Chapter 44
A Network Perspective on Mega-Engineering Projects

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44.1 Introduction

About 60 miles North of Jeddah, Saudi Arabia, where the desert meets the Red Sea is a hyper-modern metropolis in the making. Construction cranes crowd the sky. Hundreds of workers labor under the sun, turning sand and dirt into palm-lined promenades, bubbling fountains, and glass covered skyscrapers. The first phase of the project, which involves the construction of a seaport, an industrial zone, and a residential city district, is close to completion. When fully finished, in 2025, King Abdullah Economic City (KAEC: http://207.5.46.159/en/Home/index.html) will stretch over 70 square miles, house some 2 million people, and offer one of the most competitive economic investment destinations in the world.

KAEC is only one example of what is an increasingly familiar feature of our times: The mega-engineering project (MEP). The Channel tunnel, Hong Kong's Chek Lap Kok airport, Sydney's harbor tunnel, and China's Three Gorges Dam are just a few examples of projects that require multi-billion dollar investments and the technical and organizational expertise of a large network of government and private organizations. Given the massive consequences that MEPS can have for the economy of nations, the migration of people, and the environment of vast regions, it is not surprising that MEPs are currently being studied from a number of different theoretical and disciplinary perspectives, from decision making and public policy to economics and cultural studies. What has been largely missing from this rich and growing literature, however, is a direct emphasis on the social structure of MEPs. This, we believe, is a missed opportunity because the social structure of systems can powerfully influence the actions and performance of those systems.

MEPs are by definition large and complex. They typically involve a variety of governmental and nongovernmental organizations tied to each other through a mix

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of economic, interpersonal, and institutional relationships. The structure of this network of relationships deserves greater scrutiny. We call for the adoption of a network perspective because it offers two distinctive advantages for the study of MEPs. First, it offers a rich toolkit for precisely quantifying and analyzing the structure of MEPs. Second, it supplies a theoretical logic connecting these structural characteristics with the conduct and performance of MEPs.

We provide a brief introduction to the social network perspective (see Freeman, 2004, for a detailed history); and we attempt to show how this perspective could be fruitfully applied to three broad questions: (1) what is the network structure of an MEP? (2) How does the structure of the network influence the performance of MEPs and their member organizations? And (3) how does network structure drive the composition and structure of MEPs over time?

44.2 A Very Brief Introduction to Networks

44.2.1 Origins

The origins of social network analysis can be traced to Jacob Levy Moreno, a Viennese psychiatrist who immigrated to New York in the 1930s (for a detailed history, see Freeman, 2004). Moreno viewed human groups as systems of interconnected individuals. He created a methodology, "sociometry," to capture the feelings of each individual in a human group regarding every other group member; and he then used graphs, consisting of nodes, which represented people, and lines, which represented feelings, to represent the resultant network (Fig. 44.1, for example). Moreno reasoned that the ties connecting individuals in a network were important because they channeled emotion, influence, and ideas between people. The network

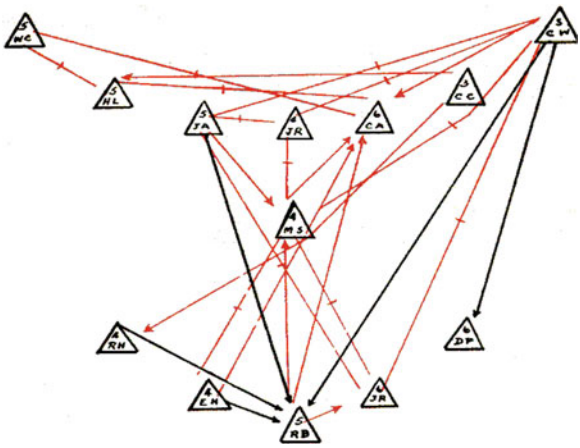


Fig. 44.1 A hand-drawn social network: Positive and negative sociometric choices in a football team. Note: *The nodes* are team members; *lines* represent positive and negative feelings towards specific others. (Moreno, 1934: 213)

of relations surrounding an individual influenced how the individual felt, thought, and behaved. Moreno viewed his approach as a kind of "social cartography" that could be used to map the invisible structure of human groups (Moreno, 1934).

From the 1940s to the 1960s, social network analysis largely disappeared from view. Its most enthusiastic promoters during this period were a group of British anthropologists who used network analysis to represent the social structure of families and small communities (e.g., Barnes, 1954; Bott, 1957). It was not until the 1970s that social network analysis became a more generalized theory—thanks in small part to a group of mathematically oriented sociologists associated with Harrison White who published a series of sophisticated quantitative models and analyses of social structure that have since become exemplars of network research (e.g., White, Boorman, & Breiger, 1976). In the 1980s, network research was increasingly being applied to the study of economic relations between firms and industries (see Mizruchi & Schwartz, 1987). It is around this time that network analysis seemed to have become an established field within the social sciences, with a professional organization ("INSNA": http://www.insna.org/), an annual conference ("SUNBELT": http://www.insna.org/sunbelt/), specialized software (e.g., UCINET: http://www.analytictech.com/) and its own journal ("Social Networks": http://www.elsevier.com/).

As Fig. 44.2, shows the number of social network articles has continued to rise steeply since the 1980s. Figure 44.3 shows a similar pattern when it comes to citations to social network articles in the "web of science." In 2007 alone, almost 1200 social network articles and reviews have been published in the database's journals.

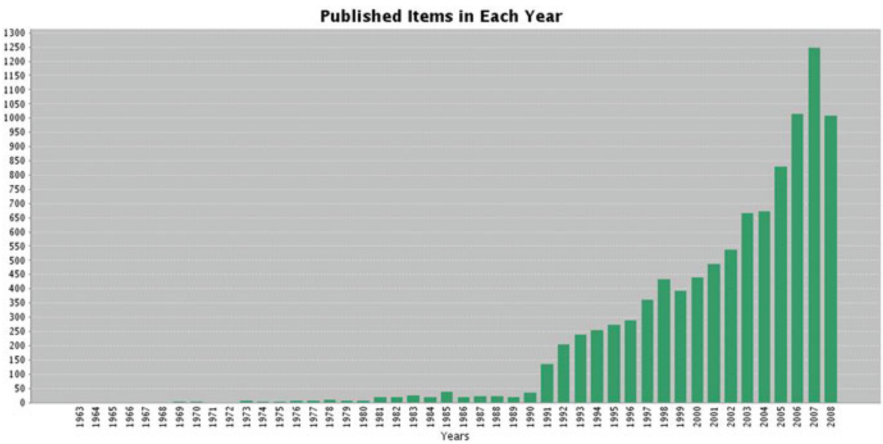


Fig. 44.2 Number of social network articles published over time (values on the *y*-axis represent number of articles published in a given year; values on the *x*-axis represent years). Note: The data come from the "Science Citation Index (1900-present)" and the "Social Sciences Citation Index (1975-present)," which are both covered by the "ISI Web of Knowledge" database. To be counted as a social network article, the piece had to contain the phrase "social networks" in the title, abstract, or keyword. The database turned up 9,852 social network articles and review pieces (we excluded book reviews, proceedings, and editorials)

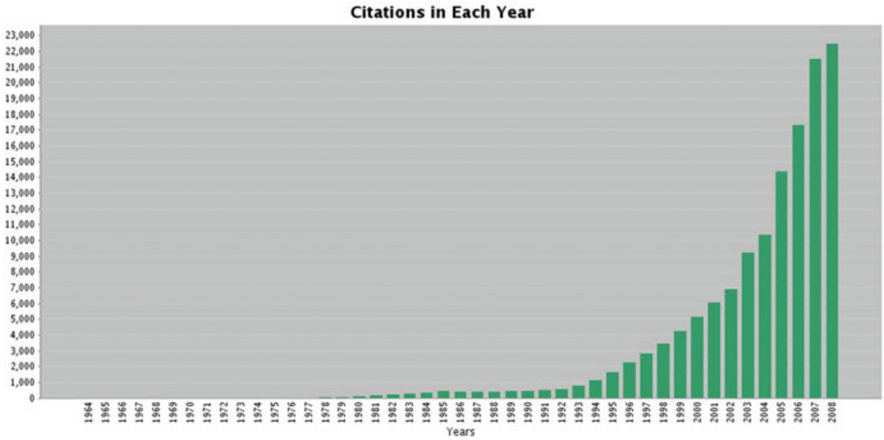


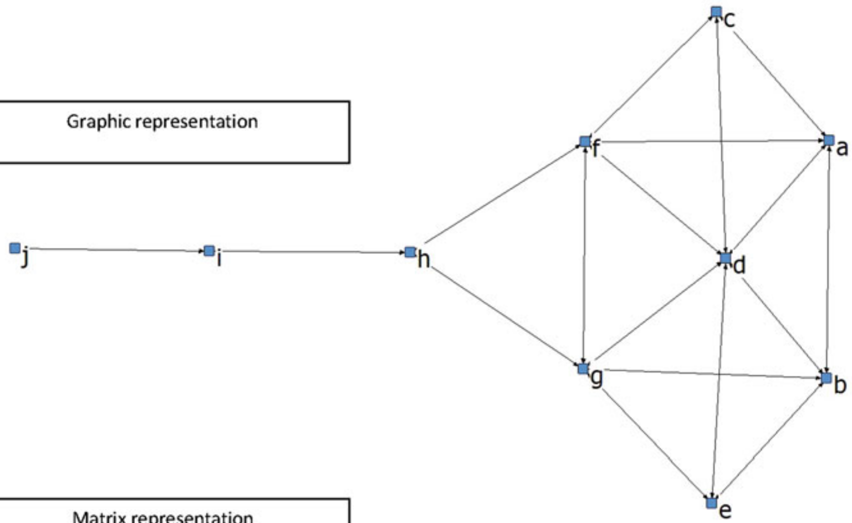
Fig. 44.3 Number of citations to social network articles over time (values on the *y*-axis represent number of citations received by social network articles in a given year; values on the *x*-axis represent years). Note: The data come from the "Science Citation Index (1900-present)" and the "Social Sciences Citation Index (1975-present)," which are both covered by the "ISI Web of Knowledge" database. To be counted as a social network article, the piece had to contain the phrase "social networks" in the title, abstract, or keyword. The database turned up 9,852 social network articles and review pieces (we excluded book reviews, proceedings, and editorials)

These articles, moreover, have appeared in a range of disciplines, with the vast majority being published in sociology, anthropology, organizational studies, epidemiology, and, more recently, physics and biology. It is noteworthy that social network analysis is one of the rare theoretical approaches in modern history to have spread from the social to the physical sciences (and then back to the social sciences). In the late 1990s, Duncan Watts and Steve Stograty (1998), two physicists, revived interest in the "small world problem," which had initially been studied by Ithiel de Sola Pool, a political scientist, and Manfred Kochen, a mathematician (1978), and then popularized by Stanley Milgram (1976), a psychologist. Since the publication of the Watts and Stograty article, hundreds of network studies on the small world problem have been published in physics and biology journals, and this has sparked renewed interest in the topic among social scientists (e.g., Uzzi & Spiro, 2005).

44.2.2 Networks are About Structure

Why is social network research enjoying such wide inter-disciplinary reception? A key reason is that networks can be, and have been, used to represent the structure of a wide variety of systems, from the neural structure of *C. elegans*, a nematode that is about 1 mm in length, to the network of informal relations in work organizations. Networks can be used to represent a wide variety of systems because they strip social systems down to "nodes," which are treated as more or less indistinguishable and

Graphic representation



Matrix representation

	a	b	c	d	e	f	g	h	i	j
a	0	1	1	1	0	1	0	0	0	0
b	1	0	0	1	1	0	1	0	0	0
c	1	0	0	1	0	1	0	0	0	0
d	1	1	1	0	1	1	1	0	0	0
e	0	1	0	1	0	0	1	0	0	0
f	1	0	1	1	0	0	1	1	0	0
g	0	1	0	1	1	1	0	1	0	0
h	0	0	0	0	0	1	1	0	1	0
i	0	0	0	0	0	0	0	1	0	1
j	0	0	0	0	0	0	0	0	1	0

Fig. 44.4 Two representations of the "kite" network. (Source: Krackhardt, 1990)

interchangeable in terms of their intrinsic properties, and, crucially, the structured pattern of "ties" connecting the nodes.

Consider the "kite" network depicted in Fig. 44.4. This network shows 10 "nodes" and the connections between them. What the connections consist of is unspecified. Each connection in this network is bi-directional (though it need not be). The identity of the nodes, too, is unspecified: nodes could represent individuals, groups, organizations, even nations. Knowing only this, could one answer the question: Which node is most influential?

The answer from the network perspective is a resounding "yes." The network tells us about structure; and structure determines who or what is influential. Network analysis offers a rich array of methods (with accompanying theoretical rationales) for capturing variance in network structure. One commonly used set of methods focuses on the "centrality" of a node within a network (Bonacich, 1972; Freeman, 1979; for some recent extensions, see Everett & Borgatti, 2005). A social network analyst might argue that influence is a function of the extent to which a node is connected to many other nodes in a network. The more connected a node, the more the node has the opportunity to exercise influence. This reasoning could be operationalized in terms of the commonly used "degree" measure of centrality (see Appendix for descriptions, including mathematical formulas, of commonly used network centrality measures). A different line of network reasoning might contend that influence is a function of occupying a position between other parties. The occupant of a bridging position can control the flow of resources and would have an enhanced opportunity to learn of new and different ideas, which could lead to the node gaining influence. This is the basic reasoning behind the "betweenness" measure of network centrality. Based on this structural logic, H would be the most influential node in the network.

One might also suggest that F and G are the most influential nodes in the kite network. These two nodes can reach all the other nodes in the network in the fewest number of lengths. They are closest to all other nodes. This logic is operationalized as "closeness" centrality.

Of course, all this is rather abstract. Even the dullest of minds would quickly protest: You have not specified what the nodes represent, nor, for that matter, what the ties represent! But different theoretical perspectives look at phenomena at different levels of aggregation. Network theory sacrifices local detail to focus on structure—and it is this focus on structure that has given the network perspective its broad generality and scope. In network research in organizational studies, for example, the same structural positions have been linked to superior performance, both when the nodes in the network represent people in a company and the ties represent friendship relations (e.g., Mehra, Kilduff, & Brass, 2001) and when the nodes represent firms in an industry and the ties represent strategic business alliances (see the review in Gulati, 2007). Although a variety of different kinds of nodes and ties have been examined in network studies (for a taxonomy, see Borgatti, Mehra, Brass, & Labianca, 2009), the main focus of social network research is on the structure of the network rather than on the identity of nodes or the content of network ties.

44.2.3 Levels of Analysis

Before moving on to discuss network theory, we want to draw attention to the distinction between "whole networks" and "ego networks." Consider the larger network on the left in Fig. 44.5. This is a trust network from a small high-tech firm. Each node represents an individual employee. Each line represents a trust relation. A line between A and B means that A and B independently identified each other as someone they trusted. The data were gathered using a network survey (see Cross & Parker, 2007: 143–166, for detailed description of how to design and administer network surveys). The network on the left in Fig. 44.5 is referred to as a "whole network." It represents the full set of ties among all the members of a bounded group (of course, it is up to the researcher to define where the boundary lies), which, in

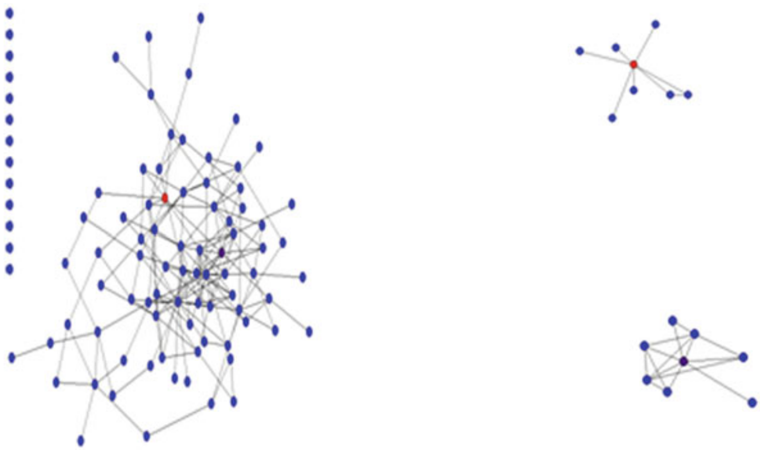


Fig. 44.5 Three commonly used indexes of whole network structure

this case, is an entire organization. On the right hand side of Fig. 44.5 are two "ego networks." The ego network represents the immediate neighborhood around a focal node. Just as one can use network indexes (e.g., the measures of centrality discussed above) to describe the structural position of a node in a whole network, one can also describe the structure surrounding a node within an ego network.

In addition to structural measures of position within whole and ego networks, there are also a number of measures that describe the overall structural properties of a network (whether a whole network or an ego network). Figure 44.6 shows two illustrative networks and reports three commonly used structural measures for each: density (which assesses the total number of ties relative to the total number of possible ties); size (which is a count of the total number of ties in a network); and network centralization (which assesses the extent to which the ties within a network are shared across nodes versus centralized in a few nodes). For precise mathematical formulas and more detailed explanations of the logic behind these and the many other graph-theoretic measures—such as core-peripheriness, clumpiness, scale-freeness—we refer the interested reader to Wasserman and Faust (1994) and Carrington, Scott, and Wasserman (2005).

Finally, network research offers a number of measures at the dyadic level of analysis that can be broadly distinguished into two families: dyadic cohesion and structural equivalence. Cohesion refers to a set of concepts that capture the social closeness of a pair of nodes using such measures as geodesic distance (the length of the shortest path from one to the other), or multiplexity (the number of different kinds of relations that bind a pair of nodes). Equivalence refers to the extent to which pairs of nodes occupy similar structural positions in the network (Burt, 1987*)*.

Network analysis therefore offers a number of different levels of analysis for the examination of network structure. The question of which level or levels of analysis

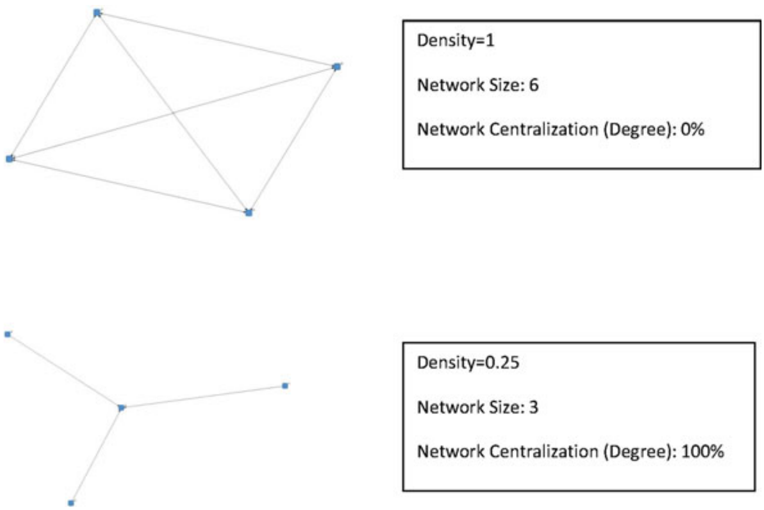


Fig. 44.6 A whole network (*left*) and two ego networks (*top* and *bottom right*). Note: Each *node* represents a firm employee. Each *line* represents a reciprocated trust relation between two employees. The ego networks at *top right* and *bottom right* are derived from the whole network on the *left*. The whole network shows all the nodes in a network and the ties among the nodes. Ego networks are a subset of whole networks. They show only the ties among a focal node and the nodes to which it is directly connected. (Source: Mehra, 1998)

a particular study should adopt will, of course, depend upon what a given study is trying to explain, and the theoretical logic it is using in its explanation.

44.2.4 Kinds of Questions

In the physical sciences, a key aim of social network research has been the formulation of universal characteristics of non-random networks, such as the property of a having a “scale-free” degree distribution (Watts, 1999). In the social sciences, by contrast, the primary focus of network research has been on the consequences of networks. Although a number of different outcomes have been studied, they can be distinguished into two broad categories: *homogeneity* and *performance*. By homogeneity we mean the similarity of actors with respect to their behaviors or internal structures. For example, network research has been used to predict which firms adopt the same governance structures (e.g., Davis & Greve, 1997). By performance we mean a node’s outcome with respect to some desirable good. For example, network researchers have shown that the occupancy of central positions in a firm’s friendship network is related to higher supervisory performance ratings (e.g., Mehra et al., 2001) and faster promotions (Burt, 1992).

44.2.5 Mechanisms in Network Theory

If mechanisms are the underlying processes that account for relationships among variables (Elster, 2007), what kinds of mechanisms are at work in network theory?

Here we describe three canonical mechanisms that seem most relevant to the study of MEPs:

Transmission. A mechanism invoked in network analysis involves direct transmission from node to node. The thing transmitted could be something tangible, like money; or it could it be something more intangible, like an innovative idea. The basic idea is that something flows along a network path from one node to the other, with an end result that the two nodes share the same state.

Adaptation. The adaptation mechanism states that nodes become homogeneous as a result of experiencing and adapting to similar social environments. If two nodes have ties to the same (or equivalent) others—the property known in social network analysis as structural equivalence—they face the same environmental forces and are likely to adapt by become increasingly similar. This mechanism can be used to explain how relational roles affect outcomes (e.g., why two firms may adopt the same governance structures at about the same time even when they do not directly compete or collaborate with each other).

Binding. According to the logic of binding, network ties can bind nodes together in such a way as to construct a new entity whose properties can be different from those of the constituent nodes. Binding is one of the mechanisms behind the performance benefits of "structural holes." A *structural hole* refers to the absence of a tie among a pair of nodes. A well-established finding in social network analysis is that nodes with lots of structural holes in their ego networks (the node in the top right network in Fig. 44.6) tend to outperform those with fewer holes (the node in the bottom right network in Fig. 44.6). The absence of structural holes around a node means that the node's contacts are "bound" together—they can communicate and coordinate so as to act as one, creating a formidable "other" to negotiate with. In contrast, a node with many structural holes can play unconnected nodes against each other, dividing and conquering (Burt, 1992).

44.3 Networks and MEPs: 3 Broad Research Questions

What does the network perspective have to offer scholars interested in MEPs? Here we point to three broad questions that could help set an agenda for network research on MEPs.

44.3.1 What is the Network Structure of MEPs?

An obvious first step in the adoption of a network perspective on MEPs is the description and analysis of MEPs in terms of their underlying network structure. The nodes might represent the set of organizations that make up a given MEP. The fact that this number could be in the hundreds for some MEPs poses no difficulty for network analysis. Existing network software can easily handle thousands of nodes in a network. Indeed, network analysis can be especially helpful in the discernment of patterns in large and complex networks. For example, network analysis can be used to identify densely connected “cliques” within a broader network; or it could be used to reduce the overall structure into underlying structural blocks containing nodes with similar patterns of ties from and to other firms within the network (see Wasserman & Faust, 1994, for a detailed discussion of these and other techniques for describing network structure).

There are, of course, a number of different types of ties between the members of a given MEP that could be studied. MEP members are tied to one another by patterns of resource flows, supplier and buyer relationships, and interlocking directorates. Each of these ties has been examined in the research on inter-organizational networks, but any single study has tended to focus on one or a very limited set of ties at a time. The specific tie or ties one included in the analysis depends, of course, upon the specific aims of a study. But they also depend more practically upon the relative ease and fidelity with which data can be collected. Researchers interested in studying MEPs could, following the lead of researchers studying inter-organizational networks, rely on publicly available information about alliances, supplier-buyer relationships, and board memberships to gather data on MEP ties among the set of organizations that make up the MEP. Once such data are gathered, they can be represented in graphic format for visual inspection and matrix format for algebraic manipulation and analysis. As discussed earlier, network structure can then be examined at various level of analysis (“whole network”; “ego network”; “dyadic”). The choice of level, like the choice of which ties to include within the network, will have to depend upon the particular goals and interests of particular studies.

44.3.2 How Does MEP Network Structure Influence Performance?

The question of what influences variance in MEP performance is of obvious importance. From a network perspective, a crucial predictor of system performance is system structure. Future research should examine the relationship between the structure of MEPs and their relative performance. It could be hypothesized, for example, that MEPs with denser network structures will outperform those with sparser network structures because network density can increase the flow of information and resources and enhance trust and coordination among system members. There is convergent support for this line of reasoning from prior work on human groups in the laboratory (Shaw, 1964), social capital in human communities (e.g., Coleman, 1988), and work on the U.S. auto industry (Gulati & Lawrence, 1999).

In addition to studying the performance of MEPs, network theory and analysis could be used to understand relative performance among the members of a given MEP. The position of an MEP member within the network of the MEP could powerfully influence the performance of that MEP member. For example, drawing on the logic of the *binding* mechanism described above, it could be hypothesized that firms that occupy a position connecting otherwise unconnected others can play the firms they are connected to against one another for their own profit and influence. Support for this line of reasoning is strong and comes from divergent settings and sources (see the summary in Burt, 2005). Whether the reasoning applies to MEPs is an empirical question, but we believe that network theory offers a plausible hypothesis for future testing.

A related set of hypotheses could focus on the relationship between network structure and firm behaviors, such as the adoption of new or innovative method by an MEP for managing its effects on the natural environment. The logic behind the *transmission* mechanism could be used to explain the pattern of diffusion of innovative environmental practices within and across MEP networks. Alternatively, the logic of *adaptation* could be used to test the competing hypothesis that the adoption of innovative practices may result not from a process of network transmission but instead may be a result of firms adapting similar innovations in response to their facing similar structural forces. Network theory and methods offer a number of different ways for conceptualizing and analyzing the links between network structure, performance, and action.

44.3.3 How Does Network Structure Drive the Composition and Structure of MEPs Over Time?

Network ties are important in part because they can be conduits for needed resources, such as financial funding, or technical knowhow. But network ties formed in one period can also influence the new ties a firm forms or does not form in a future period. Contracting hazards loom large in economic exchanges (Williamson, 1985). Connecting with new firms involves risk, uncertainty and the possibility that a partner could behave opportunistically. Ties between firms allow them and third parties to gather information about each other. In the language of organizational economics, network ties can reduce informational asymmetries. Ties between firms at one point in time can influence the ties that the firm develops at a future point in time. Building on this logic, one could examine the network factors at play in the formation of MEPs. What influences which firms are brought into and which firms are left out of a given MEP? Are firms with connections to high-status MEPs at one point in time more likely to be selected to work on other MEPs in the future? These questions have been tackled in the literature on inter-organizational networks (for a review, see Gulati, Nohria, & Zaheer, 2000) but are yet to be examined in the context of MEPs.

44.4 Conclusion

Our goal in this essay has been to present a brief introduction to network research and theory, and to make an initial case for how it might be fruitfully applied to the study of MEPs. We have argued that MEPs are, among other things, complex, relational systems made up of a complex web of inter-related firms. The network perspective is well suited to the study of MEPs because network theory and methods focus on the structure of systems and how these structures are related to system outcomes. To help set an agenda for future research on MEPs from a network perspective, we have suggested three possible research questions: (1) what is the network structure of an MEP? (2) How does the structure of the network influence the performance of MEPs and their member organizations? And (3) how does network structure drive the composition and structure of MEPs over time? We are optimistic that the use of network theory and methods will provide new answers and, no doubt, pose new questions for scholars interested in MEPs.

Appendix: 4 Commonly Used Measures of Network Centrality

1. *Degree*: The number of vertices adjacent to a given vertex in a symmetric graph is the degree of that vertex. For non-symmetric data the in-degree of a vertex u is the number of ties received by u and the out-degree is the number of ties initiated by u. In addition if the data is valued then the degrees (in and out) will consist of the sums of the values of the ties. The normalized degree centrality is the degree divided by the maximum possible degree expressed as a percentage.

   For a given binary network with vertices $v_1 \ldots v_n$ and maximum degree centrality cmax, the network degree centralization measure is $\sum(\mathrm{c}_{\mathrm{max}}–c(v_i))$ divided by the maximum value possible, where $c(v_i)$ is the degree centrality of vertex v_i.
2. *Closeness*: The farness of a vertex is the sum of the lengths of the geodesics to every other vertex. The reciprocal of farness is closeness centrality. The normalized closeness centrality of a vertex is the reciprocal of farness divided by the minimum possible farness expressed as a percentage. As an alternative to taking the reciprocal after the summation, the reciprocals can be taken before. In this case the closeness is the sum of the reciprocated distances so that infinite distances contribute a value of zero. This can also be normalized by dividing by the maximum value. In addition the routine also allows the use user to measure distance by the sums of the lengths of all the paths or all the trails. If the data is directed the routine calculates separate measures for in-closeness and out closeness.

   For a given network with vertices $v_1 \ldots . v_n$ and maximum closeness centrality cmax, the network closeness centralization measure is $\sum(\mathrm{c}_{\mathrm{max}}–c(v_i))$ divided by the maximum value possible, where $c(v_i)$ is the closeness centrality of vertex v_i.
3. *Betweenness*: Let b_{jk} be the proportion of all geodesics linking vertex j and vertex k which pass through vertex i. The betweenness of vertex i is the sum of all b_{jk} where i, j and k are distinct. Betweenness is therefore a measure of the number of times a vertex occurs on a geodesic. The normalized betweenness centrality is the betweenness divided by the maximum possible betweenness expressed as a percentage.

   For a given network with vertices $v_1 \ldots v_n$ and maximum betweenness centrality cmax, the network betweenness centralization measure is $\sum(\mathrm{c}_{\mathrm{max}}–c(v_i))$

Table 44.1 Centrality scores for nodes in the Kite network (generated by the network program UCINET [Borgatti, Everett, & Freeman, 2002])

Degree	Closeness	Betweenness	Eigenvector
44.444	52.941	2.315	49.810
44.444	52.941	2.315	49.810
33.333	50.000	0	40.423
66.667	60.000	10.185	68.027
33.333	50.000	0	40.423
55.556	64.286	23.148	56.242
55.556	64.286	23.148	56.242
33.333	60.000	38.889	27.699
22.222	42.857	22.222	6.799
11.111	31.034	0	1.579

divided by the maximum value possible, where $c(v_i)$ is the betweenness centrality of vertex v_i.

4. *Eigenvector*: Given an adjacency matrix A, the centrality of vertex i (denoted ci), is given by $ci = a\sum A_{ij}cj$ where a is a parameter. The centrality of each vertex is therefore determined by the centrality of the vertices it is connected to. The parameter ? is required to give the equations a non-trivial solution and is therefore the reciprocal of an eigenvalue. It follows that the centralities will be the elements of the corresponding eigenvector. The normalized eigenvector centrality is the scaled eigenvector centrality divided by the maximum difference possible expressed as a percentage.

   For a given binary network with vertices $v_1 \ldots v_n$ and maximum eigenvector centrality cmax, the network eigenvector centralization measure is $\sum(\mathrm{c}_{\max}- c(v_i))$ divided by the maximum value possible, where $c(v_i)$ is the eigenvector centrality of vertex v_i (Table 44.1).

References

Barnes, J. A. (1954). Class and committees in a Norwegian island parish. *Human Relations, 7*, 39–58.

Bonacich, P. (1972). Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology, 2*, 113–120.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science, 323*, 892–895.

Borgatti, S. P., Everett, M. G., & Freeman, L. C. (2002). *UCINET VI for Windows: Software for social network analysis*. Cambridge, MA: Analytic Technologies.

Bott, E. (1957). *Family and social network*. London: Tavistock.

Burt, R. S. (1987). Social contagion and innovation, cohesion versus structural equivalence. *American Journal of Sociology, 92*, 1287–1335.

Burt, R. S. (1992). *Structural holes*. Cambridge, MA: Harvard University Press.

Burt, R. S. (2005). *Brokerage and closure: An introduction to social capital*. Oxford, UK: Oxford University Press.

Carrington, P. J., Scott, J., & Wasserman, S. (Eds.). (2005). *Models and methods in social network analysis*. New York: Cambridge University Press

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology, 94*, S95–S120.

Cross, R., & Parker, A. (2004). *The hidden power of social networks: Understanding how work really gets done in organizations*. Boston, MA: Harvard Business School Publishing.

Davis, G. F., & Greve, H. R. (1997). Corporate elite networks and the governance changes in the 1980s. *American Journal of Sociology, 103*, 1–37.

Elster, J. (2007). *Explaining social behavior: More nuts and bolts for the social sciences*. New York: Cambridge University Press.

Everett, M. G., & Borgatti, S. P. (2005). Extending centrality. In P. J. Carrington, J. Scott & S. Wasserman (Eds.), *Models and methods in social network analysis*. New York: Cambridge University Press

Freeman, L. (1979). Centrality in networks: I. Conceptual clarification. *Social Networks, 1*, 215–239.

Freeman, L. (2004). *The development of social network analysis: A study in the sociology of science*. BC, Canada: Empirical Press.

Gulati, R. (2007). *Managing network resources: Alliances, affiliations, and other relational assets*. Oxford, UK: Oxford Unversity Press.

Gulati, R., & Lawrence, P. (1999). *Organizing vertical networks: A design perspective*. Paper presented at the SMJ Special Issue Conference, Northwestern University.

Gulati, R., Nohria, N., & Zaheer, A. (2000). Strategic networks. *Strategic Management Journal, 21*, 203–215.

Krackhardt, D. (1990). Assessing the political landscape: Structure, cognition, and power in organizations. *Administrative Science Quarterly, 35*(2), 342–369.

Mehra, A. (1998). *Who gets ahead? Self-monitoring, social networks, and success*. Doctoral thesis, Smeal College of Business, Pennsylvania State University.

Mehra, A., Kilduff, M., & Brass, D. J. (2001). The social networks of high and low self-monitors: Implications for workplace performance. *Administrative Science Quarterly, 46*, 121–146.

Milgram, S. (1976). The small world problem. *Psychology Today, 22*, 61–67.

Mizruchi, M. S., & Schwartz, M. (1987). *Intercorporate relations: The structural analysis of business*. Cambridge: Cambridge University Press.

Moreno, J. L. (1934/1953). *Who shall survive?* Beacon, NY: Beacon.

Pool, I. S., & Kochen, M. (1978). Contacts and social influence. *Social Networks, 1*, 5–51.

Shaw, M. E. (1964). Communication networks. In L. Nerkowitz (Ed.), *Advances in experimental social psychology* (Vol. 1, pp. 111–147). New York: Academic.

Uzzi, B., & Spiro, J. (2005). Collaboration and creativity: The small world problem. *American Journal of Sociology, 2*, 447–504.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. New York: Cambridge University Press.

Watts, D. J. (1999). Networks, dynamics, and the small-world phenomenon. *American Journal of Sociology*, *105*, 493–527.

Watts, D. J., & Strogratz, S. H. (1998). Collective dynamics of "small-world" networks. *Nature*, *393*, 440–442.

White, H. C., Boorman, S. A., & Breiger, R. L. (1976). Social structure from multiple networks I: Blockmodels of roles and positions. *American Journal of Sociology, 81*, 730–781.

Williamson, O. (1985). *The economic institutions of capitalism*. New York: Free Press.