The network demonstrates a structural tendency toward choice, mutuality, and cyclicality.

H4: The network demonstrates a structural tendency toward choice, mutuality, and transitivity.

H5: The network demonstrates a structural tendency toward choice, mutuality, transitivity, and cyclicality.

In addition, we test three hypotheses about the extent to which these structural tendencies are differentially higher among actors that have been subgrouped into blocks based on one of their exogenous attributes (that is, whether they represent an organization in the private sector or the government sector). Theories of homophily (discussed in greater detail in chapter 8) suggest that individuals are more likely to forge ties with other individuals with whom they share similar attributes—in this case their organizational affiliation in the government or private sector.

H6: The network demonstrates a structural tendency toward choice, mutuality, transitivity, and in addition a differential tendency toward choice with other actors in the same block (either private sector or government).

H7: The network demonstrates a structural tendency toward choice, mutuality, transitivity, and in addition differential tendencies toward choice with other actors in the same block and mutuality with other actors in the same block (either private sector or government).

H8: The network demonstrates a structural tendency toward choice, mutuality, transitivity, and in addition differential tendencies toward choice with other actors in the same block and transitivity with other actors in the same block (either private sector or government).

Downloading and Installing PSPAR

PSPAR, developed by Andrew Seary, a graduate student of Bill Richards at Simon Fraser University, is a DOS-based program that conducts p^* analysis on computers running the Windows operating system. The software can be downloaded from the PSPAR web site at: http://www.sfu.ca/~richards/Pages/pspar.html by clicking on the link: http://www.sfu.ca/~richards/Pdf-ZipFiles/psparw32.zip

The network data used in this example, and included at the end of this chapter, is a text file named *crada.neg*. PSPAR requires the network data to be in a linked list format. The linked list format specifies the ID of the source of a network link, followed by the target of the network link, followed by the strength of the network link. So for instance, a line that reads 3 4 1 means that actor ID 3 has a link to actor ID 4 of strength 1. The linked list format is a particularly compact form for describing relations in a large sparsely connected network. It was also the format used by Bill Richards's Negopy program. Bill Richards provides a utility program, ADJ2NEG.exe, which automates this conversion of data in adjacency matrix format (which is what UCINET, a popular network analysis software program, uses) to the linked list format. The conversion utility program can be downloaded from http://www.sfu.ca/~richards/Pages/utility.htm. The network data set used in this example has already been converted to linked list format.

The attribute data used in this example, and included at the end of this chapter, is a text file named crada.atr. PSPAR requires the attribute data to be stored in a file that has the first column for actor IDs and additional columns for actor attributes. Since in this example there is only one attribute (representing a private or government organization), the first column is the ID of the actors and the second column is a number that indicates the attribute of that actor. So, for instance, a row that reads 4 1 indicates that actor ID 4 has attribute 1 (a private sector representative). Likewise, a row that reads 11 2 indicates that actor ID 11 has attribute 2 (a government sector representative).

P* *Analysis using PSPAR*

1. To launch the PSPAR program, double click on the file named Psparw32.exe.
2. You will see a DOS window with the command prompt line reading *Enter name of network file:*
   Type *crada.neg* and hit *Enter.*
3. You will be prompted *Include diagonal* (*y or n*):
   Since diagonals are irrelevant in this context, type *n* and hit *Enter.*
4. You will be prompted *Fit to block parameters* (*y or n*):
   To test the first five hypotheses, you are not interested in the differential effects of the blocks. Type *n* and hit *Enter.*
5. You will be prompted *Enter name of output file*:
   To save the output for the first hypotheses type: *crada1.out* and hit *Enter.*
6. You will be prompted to select *How many global parameters?* to use in the model. You will be provided with a selection of various parameters that are numbered from 1 through 16.
   To test hypothesis 1, you will need one parameter: the Choice parameter.
   Type *1* and hit *Enter.*
7. You will be prompted to enter parameter numbers:
   The Choice parameter (i>j) called edges in PSPAR is Parameter Number 1.
   Type *1* and hit *Enter.*
8. The program returns the results of the analysis. These results are also saved in the crada1.out file.
   You will be prompted to *Continue?* (*y or n*):
   To continue testing additional hypotheses type *y* and hit *Enter.*
9. You will be prompted if you want to use *Same files?* (*y or n*):
   To test Hypotheses 2 through 5 type *y* and hit *Enter.*
10. You will be prompted to select *How many global parameters?* to use in the model. Repeat steps 6 through 9 for Hypotheses 2 through 5.
    For Hypothesis 2, the number of parameters will be 2: Choice or Edges (Parameter Number 1), Mutuality or R(eciprocated) Edges (Parameter Number 2).
    For Hypothesis 3, the number of parameters will be 3: Choice, Mutuality, and Cyclicality (Parameter Number 7).
    For Hypothesis 4, the number of parameters will also be 3: Choice, Mutuality, and Transitivity (Parameter Number 6).
    For Hypothesis 5, the number of parameters will be 4: Choice, Mutuality, Cyclicality, and Transitivity.
    After completing the test for Hypothesis 5, you will be prompted *Continue?* (*y or n*)
    Type *n* and hit *Enter.*
11. To continue with tests for the differential Hypotheses 6 through 8, repeat steps 1 through 3.
    You will be prompted *Fit to block parameters* (*y or n*):
    Since we want to test hypotheses about differential effects within blocks, type *y* and hit *Enter.*
12. You will be prompted *Enter name of attribute file*:
    Type *crada.atr* and hit *Enter.*
13. You will be prompted *How many attributes* (*not including id*)?
    Since the only attribute is type of organization represented type *1* and hit *Enter.*
14. To save the output for Hypothesis 6 type: *crada6.out* and hit *Enter.*
15. You will be prompted to *Enter attribute number for blocking*:
    Since there is only one attribute, type *1* and hit *Enter.*
16. You will be prompted to *Accept this block structure*? (*y or n*):
    The block structure shows how there are two blocks of actors who belong to private and government sector. Type *y* and hit *Enter.*
17. You will be prompted to select *How many parameters*?
    For Hypothesis 6 you will need to estimate four parameters: choice, mutuality, transitivity, and choice within blocks. Type *4* and hit *Enter.*
18. You will be prompted to *Enter Parameter Numbers*: it will also prompt you to *Add 100 for corresponding block parameter.*
    For Hypothesis 6 you will need to estimate Parameter 1 (for Choice), Parameter 101 (for Choice within blocks), Parameter 2 (for Mutuality), and Parameter 6 (for Transitivity). Type 1 101 2 6 and hit *Enter.*
19. You will be prompted to *Continue* (*y or n*):
    To continue testing Hypotheses 7 and 8, type *y* and hit *Enter.*
20. If you typed y, you will be prompted *Same files*? (*y or n*):
    Type *y* and hit *Enter.*
21. You will be prompted *Same blocking*?
    Type *y* and hit *Enter.*
22. Repeat steps 18 through 20. For Hypothesis 7 you will need to estimate Parameter 1 (for choice), Parameter 101 (for choice within blocks), Parameter 2 (for mutuality), Parameter 102 (for mutuality within blocks), and Parameter 6 (for transitivity). For Hypothesis 8,

Table 2.5
Summary of the* p* *Analysis Testing the Eight Multilevel, Multitheoretical Hypotheses

Hypothesis	*Model*	*Number of Parameters*	*−2L ("Badness" of fit)*
1	Choice	1	354.387
2	Choice + Mutuality	2	254.251
3	Choice + Mutuality + Cyclicality	3	241.973
4	Choice + Mutuality + Transitivity	3	228.836
5	Choice + Mutuality + Cyclicality+ Transitivity	4	228.068
6	Choice + Choice within blocks + Mutuality + Transitivity	4	222.754
7	Choice + Choice within blocks + Mutuality + Mutuality within blocks + Transitivity	5	221.723
8	Choice + Choice within blocks + Mutuality + Transitivity + Transitivity within blocks	5	218.925

you will need to estimate Parameter 1 (for Choice), Parameter 101 (for choice within blocks), Parameter 2 (for mutuality), Parameter 6 (for transitivity), and Parameter 106 (for transitivity within blocks). You are now ready to review the results of the analyses.

Table 2.5 summarizes the results obtained from the tests of all eight hypotheses. The last column in the table, the log likelihood measure, is a measure of *badness of fit*. It indicates how unlikely it is to find the observed realization of the graph if the structural tendencies are governed by the specific hypothesis posited. Hence, lower log likelihood values indicate a model that has a better fit. A quick inspection of the results reported in Table 2.5 would suggest greatest support for Hypothesis 8 since it has the lowest log likelihood value (218.925). However, since the number of parameters estimated (that is the number of explanatory variables, five) in Hypothesis 8 was the largest, it may not be the most parsimonious model. That is, the fact that it had the best fit may simply be an artifact of there being more explanatory variables in Hypothesis 8 than in the preceding hypotheses. To assess if this was the case, one can compare the fit of Hypothesis 8 with other hypotheses that had fewer explanatory variables. The best fitting model with four explanatory variables (Hypothesis 6) had a log likelihood value of 222.754. This is considerably larger than the log likelihood value (218.925) of Hypothesis 8. Further, Hypothesis 6, the best fitting model with four explanatory variables, was considerably superior to Hypothesis 4 (a log likelihood value of 228.836), the best fitting model with three explanatory variables. Likewise, Hypothesis 4 is significantly superior to Hypothesis 2 (a log likelihood value of 254.251) with two explanatory variables, which in turn was overwhelmingly superior to Hypothesis 1 (a log likelihood value of 354.387) with one explanatory variable. Hence, one can conclude that Hypothesis 8 is the best supported of the eight hypotheses. It offers the best explanation of the structural tendencies observed in the network after accounting for the fact that it had more explanatory variables than the remaining hypotheses.

Substantively, Hypothesis 8 suggests that the structure of ties among the individuals in the network was influenced by desire to engage in mutual ties, as proposed by theories of exchange and dependency at the dyadic level, and transitive ties, as proposed by theories of consistency at the triadic level. Further, consistent with theories of homophily, individuals demonstrated a structural tendency to enhance their direct and transitive triadic ties with other individuals who shared similar attributes, in this case membership in governmental or private sector organizations.

This example has attempted to illustrate how one can use p^* analytic techniques to provide one omnibus test of the structural tendencies of a network based on multiple theories (theories of exchange and dependency, theories of consistency, and theories of homophily) at multiple levels of analysis (individual, dyadic, and triadic). The first five hypotheses illustrate how to test endogenous hypotheses about the network, structural tendencies at the individual, dyadic, and triadic levels. The three additional hypotheses illustrate how to incorporate into the MTML framework the influence of the individuals' exogenous attributes on the structural tendencies of the network. The results of the analyses provide a straightforward test to assess how probable is the observed realization of the network among all possible realizations of the network that exhibit the hypothesized structural tendencies.