Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study

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To assess the effects of a firm's network of relations on innovation, this paper elaborates a theoretical framework that relates three aspects of a firm's ego network—direct ties, indirect ties, and structural holes (disconnections between a firm's partners)—to the firm's subsequent innovation output. It posits that direct and indirect ties both have a positive impact on innovation but that the impact of indirect ties is moderated by the number of a firm's direct ties. Structural holes are proposed to have both positive and negative influences on subsequent innovation. Results from a longitudinal study of firms in the international chemicals industry indicate support for the predictions on direct and indirect ties, but in the interfirm collaboration network, increasing structural holes has a negative effect on innovation. Among the implications for interorganizational network theory is that the optimal structure of interfirm networks depends on the objectives of the network members.●

Several recent studies have indicated that the positions of firms in interorganizational networks influence firm behavior and outcomes (e.g., Powell, Koput, and Smith-Doerr, 1996; Walker, Kogut, and Shan, 1997). Because of their facilitative role in various interorganizational contexts, network relationships have even been described as network resources (Gulati, 1999). In spite of the growing consensus that networks matter, however, the specific effects of different elements of network structure on organizational performance remain unclear. In the social networks literature, a debate has arisen over the form of network structures that can appropriately be regarded as beneficial (Walker, Kogut, and Shan, 1997). According to one view, densely embedded networks with many connections linking ego's alters are facilitative for ego, and social structures are seen as advantageous to the extent that networks are "closed" (Coleman, 1988; Walker, Kogut, and Shan, 1997). According to an alternate view, however, social structural advantages derive from the brokerage opportunities created by an open social structure (Burt, 1992). Actors can build relationships with multiple disconnected clusters and use these connections to obtain information and control advantages over others (Burt, 1992). From the perspective of the network theorist, these differences have different, even contradictory, normative implications (Walker, Kogut, and Shan, 1997). From Coleman's (1988) standpoint, the optimal social structure is one generated by building dense, interconnected networks. From Burt's (1992) position, constructing networks consisting of disconnected alters is the optimal strategy. Clarifying the implications of cohesive versus disconnected network structures for various organizational outcomes is important to our understanding of network resources.

Relatedly, recent research has led to the important insight that building networks with large numbers of indirect ties may be an effective way for actors to enjoy the benefits of network size without paying the costs of network maintenance associated with direct ties (Burt, 1992). Although such a strategy is undoubtedly conceptually attractive, it appears likely that its value in a given circumstance will be contingent on several factors. Specifically, the relative value of direct ver-

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sus indirect ties is likely to depend on the degree to which the benefits provided by direct and indirect ties are similar in magnitude and content. To the extent that direct ties provide different types or amounts of benefits, the possibilities of substitution between direct and indirect ties may be limited. Thus, examining the content and relative contribution of direct and indirect ties may also be relevant from the perspective of designing effective and efficient networks.

In this study, I examine the relationship between a firm's position in the industry network of interfirm collaborative linkages and its innovation output, a significant organizational outcome. Scholars in the innovation and interorganizational learning literatures have argued that linkages and the resultant collaboration networks are key vehicles through which firms obtain access to external knowledge (Powell, Koput, and Smith-Doerr, 1996). Examining the relationship between network position and innovation output can provide both an elucidation of the role of different elements of network structure in the innovation process and an empirical indicator of the effectiveness of knowledge flows through such networks. For the purposes of this study, I define an interfirm collaborative linkage as a voluntary arrangement between independent organizations to share resources. Further, following past research, I make a distinction between collaborative arrangements that involve a technological component, such as developing a new technology or sharing a manufacturing process, and collaborative arrangements that are focused purely on sharing marketing assets or brand names (Hagedoorn and Schakenraad, 1994; Singh and Mitchell, 1996). Similarly, I make a distinction between horizontal and vertical linkages (Stuart, 1998; Gulati and Lawrence, 1999). For analytic clarity and focus, in this paper, I restrict my attention to horizontal, technical linkages, i.e., technical linkages between firms in the same industry.

NETWORK STRUCTURE AND INNOVATION OUTPUT

Although sociologists have long studied the relationship between network structure and innovation, most research in this tradition has largely focused on the adoption or diffusion of innovations. Even though articles in the popular press and academic reports of the innovation-generation process have consistently used network metaphors, until recently, relatively little work has actually used a network analytic approach to study innovation generation. Recently, however, a few pioneering studies have explored network structure from the perspective of innovation generation (Shan, Walker, and Kogut, 1994; Podolny and Stuart, 1995; Powell, Koput, and Smith-Doerr, 1996). For instance, Podolny and Stuart (1995) explored the factors that determine whether an innovation becomes a technological dead end or serves as the basis for subsequent innovations. They found that this outcome was predicted by the pattern of ties in the technological niche of the innovation as well as by the quality of the innovation and the status of the innovator, but they did not directly examine the role of the interfirm network structure as a predictor of innovation output.

Two other studies that have explored the nexus between network structure and innovation performance serve as one proximate point of departure for the current research.[1] In a study of biotechnology start-ups, Shan, Walker, and Kogut (1994) predicted and found that one element of a firm's network position, the number of collaborative relationships it formed, was positively related to its innovation output. Through block modeling, they also developed a more sophisticated measure of a firm's network position and found that this measure was a good predictor of linkage formation, but they did not explore the possibility that elements of a firm's ego network, other than the number of direct ties, might influence innovation output. In another study, Powell, Koput, and Smith-Doerr (1996) traced the formation of interfirm learning networks for biotechnology start-ups and found that centrality in such networks is related to faster subsequent growth (in number of employees) for the start-ups, but they also did not directly examine the impact of network positions on innovation.

A recent stream of literature that has examined the role of different network structures in facilitating outcomes for network constituents forms the other point of departure for this study. In his book, Burt (1992) made a strong case for the strategic configuration of networks. According to this conception, designing networks to maximize disconnections (or structural holes) between alters and selecting alters with many other partners (or many indirect ties) are two mechanisms by which actors can develop efficient and effective networks. This conception, however, raises two issues. First, as some scholars have noted, the normative importance accorded to structural holes by this approach is at odds with other theoretical perspectives that stress the importance of closed social networks (Walker, Kogut, and Shan, 1997). Second, the strategy of substituting indirect ties for direct ones that is endorsed by the effective networks conception presumes that direct and indirect ties offer the same content to the focal actor. The validity of that assumption may vary significantly across networks.

The two issues raised above have important implications for modeling the impact of network structure on organizational outcomes. For instance, the debate on structural holes suggests that an accurate understanding of the role of structural holes in the collaboration network must account for both Coleman's and Burt's variants of the argument. Similarly, recognizing the possibility that even within the same network, direct and indirect ties may vary in their content highlights the importance of decomposing the firm's ego network into distinct and separate elements and identifying the contents transmitted through each type of tie.

In the technological collaboration network that I studied, interfirm collaborative linkages are associated with two distinct kinds of network benefits. First, they can provide the benefit of resource sharing, allowing firms to combine knowledge, skills, and physical assets. Second, collaborative linkages can provide access to knowledge spillovers, serving as information conduits through which news of technical breakthroughs, new insights to problems, or failed approaches

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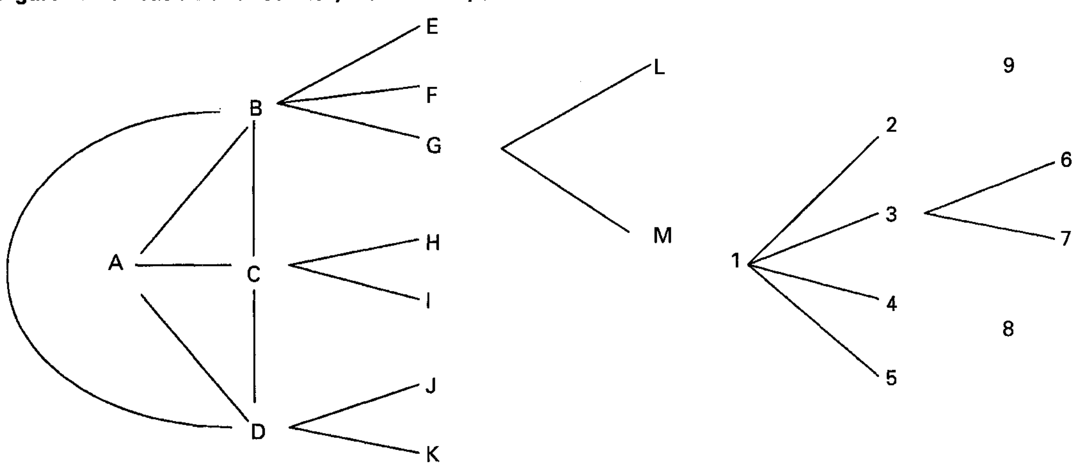
Other studies that have examined the relationship between collaboration and innovation include Berg, Duncan, and Friedman (1982) and Hagedoorn and Schakenraad (1994), albeit from slightly different perspectives. Berg, Duncan, and Friedman (1982) examined the impact of research collaboration on research expenditures and profitability. Similarly, Hagedoorn and Schakenraad (1994) related collaboration to profitability. Neither of these studies, however, directly examined the impact of collaboration on innovative output or used a network perspective.

travels from one firm to another. In distinguishing between the resource-sharing and knowledge-spillover benefits of collaboration, it is important to distinguish between know-how and information (Kogut and Zander, 1992). Know-how entails accumulated skills and expertise in some activity and is likely to include a significant tacit or noncodifiable dimension. Information refers primarily to facts, discrete quanta of information that can be transmitted through simple communication in relatively complete form and without loss of integrity (Kogut and Zander, 1992; Szulanski, 1996). The resource-sharing benefits of collaboration relate primarily to the transfer and sharing of know-how and physical assets, while the knowledge-spillover benefits are likely to involve predominantly information.

Three aspects of a firm's network structure are likely to be relevant in connection with the above benefits: (1) the number of direct ties maintained by a firm, (2) the number of indirect ties maintained by the firm (the firms it can reach in the network through its partners and their partners), and (3) the degree to which a firm's partners are linked to each other (i.e., whether there are structural holes in the firm's ego network). Figure 1 identifies these three dimensions in the ego networks of two illustrative firms. Firm A has three direct ties, to partners B, C, and D. Firm A also has nine indirect ties, the nine firms (E through M) that it can reach through its partners or their partners. Further, its partners, B, C, and D, are all tied to each other, creating a closed network with no structural holes (from Firm A's perspective). In comparison, Firm 1 has more direct ties (Firms 2, 3, 4, and 5) but fewer (only two) indirect ties (Firms 6 and 7). Finally, its partners are unconnected to each other, creating an open network with several structural holes (the gaps between partners 2, 3, 4, and 5).

Each of these three dimensions of a firm's network, its direct ties, indirect ties, and connections between partners, can influence the firm's innovation performance. A firm's direct ties potentially provide both resource-sharing and knowledge-spillover benefits. Indirect ties do not entail formal resource-sharing benefits but can provide access to knowledge

Figure 1. Illustration of direct ties, indirect ties, and structural holes in two networks.



spillovers. Finally, the degree of connectivity between a firm's partners influences both resource sharing and access to novel information, albeit in contradictory ways.

Direct Ties, Indirect Ties, and Innovation

The number of direct ties a firm maintains can affect its innovative output positively by providing three substantive benefits: knowledge sharing, complementarity, and scale. First, direct ties enable knowledge sharing (Berg, Duncan, and Friedman, 1982). When firms collaborate to develop a technology, the resultant knowledge is available to all partners. Thus, each partner can potentially receive a greater amount of knowledge from a collaborative project than it would obtain from a comparable research investment made independently. For instance, if two firms contribute an amount of $X each to a collaborative R&D effort, then $2X should be the amount of collaborative R&D available to each firm, in addition to any internal R&D done by each firm.

Second, collaboration facilitates bringing together complementary skills from different firms (Richardson, 1972; Arora and Gambardella, 1990). Technology often demands the simultaneous use of different sets of skills and knowledge bases in the innovation process (Arora and Gambardella, 1990; Powell, Koput, and Smith-Doerr, 1996). Developing multiple, broad competencies or maintaining them in the face of rapid technological changes, however, are difficult for firms (Mitchell and Singh, 1996). Transactional considerations may make the purchase of such technologies infeasible or prohibitive, leaving internal development and collaboration as the only viable alternatives (Mitchell and Singh, 1996). Under such circumstances, collaboration can enable firms to enjoy economies of specialization without the prior investments entailed by internal development. By tapping into the developed competencies of other firms, firms can enhance their own knowledge base and thereby improve their innovation performance.

A third positive effect of direct ties emerges through scale economies in research that arise when larger projects generate significantly more knowledge than smaller projects. Collaboration enables firms to take advantage of such scale economies. If individual firms have the wherewithal to invest an amount X in a given research project, then two firms combining resources can potentially invest twice as much. If the transformation technology is characterized by increasing returns, such an investment will lead to a more than proportionate return in terms of innovation output, benefiting both firms significantly. Prior research has also shown a positive impact of interfirm collaboration on innovation output. In a study of biotechnology start-ups, Shan, Walker, and Kogut (1994) found that the greater the number of collaborative linkages formed by a start-up, the higher the number of patents it obtained. Thus, other things being equal, I suggest:

Hypothesis 1: The more direct ties that a firm maintains, the greater the firm's subsequent innovation output.

A firm's collaborative linkages can also provide access to knowledge spillovers. Knowledge flows between firms and industries are constituted of both contractual knowledge transfers and relatively informal, uncompensated knowledge spillovers or leakages (Jaffe, 1986; Bernstein and Nadiri, 1989; Jaffe, Trajtenberg, and Henderson, 1993). Collaborative linkages represent arenas of sustained, focused, and relatively intense interaction (Auster, 1992). They involve repeated and regular meetings between the partners, a focus on specified objectives, and entail coordination, close contact, and mutual dependency (Gulati and Singh, 1998). Sustained interaction is characterized by frequent communication. Focused interaction implies that these ties will be used, significantly, and perhaps predominantly, to communicate on a narrow range of issues relating to the objectives and subject of collaboration (Rogers and Kincaid, 1981). Intense interaction indicates that the partners have both a great incentive and opportunity to share information (Granovetter, 1973, 1982; Boorman, 1975; Krackhardt, 1992). Given these characteristics of the information-exchange process embodied in an interfirm linkage, an interfirm linkage is an important channel of communication between the firm and its direct partners.

An interfirm linkage can also be a channel of communication between the firm and many indirect contacts (Mizruchi, 1989; Davis, 1991; Haunschild, 1993; Gulati, 1995). A firm's partners bring the knowledge and experience from their interactions with their other partners to their interaction with the focal firm, and vice versa (Gulati and Garguilo, 1999). A firm's linkages therefore provide it with access not just to the knowledge held by its partners but also to the knowledge held by its partner's partners (Gulati and Garguilo, 1999). The network of interfirm linkages thus serves as an information conduit, with each firm connected to the network being both a recipient and a transmitter of information (Rogers and Kincaid, 1981).

The role of the interfirm network as an information channel and facilitator of knowledge exchange between firms can be significant in the technological context (Powell, Koput, and Smith-Doerr, 1996). Innovation is often an information-intensive activity in terms of both information collection and information processing. Individual firms can pursue only a limited number of technologies and lines of research, but the network can increase a firm's catchment area for information and provide benefits in two forms. First, it can serve as an information-gathering device (Freeman, 1991). Firms can receive information on the success and failure of many simultaneous research efforts (Rogers and Larsen, 1984). Promising technological trajectories as well as technological dead ends can be brought to the early notice of a firm that is plugged into the network. Second, the network can serve as an information-processing or screening device (Leonard-Barton, 1984). Each additional node that a firm has access to can serve as an information-processing mechanism, absorbing, sifting, and classifying new technical developments in a manner that goes well beyond the information-processing capabilities of a single firm. Relevant developments in different technologies may be brought to the firm's attention through its links, some of whom may specialize in those technologies or work with partners who specialize in them (Freeman, 1982). Alternately, faced with a specific problem, a firm can activate its network to identify the sources that are likely to be well informed about the specific issue at hand (Freeman, 1982). Other things being equal, firms that have many indirect ties, are privy to more information than firms whose reach in the network is more limited, which is likely to have an effect on innovation:

Hypothesis 2: The greater a firm's number of indirect ties, the greater the subsequent innovation output of the firm.

The degree to which indirect ties benefit the focal firm, however, is likely to be contingent on the number of the focal firm's existing direct ties, such that firms with few direct ties are likely to enjoy greater benefits from their indirect ties than firms with many direct ties. Two arguments support this line of reasoning. First, the relative addition to knowledge through indirect ties is likely to be greater for firms with few direct ties than for firms with many direct ties. For firms with limited access to the network through direct ties, the information provided by indirect ties may represent a significant increment to the firm's existing information base, while firms with many direct ties are already privy to a significant proportion of the knowledge flow of the network through their direct ties. The additional access to information provided by their indirect ties may then represent only a marginal increment in their knowledge base.

Second, firms with many direct ties may also be more limited in their ability to profit from information from their indirect ties. When a firm's partners have many connections, the information that reaches the firm through the network also reaches many others, the other partners of its partners. These partners potentially represent competition for the firm in using this information. When information circulates among many potential users, the alertness, responsiveness, and flexibility of individual users is likely to determine the benefit that they obtain from it (Zaheer and Zaheer, 1997). Firms with many direct ties may be more constrained in their ability to absorb new information or respond to it as flexibly as firms with few direct ties (Glasmeier, 1991). Firms with many direct ties, being in the thick of things, are less likely to add to their knowledge or to absorb as much knowledge through their indirect ties than are firms with few direct ties, which is likely to have an effect on innovation:

Hypothesis 3: The impact of indirect ties on a firm's innovation output will be moderated by the level of the firm's direct ties: the greater the number of direct ties, the smaller the benefit from indirect ties.

Structural Holes and Innovation

Recent research suggests that a third dimension of a firm's ego network is also likely to be important to innovation: the degree of connectivity (or the lack of it) between a firm's partners (Burt, 1992). According to Burt's structural hole theory, ties are redundant to the degree that they lead to the same actors. Structural holes are gaps in information flows between alters linked to the same ego but not linked to each other. A structural hole indicates that the people on either side of the hole have access to different flows of information (Hargadon and Sutton, 1997). Ego networks rich in structural holes imply access to mutually unconnected partners and, consequently, to many distinct information flows. Thus, maximizing the structural holes spanned or minimizing redundancy between partners is an important aspect of constructing an efficient, information-rich network (Burt, 1992).

From the perspective of structural hole theory, ego networks in which a firm's partners have no links with each other are preferred to networks in which its partners are densely tied to each other, but examining the impact of a network rich in structural holes on the resource-sharing benefits of the network reveals a conclusion that is almost diametrically opposite to the conclusion reached by relating knowledge spillover or information benefits to the same network structure. The resource-sharing benefits of collaboration arise from firms combining their skills, sharing their knowledge, and conducting joint projects to obtain scale economies, all of which presume the existence of significant trust between the partners. Without trust and shared norms of behavior, sharing knowledge, combining skills, and making large joint investments are likely to be difficult and unproductive in any context (Coleman, 1988). In horizontal networks of competitors, the basic problem of coordinating interorganizational relationships is worsened by a heightened threat of opportunistic behavior (Gulati and Singh, 1998). From stealing partners' technology to providing poorer quality investments on joint projects, to not fulfilling ex ante commitments, alliances offer many opportunities for cheating. The development of trust and the reduction of opportunism are then likely to be necessary preconditions for successful resource sharing.

Extensive relations between partners can foster the development of shared norms of behavior and explicit interorganizational knowledge-sharing routines (Uzzi, 1997; Walker, Kogut, and Shan, 1997; Dyer and Noboeka, 2000). The social constraints associated with dense, embedded networks can facilitate large relationship-specific investments that help maximize the benefits from collaboration (Walker, Kogut, and Shan, 1997). Common partners can serve as referral agents and relay expectations and responsibilities as part of the process of bringing together two hitherto unconnected firms (Gulati, 1995; Uzzi, 1997). They can also use their relationships with both parties to encourage cooperation, reciprocity, and sharing (Uzzi, 1997; Gulati, 1999). Deeply embedded networks can also foster fine-grained information transfer and joint problem solving (Uzzi, 1997), two essential components of successful resource sharing.

Dense ties between partners are also likely to help in curbing opportunism (Coleman, 1988; Walker, Kogut, and Shan, 1997; Rowley, Behrens, and Krackhardt, 2000). In closed networks, in which ego's partners are connected to each other, information about one actor's opportunistic acts diffuses rapidly to other related actors, and sanctions for deviant behavior are more easily imposed (Walker, Kogut, and Shan, 1997). Further, in such a highly interconnected system, deviant behavior is less likely to arise because the threat of reputation loss with respect to multiple partners will discourage firms from behaving opportunistically with any single partner. By contrast, in an open network in which ego's partners are not linked to each other, the possibility of opportunistic actions is greater.

The contradictory effects of connections between partners thus prompt two competing predictions with respect to the relationship between structural holes and innovation. Many structural holes in ego's network will increase ego's access to diverse information and, hence, enhance innovation output. Conversely, ego networks with fewer structural holes might promote trust generation and reduce opportunism, leading to more productive collaboration from the perspective of resource sharing.

Hypothesis 4a: The greater the structural holes spanned by a firm, the greater the firm's subsequent innovation output.

Hypothesis 4b: The greater the structural holes spanned by a firm, the less the firm's subsequent innovation output.

METHODS

I chose to conduct my research in the chemicals industry for several reasons. First, technological collaboration has been and continues to be a significant feature of this industry. Second, patents are a meaningful measure of innovation in this industry. The link between patents and innovation is likely to be stronger in industries in which patents provide firms with fairly strong protection for their proprietary knowledge. Prior research indicates that the chemicals industry is one in which patents are generally regarded to be effective and used widely and consistently, relative to most other industries (Levin et al., 1987). I tested the hypotheses on a longitudinal data set comprising the linkage and patenting activities of 97 leading firms from the chemicals industry in Western Europe, Japan, and the United States. The sample was selected to include the largest chemicals firms in these three areas, which constitute the core of the global chemicals industry, to ensure the availability and reliability of data. Information on the key variable, collaborative linkages, is extremely difficult to obtain for smaller firms over an extended time period. Past network studies on alliances have used a similar strategy of focusing on the leading firms in an industry (Gulati, 1995; Gualti and Garguilo, 1999).

Innovation output, the dependent variable, was measured through the patenting frequency of each firm, the number of patents received in a given year. Patents are an important measure of innovation output because they are directly related to inventiveness, they represent an externally validated measure of technological novelty (Griliches, 1990), and they confer property rights on the assignee and therefore have economic significance (Kamien and Schwartz, 1982; Scherer and Ross, 1990). Further, empirical studies have shown that patents are closely related to measures such as new products (Comanor and Scherer, 1969), innovation and invention counts (Kleinecht, 1982; Basberg, 1983; Achilladelis, Schwarzkopf, and Cines, 1987), and sales growth (Scherer, 1965). Expert ratings of corporate technological strength have also been found to be highly correlated with the number of patents held by corporations (Narin, Noma, and Perry, 1987).

The use of patents as a measure of innovative output has some limitations, too. Some inventions are not patentable, others are not patented for strategic reasons. Further, firms may differ in their patenting propensity (Cohen and Levin, 1989; Griliches, 1990). Research, and the logic of appropriability, indicate that the degree to which these factors are a problem varies significantly across industries (Levin et al., 1987; Cohen and Levin, 1989). This insight provides a partial solution to the problem, in that an appropriate research design can be used to control for interindustry differences in patenting propensity (Basberg, 1987). Limiting the study to a single industrial sector in which patents are a meaningful indicator of innovation minimizes such problems, as the factors that affect patenting propensity are likely to be stable within such a context (Basberg, 1987; Cohen and Levin, 1989; Griliches, 1990). Because, even within an industry, firms might differ in patenting propensity for unobserved reasons, I treated this as a problem of unobserved heterogeneity and controlled for such variations through my statistical approach.

I identified the leading firms in the chemicals industry from lists that are published annually by trade journals such as *Chemical Week* and *C&E News*. To minimize survivor bias, I selected the sample from the lists at the beginning of the study period. In these published lists subsidiaries were often listed separately from parent firms. From an original sample of approximately 120 firms, after matching subsidiaries with their parent firms, a sample of 107 firms remained. For ten of these firms, reliable patent data or covariate data could not be obtained, and they were dropped from the analysis. The remaining firms include all the key players in the industry over the study period. The panel is unbalanced, as some of the firms were acquired by other firms or restructured so as to make comparison difficult beyond a particular year. A full list of the sample firms is available from the author.

Data

I obtained yearly patent counts, collaboration data, and firm-attribute data for the firms in the sample. The panel used for the analysis includes collaborative activity for the period 1981–1991 and patenting activity for the period 1982–1992, reflecting a one-year lag between collaboration and patenting. I used U.S. patent data for all firms, including the foreign firms in the sample, to maintain consistency, reliability, and comparability, as patenting systems across nations differ in the application of standards, system of granting patents, and value of protection granted. The U.S. represents one of the largest markets for chemicals, and firms desirous of commercializing their inventions would patent in the United States if they were to patent anywhere at all. This observation is supported by statistics from the U.S. Patent Office, which indicate that almost half of all U.S. patents are issued to foreign entities. Prior research using patent data on international samples has followed a similar strategy of using U.S. patent data for international firms (Stuart and Podolny, 1996; Stuart, 1998).

To obtain patent counts for each firm, I prepared a list for each firm in the sample of all its divisions, subsidiaries, and joint ventures, using *Who Owns Whom* (United States, United Kingdom and Ireland, Continental Europe, and Asia editions) and the *Directory of Corporate Affiliations.* Thereafter, I traced each firm's history through the study period to account for any name changes and reorganizations and to obtain information on the timings of events such as the founding and dissolution of joint ventures. This master list was used to identify all patents issued to the sample firms.

The list of chemicals patents owned by these firms was derived from the above master list using the technology-class information on the patents. The U.S. patent system classifies the technology domain into 400 broad classes and several hundred thousand subclasses nested within the classes. Patent examiners assign each patent to a primary technology class. The *Patent Manual* was used to identify the technology classes corresponding to chemicals. Using the identified technology classes, I separated the chemicals patents of the sample firms from other patents they obtained. Finally, I computed the patent count for each firm for each year by assigning to that firm all chemicals patents issued solely to the firm or to its subsidiaries and half of the chemicals patents issued jointly to the firm and a partner or issued to joint ventures of the firm. This was done to avoid spurious inflation of patent counts through double counting of jointly held patents.

I obtained data on collaboration through detailed archival research on the chemicals and materials sector, using three main types of data sources to identify linkage activity: (1) electromagnetic databases, including both general business news media such as the Dow Jones News Retrieval Text Index and sector-specific databases such as *Metadex*, (2) general business print media, such as the *Frost and Sullivan Predicasts Index* (U.S., International, and Europe), as well as industry-specific publications, such as *Chemical Week* and *Plastics Technology*, and, (3) government publications and consultant reports for the chemicals industry. The data collection and coding exercise for the entire data set involved studying over 130,000 electronic news stories and dozens of text works. The full data set includes details on corporate collaborative actions across all functional areas in the chemicals and materials sector. For the current study, I used a subset of the data covering the technical collaboration activities of the sample firms over the period 1981 to 1991. The linkages used here include 268 joint ventures, in which the collaborating firms formed a new organizational entity, and 152 joint research or technology-sharing agreements, in which no new organization was formed.

In previous studies, lack of available data on linkage dissolution has meant that a distinction has not usually been made between linkages formed by the firm and the linkages maintained by the firm at any point in time. Thus, I attempted to record dissolution or continuity information for all linkages. This also helped to ensure that linkages that were announced but subsequently did not materialize were identified and removed from the data. This effort produced mixed results. For the joint ventures in the sample, the exercise was quite successful. For 191 of the 268 joint ventures, I was able to establish either the date of dissolution or the survival of the joint venture beyond 1991, the concluding year of this study. For several of the remaining joint ventures I was able to establish continuity of operations until some date between the date of founding and 1991. This occurred when the last information available about the joint venture was dated prior to 1991 but did not refer to dissolution activity. I treated all joint ventures for which I did not have a record of dissolution as continuing to exist until 1991 for two reasons. First, my success at identifying dissolutions in the majority of cases led me to believe that, at least for this sample of firms, joint venture dissolution tends to be reported. Hence, the absence of a confirming report of dissolution was best interpreted as an indicator of continuing operations. Second, in many of the cases, trade and news reports indicated ongoing operations or specific activities at these joint ventures for several years after founding. The fact that other news about these ventures was being reported made it seem likely that their dissolution would also be reported. Assuming continuity in the absence of news of dissolution seemed to be the more accurate assumption to make about these ventures.

The situation was quite different for research agreements and technology development and sharing arrangements not involving the formation of a separate entity. For such agreements, I coded dissolution based on the tenure specified in the formation announcement or on a formal notice of conclusion of the research, when available. For long-term (multiyear) or general programs of research, one of the two above conditions was often the case. In the majority of cases, however, I was unable to establish formal dissolutions. In such cases, I presumed the agreement to exist until the last year in which it was documented or until the year after the year it was founded, whichever was later. The assumption that such agreements have a short life relative to joint ventures is consistent with the specific and short-term nature of their objectives in most cases. For research agreements, there were also cases in which the existence or ongoing activities of a collaboration were discussed but the founding of the collaboration itself was not reported or indicated. In such cases, I treated the collaboration as having been founded in the year immediately prior to the year in which it was first documented.

Financial figures and employment data came from COMPUSTAT, *Worldscope* (several volumes), trade publications, company annual reports, Japan Company handbooks and Daiwa Institute research guides. For all firms, financial data were converted to constant (1985) U.S. dollars to ensure standardization within the sample.

Model Estimation and Econometric Issues

Model specification. The dependent variable, innovation output as represented by patent counts, is a count variable and takes only non-negative integer values. The linear regression model assumes homoskedastic, normally distributed errors. Because these assumptions are violated with count variables, a Poisson regression approach is more appropriate (Hausman, Hall, and Griliches, 1984). To account for unobserved heterogeneity, the possibility that observationally equivalent firms may differ on unmeasured characteristics, I used the panel Poisson approach (Hausman, Hall, and Griliches, 1984) and estimated random effects Poisson models. In the random effects Poisson model, an additional effect, μ_i, is included in the Poisson specification to reflect firm-specific heterogeneity:

$$E(P_{it}/X_{it-1}) = e^{X_{it-1}\beta+\mu_i}.$$

This firm-specific effect permits observations of the same firm to be correlated across periods and thus builds serial correlation directly into the model. Further, the μ_i is assumed to be drawn from the gamma distribution. This specification of μ_i implies that the variance to mean ratio is no longer unity, as is assumed in the regular Poisson model but, instead, becomes $(1 + \alpha\lambda_{it})$, in which α is the reciprocal of the standard deviation of the heterogeneity distribution. Thus, in this model, the ratio of the variance to the mean is permitted to grow with the mean (Hausman, Hall, and Griliches, 1984). The model estimates α from the observed data and thus directly captures any overdispersion.

Hausman, Hall, and Griliches (1984) also provided a fixed-effects estimator for count data that handles unobserved heterogeneity by computing within-firm estimates of the coefficients. In this approach, only the variation within a firm across time is used to estimate the regression coefficients. Thus, unobserved variations between firms are not problematic because between-firm variation is not used in the computations of the estimates. In this paper, for robustness, I used both fixed effects and random effects to estimate the models.

Measures

Dependent Variable. I measured $Patents_{it}$, as the number of successful patent applications, or granted patents, for firm i in year t. The majority of patent applications are examined and ruled upon within two to three years of application. The granted patent carries the date of the original application. I used this date to assign a granted patent to the particular year in which it was originally applied for. For instance, a patent applied for in 1986 but granted in 1988 is considered a 1986 patent. This procedure permitted consistency in the treatment of all patents and controlled for differences in delays that may occur in granting patents after the application is filed. Because patents are likely to correspond to activity immediately preceding the patent application, I used a one-year lead with respect to key influences, such as R&D and linkages. Thus, the patent count for 1986 is regressed against the 1985 values of other covariates such as R&D and direct ties.

Independent Variables

Direct and indirect ties. To obtain a count of the *direct ties* maintained by a firm in any year, I counted the number of direct partners of the focal firm, or its degree centrality in the network. Hypothesis 1 predicted a positive impact of this variable on patenting frequency. I used three alternative measures to capture a firm's reach in the network through its indirect ties. The first variable was a simple count of indirect ties *(indirect ties, count)*. For each firm, I computed the number of other firms in the network that it was tied to at path distances of two or greater, which thus excluded direct ties. But this simple count of indirect ties does not account for the weakening or decay in tie strength between firms that are connected by increasingly large path distances. For instance, this measure counts both two-step-distant ties (firms that are linked to the focal firm through only one intermediary firm when using the shortest path between the two firms) and five-step-distant ties (firms that are linked to the focal firm through four intermediary firms when using the shortest path between the two firms) as the same. Yet it is probable that as the shortest paths connecting two firms grow longer, the likelihood of information transmission between them decreases. Burt (1991) provided a frequency decay measure that accounts for this decline in tie strength across progressively distant ties. This measure *(indirect ties, distance-weighted count)* attaches weights of the form $1 - [f_i/(N+1)]$ to each tie, where f_i is the total number of nodes that can be reached up to and including the path distance i, and N is the total number of firms that can be reached by the focal firm in any number of steps. The argument for this weighting scheme is that the rate at which the strength of a relation decreases with the increasing length of its corresponding path distance should vary with the social structure in which it occurs (Burt, 1991). The larger the number of firms to which the focal firm must devote its network time and energy, the weaker the relationship that it can sustain with any individual firm. Thus, decay in relationship strength is related to the number of other firms reached at each path distance. For example, for a firm with 3 direct ties, 5 two-step ties, and 7 three-step ties (here N = 15, i.e., 3 + 5 + 7), the frequency decay formula will attach weights of $1 - (3/16) = 13/16$ to each direct tie, $1 - 8/16 = 8/16$ to each two-step tie, and $1 - 15/16 = 1/16$ to each three-step tie. Thus, ties at progressively longer path distances receive progressively smaller weights. The total number of indirect ties weighted by their path distances can now be computed easily. In this illustration, the weighted count of indirect ties for this hypothetical firm is $5(8/16) + 7(1/16) = 47/16$.

I devised a third measure *(indirect ties, distance and information weighted count)* that is a refinement of Burt's frequency-decay measure. Burt's measure accounts for lowered probabilities of information transmission across longer path distances but implicitly assumes that all nodes generate the same amount of new information. In a technology network, some firms may create more knowledge than others and could hence be the source of more information. Accordingly, each node could be weighted by the amount of new information it generates. The number of new patents created by a firm provides at least a crude measure of the variations across firms in their new knowledge creation capabilities. Hence, for each node (firm), I used the number of patents applied for by the firm in that period as the weight for that node in the computation. Operationally, for each firm, I multiplied the vector of Burt's frequency-decay weighted path distances by the vector of patent counts to compute this new variable. For example, if the 5 two-step ties of the hypothetical firm described above produced 1, 2, 4, 6, and 8 patents, respectively, while the 7 three-step ties produced 2, 4, 6, 8, 10, 0, and 5 patents, respectively, then the patent-weighted measure of indirect ties would have a value of 12 and 11/16 [(8/16)(1 + 2 + 4 + 6 + 8) + (1/16)(2 + 4 + 6 + 8 + 10 + 0 + 5)] for this firm.

Direct ties × Indirect ties represents the interaction between the two prior variables. Hypothesis 3 predicted a negative impact of this variable on patenting frequency. There are three versions of this variable, based on the three measures of indirect ties. I used the ratio of nonredundant contacts to total contacts for the i^{th} firm (Burt, 1991) to measure the *structural holes* in the ego network of a firm. This measure is computed as

$$[\Sigma_j[1-\Sigma_q\ p_{iq}m_{jq}]\ ]\ /\ C_i,$$

where p_{iq} is the proportion of i's relations invested in the connection with contact q, m_{jq} is the marginal strength of the relationship between contact j and contact q, and C_i is the total number of contacts for firm i. Higher values on this index reflect firms whose ego networks are rich in structural holes, i.e., the firms' partners are not connected to each other. If all of a firm's partners are unconnected to each other, the index takes a value of 1, indicating that none of the firm's contacts are redundant. Connections between a firm's partners imply a higher $\Sigma_q p_{iq} m_{jq}$ and thus a lower value for this index, reflecting higher redundancy and fewer structural holes. For firms without any partners, the index is set to 0. I used STRUCTURE (Burt, 1991) to compute this measure.

Control variables. *R&D* expenditures are likely to be a significant determinant of innovative outcomes. I collected R&D data from COMPUSTAT, *Worldscope*, DIR Analyst's guides, Japan Company handbooks, industry and company journals, and annual reports. When R&D data were not available for some periods, I used a regression imputation procedure (Little and Rubin, 1987) to impute missing values for this variable and complete the data. In a few cases, this imputation procedure led to negative or improbable values for R&D, so I estimated R&D individually using data from the most recent available periods for that firm. Since the dependent variable, patents, includes only chemicals patents, an appropriate control would be to include only the R&D expenditures on chemicals-related businesses rather than corporate R&D. Unfortunately, business-level research expenditures are not commonly reported. As an approximation, I obtained the ratio of chemicals sales to total sales for each firm and applied it to the corporate R&D figures to obtain chemicals R&D. I used the natural log of chemicals R&D expenditures as a control variable in all models.

It is conventional to control for firm-size effects in analyses of innovative productivity (Cohen and Levin, 1989). I used the natural log of number of chemicals employees as a measure of *firm size*. Number of employees was obtained from COMPUSTAT, *Worldscope*, Japan Company handbooks, and industry and company journals and reports. As with R&D, to obtain the number of employees in the chemicals businesses of the firm, I multiplied the total number of employees by the ratio of chemicals sales to total sales.

Arguments have been made for both positive and negative impacts of diversification on innovation performance (Cohen and Levin, 1989). I do not make any prediction on the sign of this effect but control for its influence by including the variable *diversification, entropy*. The following formula was used to calculate the measure: $\Sigma P_j \times \ln(1/P_j)$, where P_j is defined as the percentage of firm sales in business segment j and ln $(1/P_j)$ is the weight for each segment j (Palepu, 1985).

Firms can vary in their area of strategic focus within an industry, and different industry segments can offer differing degrees of opportunity to innovate. Thus, some firms may be active in relatively richer technological domains than other firms. To capture the firm-specific differences in areas of strategic focus, I constructed a measure of *technological opportunity*. For each firm, I identified the technological classes in which it was active in any year. I then identified the number of total patents in that set of classes by the U. S. Patent Office in that year. Thereafter, using the firm's own distribution of patenting effort across classes as weights, I computed a weighted indicator of the relative richness of the firm's specific environment. The weights reflect the fact that the firm's own efforts across those classes were not distributed equally. As an illustration, say that Firm A has patented in technological classes 1, 2, and 3 in 1983 and obtained 5, 20, and 25 patents in these classes, respectively. I obtained the total patents in these classes from the U.S. Patent database in that year, as 400, 1000, and 600. The value of the technological-opportunity variable for this firm-year observation would then be 400(5/50) + 1000(20/50) + 600(25/50) = 740. Essentially, high values of this variable indicate that the firm was involved in technology segments that offered relatively higher opportunity to innovate than other segments.

Firms conducting research in multiple geographic regions may enjoy access to more diverse knowledge environments, which may influence innovation output. To control for the geographic breadth of a firm's research efforts, I computed the variable *international research presence* as the Herfindahl index of the firm's patenting across nations in that year. The U.S. Patent database provides information on the physical location of the inventor at the time of the invention. Based on this, it is possible to construct an indicator of the distribution of a firm's inventive efforts across nations. The Herfindahl index is computed as ΣN_i^2, where N_i is the proportion of the firm's patents in nation i. A firm with a research presence distributed across several nations will have a lower score on this index than one whose research efforts are concentrated in a single nation. For instance, a firm with 100 patents split equally over five nations will have a Herfindahl index score of

5 $(0.20)^2 = 0.20$. Another firm with the same number of patents, but active in only one nation, will have a Herfindahl index score of 1.

It is possible that in an interfirm technology network the structural-holes measure might capture the technical diversity of the skill bases in a firm's alliance network rather than the social structural effects postulated here. If a firm's partners are active in widely divergent technological areas, they may be unconnected to each other and, hence, generate structural holes in the focal firm's network. At the same time, such diversity in the partner base may make successful collaboration unlikely for largely technical reasons, such as absorptive capacity (Cohen and Levinthal, 1989; Lane and Lubatkin, 1998; Stuart, 1998). If so, then the structural-holes measure might reflect the negative effects of this technological distance between partners rather than social structural effects. To control for this possibility, I created a variable, *technological distance between partners*, to capture the degree of diversity of a firm's partners. To compute the technological distance between partners, I used the approach suggested by Jaffe (1986). First, I used the distribution of a firm's prior patenting across the patent classes provided by the United States Patent and Trademark Office (USPTO), to construct a vector representing each firm's position in technology space. In this vector, each USPTO technology class represents a distinct dimension, and for any firm, the proportion of the firm's patents that fall within the technology class is the value of the corresponding element in this vector. For instance, if a firm had obtained 20 percent of its patents in the K^{th} technology class, then the K^{th} element of the vector for this firm would have a value of 0.20. After representing all the firms in this technology space, for each firm, I calculated the Euclidean distance between all pairs of its partners and took the average of these distances as the value of the variable, *technological distance between partners*. If partners are technologically distant from each other, in that they have very different technological backgrounds as represented by their prior patenting focus, then this variable should have a relatively high value. If they focus on the same technology classes and have very similar patenting profiles across the classes, then the value of this variable will be relatively low. To illustrate, if Firm A has 10 percent of its patents in Class A, 40 percent in Class B, 50 percent in Class C, and 0 percent in Class D, while Firm B has 40 percent of its patents in Class A, 0 percent in Class B, 10 percent in Class C, and 50 percent in Class D, then the technological distance between the two firms can be computed as the Euclidean distance between the vectors: 0.1, 0.4, 0.5, 0 and 0.4, 0, 0.10, 0.5, i.e., the square root of the sum $[(0.1 - 0.4)^2 + (0.4 - 0.0)^2 + (0.5 - 0.1)^2 + (0.0 - 0.5)^2]$. Computing this distance between all of a firm's partners and taking the average of these distances provides the value of this variable for a given firm-year.

I also included variables to control for the profitability and liquidity of firms. Profitability was captured through a *return on assets* variable, while liquidity was represented through the *current ratio* (ratio of current assets to current liabilities). Over time, innovation rates can increase or decrease for all firms. I controlled for such period effects by including a series of dummies for every year from 1981 to 1990, 1991 being the omitted category. I also included control variables for the nationality of the firms; *Japan* and *USA* were dummy variables coded to equal 1 for Japanese and American firms, respectively. European firms constituted the omitted category.

RESULTS

Table 1, which provides descriptive statistics for the linkage network over time, shows that the mean number of direct ties grew steadily over the period of the study, reaching a peak in 1990 and then declining in 1991. The overall density of the network indicates the proportion of potential network ties that are actually realized and reflects the same trend, peaking at 5.7 percent. Thus, the network is relatively sparse, with less than 6 percent of potential connections actually being realized. The distribution of ties is captured by the two remaining variables in table 1. The percentage of isolates indicates the firms that maintain no ties at all. The percentage of such firms steadily declines from 26 percent in 1981 to 9 percent in 1989 before increasing to 11 percent by 1991. Thus, in most years, over 80 percent of the firms had at least one direct tie. The network centralization measure indicates the degree to which a single actor dominates the network. If linkages are distributed equally among all nodes, this index has a low value. It reaches zero when all firms have the same number of ties. High values on this variable indicate that linkage activity is centered in one leading firm, and relatively few linkages occur between other firms. The observed values indicate that network centralization is moderate, reaching a peak of around 22 percent in the mid-eighties. Thus, it appears that even though most firms are linked to the network, some are significantly more active than others.

Table 2 provides descriptive statistics and correlations for all variables for the 996 observations in the sample. Even though the sample represents the prominent firms in the industry, there is considerable variance on all the key variables, such as patents, R&D, direct ties, and log employees. The three measures for indirect ties are relatively highly cor-

Table 1

Descriptive Statistics on the Linkage Network

Year	Mean degree	Network density (%)	S. D. Degree	Min.	Max.	Network centralization (%)	% Isolates
1981	3.34	2.9	3.64	0.0	18	14	26
1982	3.77	3.4	4.19	0.0	25	18	22
1983	4.23	3.7	4.52	0.0	27	19	20
1984	4.31	3.9	4.53	0.0	27	18	14
1985	4.64	4.1	4.69	0.0	29	21	13
1986	5.11	4.3	5.13	0.0	31	22	14
1987	5.38	4.6	5.25	0.0	28	20	11
1988	5.86	5.2	5.53	0.0	28	16	11
1989	6.19	5.4	5.88	0.0	34	19	9
1990	6.70	5.7	6.64	0.0	34	19	11
1991	6.43	5.6	6.40	0.0	29	18	14

related with each other, as would be expected. Among the independent variables, the measure for structural holes is correlated with the three measures for indirect ties.[2]

In table 3, I report the results of the regression analyses using the random-effects Poisson estimators. Model 1 presents the base model with only the control variables. Model 2 adds the direct ties variable to the specification. Models 3a through 3c add the three measures of indirect ties, respectively. Models 4a through 4c add the interaction terms, Direct ties × Indirect ties (three measures), and models 5a through 5c add the structural holes variables to complete the specification. I use the complete specification (models 5a to 5c) to discuss the results.

The results support the predictions for all four hypotheses. The coefficient of direct ties is positive and significant, supporting hypothesis 1, which predicted a positive impact of direct ties on firm innovation output. The indirect ties coefficient (all three measures) is positive and significant, supporting hypothesis 2's prediction of a positive relationship between indirect ties and firm innovation output. Hypothesis 3, predicting a negative impact of the interaction between direct ties and indirect ties on the innovation output of a firm is supported, the negative and significant coefficient indicating that having a higher number of direct ties reduces the impact of indirect ties. Finally, hypothesis 4 proposed competing predictions for the effect of structural holes on firm innovation output. The data indicate, in support of Coleman's position, that having many structural holes is associated with reduced innovation output.

Two aspects of the above results are worth probing further. First, providing some quantitative indication of the interaction effect could help in interpreting the results. Second, examining the relative magnitude of the effects of direct and indirect ties is of intrinsic interest. To illustrate the interaction effect first, suppose that a firm is at the mean level of direct ties (5) and has 20 indirect ties. For this firm, indirect ties increase the patenting rate by a multiplier of 1.03 (= exp[0.051*2 – 0.007*5*2]). Now, consider another firm that is also at the same level of indirect ties (20) but has 6 direct ties. For this firm, indirect ties raise the patenting rate by a multiplier of 1.016 (= exp[0.051*2 – 0.007*6*2]). Thus, having a higher level of direct ties reduces the benefit from indirect ties.

To compare the relative strength of the direct and indirect tie effects, we can examine the impact of a one-standard-deviation increase in each on the patenting output of a firm. Consider a firm (as above) that has 5 direct ties and 20 indirect ties. For such a firm, a one-standard-deviation increase in direct ties increases the patenting rate by 23 percent [5.4(0.057 – 0.007*2) = 0.23]. For the same firm a one-standard-deviation increase in indirect ties increases the patenting rate by 4 percent [2.746(0.051 – 0.007*5) = 0.04]. Thus, the coefficient on the indirect-ties variable suggests that indirect ties do contribute to innovation output; however, the magnitude of this contribution is significantly smaller than the contribution made by direct ties.

2
For the interaction variable, the correlations between the component terms and the interaction terms were high. I took several steps to address this issue. For instance, I also reran the analyses, after centering both component variables on their means prior to constructing the interaction term, for all three versions of the Direct ties × Indirect ties variable (Cronbach, 1987; Jacquard, Turrisi, and Wan, 1990). This transformation reduced the higher correlation between the component terms and the interaction term in all cases. For the transformed (mean-deviated) variables the correlations between the component terms and the interaction terms were –.20, and –.92 (versus –.11 and .99 earlier) for Direct ties × Indirect ties, count, –.57 and –.67 (versus .22 and .94 earlier) for Direct ties × Indirect ties, distance weighted count, and –.50 and –.60 (versus .32 and .89 earlier) for Direct ties × Indirect ties, distance and information weighted count. Additionally, since some of the variables are meaningful only for firms with two or more ties (structural holes, technological distance between partners), I also reran the analysis using only the 744 observations that represent firm-years with two or more linkages. Since firms with no ties have zeroes on all network variables (direct ties, indirect ties, structural holes), omitting these observations leads to a sample with lower correlations between the network variables. Finally, as a further cross-check against collinearity, I estimated the models on subsamples after randomly omitting observations to check the stability of the estimated coefficients. I report these results below.

Table 2

Means, Standard Deviations, and Correlations (N = 996)

	Mean	S. D.	1	2	3	4
1. Patents$_{it}$	51.18	82.67				
2. Direct ties$_{it-1}$	5.27	5.40	.30			
3. Indirect ties/10, count$_{it-1}$	6.37	2.75	.11	.28		
4. Indirect ties, dist. wtd.$_{it-1}$	19.42	8.92	.04	.05	.96	
5. Indirect ties, dist. & info. wtd.$_{it-1}$*	12.25	6.50	–.03	.06	.88	.88
6. Direct ties X Indirect ties/10, count$_{it-1}$	37.70	36.25	.31	.99	.35	.11
7. Direct ties X Indirect ties, dist. wtd.$_{it-1}$	104.4	84.15	.32	.94	.44	.22
8. Direct ties X Indirect ties, dist. & info. wtd.$_{it-1}$*	66.54	58.04	.25	.89	.43	.21
9. Structural holes$_{it-1}$	.79	.32	.14	.31	.86	.82
10. Diversification, entropy$_{it-1}$	1.29	.33	.36	.18	.10	.07
11. International research presence$_{it-1}$	.86	.20	–.24	–.00	–.03	–.04
12. Technological opportunity$_{it-1}$	15.68	6.02	.17	.24	.18	.10
13. Return on assets$_{it-1}$	.03	.03	.15	–.07	–.02	–.01
14. Current ratio$_{it-1}$	1.58	.62	.23	–.18	–.19	–.15
15. Japan	.43	.50	–.28	.27	.14	.06
16. USA	.26	.44	.17	–.23	–.10	–.05
17. R&D$_{it-1}$	3.48	1.56	.66	.39	.18	.08
18. Firm size$_{it-1}$	1.94	1.30	.65	.22	.05	.01
19. Tech. Distance between partners$_{it-1}$	.28	.21	.10	.40	.50	.43
20. Year 1981	.09	.28	–.03	–.11	–.18	–.13
21. Year 1982	.09	.29	–.04	–.08	–.11	–.07
22. Year 1983	.09	.29	–.04	–.06	–.13	–.07
23. Year 1984	.09	.29	–.02	–.05	.01	.05
24. Year 1985	.10	.29	–.02	–.03	.02	.02
25. Year 1986	.09	.29	–.01	.00	–.05	–.08
26. Year 1987	.09	.29	.02	.02	.09	.08
27. Year 1988	.09	.28	.05	.05	.13	.13
28. Year 1989	.09	.29	.04	.07	.14	.11
29. Year 1990	.09	.28	.03	.11	.09	.01

	5	6	7	8	9	10	11	12	13
6. Direct ties X Indirect ties/10, count$_{it-1}$	.13								
7. Direct ties X Indirect ties, dist. wtd.$_{it-1}$	.22	.97							
8. Direct ties X Indirect ties, dist. & info. wtd.$_{it-1}$*	.32	.94	.95						
9. Structural holes$_{it-1}$	.71	.33	.40	.37					
10. Diversification, entropy$_{it-1}$	.00	.19	.21	.16	.13				
11. International research presence$_{it-1}$	–.03	–.02	–.04	–.03	–.03	–.20			
12. Technological opportunity$_{it-1}$	.20	.27	.27	.33	.09	.07	.17		
13. Return on assets$_{it-1}$	.01	–.04	–.04	–.03	–.03	–.11	–.14	.01	
14. Current ratio$_{it-1}$	–.14	–.18	–.20	–.20	–.16	.03	–.16	.02	.39
15. Japan	.10	.27	.27	.28	.06	–.10	.48	.26	–.38
16. USA	–.07	–.23	–.25	–.24	–.08	–.13	.12	–.01	.42
17. R&D$_{it-1}$	.07	.42	.43	.40	.20	.24	–.37	.27	.22
18. Firm size$_{it-1}$	–.08	.23	.25	.18	.10	.35	–.52	.00	.21
19. Tech. Distance between partners$_{it-1}$	.33	.42	.51	.44	.43	.19	.02	.14	–.18
20. Year 1981	–.17	–.14	–.14	–.16	–.12	–.01	.06	–.10	–.02
21. Year 1982	–.15	–.11	–.11	–.14	–.09	.02	.02	–.08	–.15
22. Year 1983	–.20	–.09	–.07	–.14	–.07	.02	.00	–.16	–.06
23. Year 1984	–.13	–.05	–.04	–.13	–.01	.00	.01	–.11	.06
24. Year 1985	–.05	–.03	–.03	–.07	.01	.00	.03	–.08	–.07
25. Year 1986	–.09	–.02	–.04	–.05	.00	.02	–.01	–.04	–.01
26. Year 1987	.06	.04	.05	.03	.06	–.01	.00	.00	.08
27. Year 1988	.22	.09	.12	.16	.07	–.01	–.01	.10	.16
28. Year 1989	.28	.11	.12	.21	.07	.00	–.04	.18	.11
29. Year 1990	.18	.13	.09	.19	.06	.00	–.03	.19	.03

Several of the control variable results are also significant (models 5a, 5b, and 5c). Technological distance between partners was negative and significant, supporting the argument that absorptive capacity issues are likely to be important in the context of technology alliances (Lane and Lubatkin, 1998; Stuart, 1998). R&D and firm size are both positively associat-

Table 2 *(continued)*

	14	15	16	17	18	19	20	21	22
15. Japan	–.51								
16. USA	.28	–.51							
17. R&D$_{it-1}$	.20	–.40	.17						
18. Firm size$_{it-1}$	.22	–.64	.26	.80					
19. Tech. Distance between partners$_{it-1}$	–.31	.23	–.21	.17	.11				
20. Year 1981	.00	.01	.00	–.12	.00	–.02			
21. Year 1982	–.03	.00	.00	–.11	.00	–.01	–.10		
22. Year 1983	–.04	–.01	.00	–.08	.00	.02	–.10	–.10	
23. Year 1984	–.04	.00	.01	–.07	.01	.02	–.10	–.10	–.10
24. Year 1985	–.04	–.01	.00	–.05	.01	.04	–.10	–.10	–.10
25. Year 1986	–.03	.00	–.01	.02	.01	.00	–.10	–.10	–.10
26. Year 1987	.05	.00	.00	.05	–.01	–.01	–.10	–.10	–.10
27. Year 1988	.03	.01	.00	.08	–.01	–.03	–.10	–.10	–.10
28. Year 1989	.05	.00	–.01	.08	–.01	–.01	–.10	–.10	–.10
29. Year 1990	.02	.01	.00	.10	.00	.01	–.10	–.10	–.10

	23	24	25	26	27	28
24. Year 1985	–.10					
25. Year 1986	–.10	–.10				
26. Year 1987	–.10	–.10	–.10			
27. Year 1988	–.10	–.10	–.10	–.10		
28. Year 1989	–.10	–.10	–.10	–.10	–.10	
29. Year 1990	–.10	–.10	–.10	–.10	–.10	–.10

* Measured in 100's.

ed with patenting frequency. The estimated coefficient, however, is significantly less than unity in all three specifications. If the regressor variables are in log form, as it is for these two variables, then the coefficients of the Poisson specification can also be interpreted as elasticities of the regressor variable with respect to the dependent variable. Here, the positive but less than unity coefficient on R&D and firm size indicates that patenting frequency increases with R&D expenditures and firm size, but it does so less than proportionately. This is broadly consistent with past research (Acs and Audretsch, 1988, 1991).

Being a diversified firm is negatively associated with patenting frequency in this research. Prior research on the impact of diversification on innovative activity has been mixed, with studies showing both a positive and a negative impact of diversification on innovation (Cohen and Levin, 1989). Two broad arguments relate diversification to innovative output. Diversification can encourage innovation by providing a stimulus of multiple knowledge bases within a single firm, leading to cross-fertilization of ideas. Diversification can also imply increased bureaucratization and operational controls within firms and inhibit innovation. The results of this research support the latter interpretation, that being active in multiple businesses is associated with a negative effect on patenting.

Among the other control variables, current ratio, the measure of liquidity, was positively associated with patenting. The estimated alpha coefficient is positive and significantly different from 0. This indicates that there were significant firm-level unobserved effects in the data that were captured by the heterogeneity parameter.[3]

3
I also conducted several supplementary analyses to evaluate the robustness of the results, including reestimating the models after centering the direct ties and indirect ties variables on their means prior to creating the interaction terms, using a Poisson fixed-effect specification instead of the random effects reported here, and repeating the analyses with a sample of firms with two or more linkages only. The results (available from the author) were very similar to the reported results. To further investigate the possibilities of collinearity problems, I randomly omitted observations from the full sample to create 300 subsamples, each of which had between 650 and 900 observations. I then reestimated these models on all 300 subsamples. A warning sign of collinearity problems is that omitting even a few observations can cause significant changes in the coefficient estimates and drive them to insignificance or cause the coefficients to be significant but reversed in sign (Greene, 1997: 420). Even though in half the samples more than one-third of the observations were omitted, these sensitivity analyses provided strong support for the reported results.

Table 3

Maximum Likelihood, Random Effects Poisson Estimates of Firm Patenting Rates (N = 996)*

Variable	Model 1	2	3a	3b	3c	4a	4b	4c	5a	5b	5c
Constant	2.899•••	2.898•••	2.740•••	2.713•••	2.736•••	2.752•••	2.673•••	2.676•••	2.734•••	2.669•••	2.691•••
	(.164)	(.169)	(.169)	(.171)	(.169)	(.168)	(.182)	(.168)	(.173)	(.183)	(.170)
Direct ties$_{it-1}$		.009•••	.009•••	.011•••	.011•••	.038•••	.036•••	.028•••	.057•••	.046•••	.040•••
		(.001)	(.001)	(.001)	(.001)	(.008)	(.003)	(.002)	(.008)	(.003)	(.002)
Indirect ties/10, count$_{it-1}$			.016•••			.016•••			.051•••		
			(.003)			(.003)			(.004)		
Indirect ties, dist. wtd. $_{it-1}$				.005•••			.007•••			.019•••	
				(.000)			(.001)			(.001)	
Indirect ties, dist. & info wtd. $_{it-1}$					.007•••			.010•••			.023•••
					(.001)			(.001)			(.002)
Direct ties X Indirect ties/10, count$_{it-1}$						–.004•••			–.007•••		
						(.001)			(.001)		
Direct ties X Indirect ties, dist. wtd.$_{it-1}$							–.002•••			–.002•••	
							(.000)			(.000)	
Direct ties X Indirect ties, dist. & info. wtd$_{it-1}$								–.002•••			–.002•••
								(.000)			(.000)
Structural holes$_{it-1}$									–.310•••	–.373•••	–.284•••
									(.029)	(.029)	(.025)
Diversification, entropy$_{it-1}$	–.063•••	–.081•••	–.077•••	–.076•••	–.077•••	–.077•••	–.057•••	–.063•••	–.072•••	–.049•••	–.054•••
	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)	(.013)	(.013)	(.013)	(.014)	(.014)
International research presence$_{it-1}$	–.062	–.047	–.054	–.057	–.056	–.074	–.094•	–.081	–.048	–.059	–.058
	(.038)	(.041)	(.043)	(.043)	(.042)	(.042)	(.043)	(.043)	(.041)	(.043)	(.042)
Technological opportunity$_{it-1}$	–.002•	–.002	–.001	–.001	–.001	–.001	–.000	–.000	–.002	–.001	–.001
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Return on assets$_{it-1}$	–.220•	–.292••	–.246•	–.221•	–.271••	–.223•	–.115	–.174	–.218•	–.077	–.199
	(.106)	(.105)	(.106)	(.106)	(.104)	(.105)	(.120)	(.111)	(.105)	(.118)	(.106)
Current ratio$_{it-1}$	.043•••	.032•••	.034•••	.034•••	.035•••	.342•••	.051•••	.035•••	.028•••	.043•••	.031•••
	(.006)	(.006)	(.007)	(.007)	(.006)	(.007)	(.007)	(.006)	(.007)	(.007)	(.006)
Japan	–.193	–.256	–.234	–.216	–.241	–.242	–.218	–.226	–.272	–.223	–.263
	(.318)	(.316)	(.313)	(.310)	(.314)	(.342)	(.339)	(.314)	(.330)	(.346)	(.328)
USA	.360	.358	.376	.382	.372	.373	.371	.378	.357	.355	.353
	(.374)	(.374)	(.370)	(.372)	(.376)	(.374)	(.407)	(.374)	(.384)	(.409)	(.382)
R&D$_{it-1}$	.171•••	.174•••	.182•••	.180•••	.184•••	.188•••	.192•••	.195•••	.205•••	.202•••	.211•••
	(.008)	(.009)	(.009)	(.009)	(.010)	(.009)	(.009)	(.010)	(.010)	(.010)	(.010)
Firm size$_{it-1}$	.108•••	.094•••	.093•••	.100•••	.092•••	.085•••	.083•••	.081•••	.073•••	.086•••	.069•••
	(.013)	(.013)	(.013)	(.013)	(.013)	(.013)	(.013)	(.014)	(.013)	(.014)	(.015)
Tech. distance between partners$_{it-1}$	–.118•••	–.139•••	–.207•••	–.223•••	–.216•••	–.200•••	–.142•••	–.220•••	–.256•••	–.201•••	–.261•••

Table 3 *(continued)*

Variable	Model 1	2	3a	3b	3c	4a	4b	4c	5a	5b	5c
	(.028)	(.028)	(.031)	(.032)	(.336)	(.032)	(.035)	(.034)	(.031)	(.032)	(.034)
Year 1981	−.134•••	−.083•••	−.048•	−.059••	−.303	−.609•	−.061•	−.036	−.019	−.043	.018
	(.023)	(.023)	(.024)	(.023)	(.025)	(.024)	(.025)	(.027)	(.026)	(.025)	(.029)
Year 1982	−.211•••	−.164•••	−.135•••	−.145•••	−.114•••	−.141•••	−.138•••	−.119•••	−.116•••	−.138•••	−.074••
	(.021)	(.022)	(.022)	(.022)	(.023)	(.024)	(.022)	(.025)	(.025)	(.023)	(.026)
Year 1983	−.214•••	−.172•••	−.141•••	−.154•••	−.116•••	−.150•••	−.139•••	−.127•••	−.109•••	−.125•••	−.065•
	(.025)	(.025)	(.025)	(.024)	(.026)	(.026)	(.025)	(.027)	(.025)	(.025)	(.026)
Year 1984	−.106•••	−.065••	−.057•	−.071••	−.023	−.049•	−.046•	−.038†	−.035	−.064••	.015
	(.019)	(.023)	(.023)	(.024)	(.022)	(.023)	(.023)	(.022)	(.022)	(.021)	(.024)
Year 1985	−.082•••	−.047•	−.039	−.045•	−.018	−.030	−.025	−.020	−.018	−.032	.016
	(.021)	(.021)	(.021)	(.021)	(.218)	(.021)	(.022)	(.022)	(.021)	(.023)	(.021)
Year 1986	−.072•••	−.045•	−.033	−.033	−.015	−.034	−.032	−.026	−.020	−.019	.006
	(.017)	(.019)	(.019)	(.018)	(.019)	(.019)	(.019)	(.020)	(.020)	(.020)	(.021)
Year 1987	.036	.057••	.050•	.044	.630•	.067••	.075••	.612••	.718••	.064••	.080•••
	(.021)	(.021)	(.023)	(.023)	(.022)	(.024)	(.023)	(.023)	(.024)	(.023)	(.026)
Year 1988	.102•••	.114•••	.099•••	.089•••	.095•••	.123•••	.137•••	.117•••	.124•••	.115•••	.115•••
	(.018)	(.018)	(.019)	(.020)	(.019)	(.019)	(.021)	(.020)	(.019)	(.020)	(.020)
Year 1989	.119•••	.130•••	.117•••	.113•••	.110•••	.145•••	.147•••	.137•••	.148•••	.134•••	.132•••
	(.021)	(.022)	(.024)	(.023)	(.022)	(.025)	(.025)	(.022)	(.023)	(.023)	(.021)
Year 1990	.034	.033	.024	.027	.020	.037	.020	.024	.037	.023	.017
	(.024)	(.025)	(.025)	(.025)	(.025)	(.025)	(.024)	(.025)	(.025)	(.024)	(.025)
Alpha	.887•••	.874•••	.855•••	.085•••	.859•••	.856•••	.857•••	.851•••	.848•••	.850•••	.855•••
	(.133)	(.129)	(.128)	(.128)	(.127)	(.127)	(.131)	(.127)	(.126)	(.130)	(.129)
Chi Sq/df vs. previous nested model (d.f.=1)		16•••	15.4•••	23.4•••	19.4•••	6.4•	56.4•••	27.4•••	32.2•••	51.6•••	38.4•••

•$p < .05$; ••$p < .01$; •••$p < .001$ (one–tailed tests for hypothesized variables, two-tailed tests for controls).
* Standard errors are in parentheses.

DISCUSSION AND CONCLUSION

This study examined the impact of three aspects of a firm's ego network—direct ties, indirect ties and structural holes—on the innovation output of the firm. The theoretical framework suggested that the three aspects of network structure play different roles in the innovation process. According to this framework, direct ties serve as sources of resources and information, indirect ties serve primarily as sources of information, and structural holes between partners serve two contradictory roles. They expand the diversity of information that the firm has access to but also increase the firm's exposure to potential malfeasance. In this study, I predicted, and found, that direct and indirect ties influence innovation output positively, but the impact of indirect ties is moderated by the firm's level of direct ties. Finally, I presented competing predictions about the effect of structural holes in the focal firm's network and found that, at least in this interfirm collaboration network, increasing structural holes decreases innovation output. The findings have some important theoretical implications.

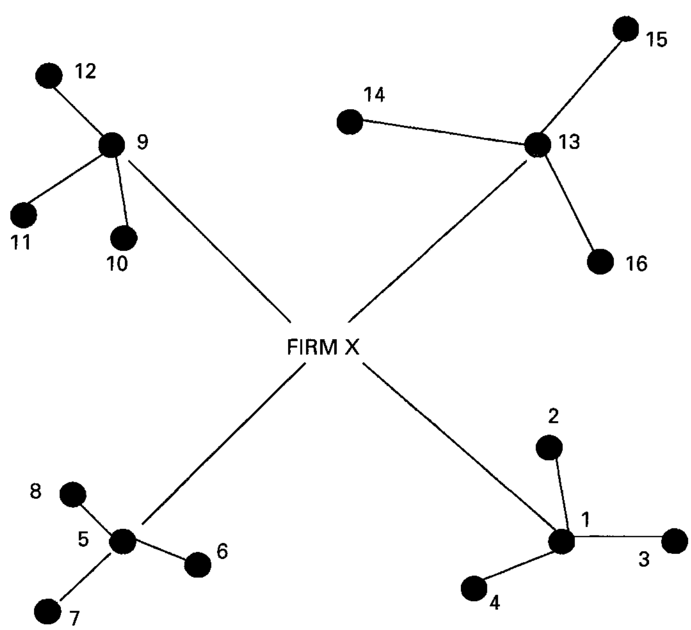
This study was motivated by two theoretical puzzles and their implications for firms in interorganizational networks. First, I sought to evaluate the idea that building networks with large numbers of indirect ties may be an effective way for actors to enjoy the benefits of network size without paying the costs of network maintenance associated with direct ties (Burt, 1992). Second, I sought to understand the degree to which closed or open networks could be appropriately regarded as the normative ideal (Coleman, 1988; Burt, 1992; Walker, Kogut, and Shan, 1997). The arguments and conclusions of this study shed some light on both of these issues.

The results of this study both vindicate and qualify the prescription to use indirect ties as an efficient and effective way of maximizing network benefits. In an interfirm technology linkage network, a firm's indirect ties serve as a mechanism for knowledge spillovers and contribute positively and significantly to its innovation output. Given that, unlike direct ties, indirect ties entail relatively low or no maintenance costs for the firm, these benefits are extremely welcome. Thus, the results provide support for the basic premise that network effectiveness can be enhanced through indirect ties (Burt, 1992). But the paper also suggests that caution is required before interpreting these results as a mandate to build large networks of indirect ties. The arguments and findings of this paper draw attention to three factors that need to be considered before embarking on a strategy of substituting indirect for direct ties.

First, this study highlights the fact that even within the same network, direct ties and indirect ties can differ significantly in the nature or content of benefits that they provide to the focal actor. Although I did not directly measure the contents of direct and indirect ties, I argued that in the interfirm linkage network these ties differ in the nature of benefits offered: direct ties provide resource-sharing and information-spillover benefits, but indirect ties provide only the latter. Clearly, under these circumstances, the degree of substitution possible between direct and indirect ties is limited. More generally, this finding suggests that the value of a strategy of substituting indirect ties for direct ties will vary significantly across networks. In any network, an analysis of the substantive benefit provided by each kind of tie must be conducted before a network reconfiguration is attempted.

A second aspect, closely related to the previous one, is that even when direct and indirect ties provide the same kind of benefit, the magnitude of the benefits provided by indirect ties may be significantly different from those provided by direct ties. The results of this paper suggest that the actual magnitude of benefits from indirect ties is relatively low. Although this result could be peculiar to this setting, one argument suggests that this result may actually be more widely applicable. This conclusion is based on one key insight: in many networks, indirect ties simultaneously play two different roles vis-à-vis the focal actor. On the one hand, they are resources that extend the actor's reach in the network and improve his or her access to information. On the other hand, in many networks, such indirect ties are also competitors of the focal actor in terms of using such information. To illustrate this dual aspect of indirect ties, figure 2 (adapted from Burt, 1992) shows a firm X that builds a direct tie to a partner (1) who has three other partners (2, 3, and 4). These three indirect ties (firms 2, 3, and 4) are now potentially providers of information to the focal firm (X), and news of new technical developments arising in one of these firms can make its way to the focal firm through the common partner (1). Thus, adding the indirect ties has extended the focal firm's information reach in the network significantly. Yet moving our focus away from the focal firm and onto the indirect ties themselves draws attention to another, less benign

Figure 2. Illustration of indirect ties in a network as both resources and competitors (adapted from Burt, 1992: 20).



aspect of this network. These indirect ties, linked to the focal firm through the common partner, are also linked to each other through the same common partner. Information that arises in one of these indirect ties, say Firm 2, reaches the focal firm, but it also reaches the other indirect ties, Firms 3 and 4. If the same information can be used profitably by the other firms, and one firm's use of it precludes its most fruitful use by another, then the network benefits that accrue to the focal firm are likely to be much smaller than might otherwise be anticipated by a simple consideration of its expanded reach. More generally, this argument suggests that the degree to which indirect ties provide benefits of greater informational reach will vary by the nature of the information and the network. To the extent that the sources of information in many networks are also potential users of similar information, competition to use the information within the clusters in which it originates can reduce the benefits that ego can expect from even an effectively configured network.

The negative interaction between direct and indirect ties suggests a third reason to be careful in terms of evaluating the impact of indirect ties. Although individually higher numbers of direct ties and indirect ties are both beneficial, having many indirect and many direct ties is not necessarily better. Between the more limited addition to their knowledge base through their indirect ties and their more constrained ability to absorb and act on the information, actors with many direct ties may be unable to profit from their indirect ties as can actors with fewer direct ties. Thus, in addition to being limited in magnitude, the value of indirect ties is also likely to be contingent on the number of a firm's direct ties (see also Burt, 1997). This conclusion is likely to apply in particular to networks such as the one described above, in which many actors can potentially use the same information. In such networks, alertness, responsiveness, and flexibility are likely to be important in terms of profitably using information obtained through network ties (Zaheer and Zaheer, 1997).

The above arguments suggest several mechanisms that potentially limit the benefits of indirect ties, but my objective in presenting these arguments is not to indicate that indirect ties are inferior to direct ties or vice versa. Rather, it is to draw attention to a broader conclusion: whether direct ties are more productive than indirect ties depends on the context being studied, and the effects of ties, whether direct or indirect, are likely to be contingent on several factors. The nature and content of the ties, the type of outcome being studied, and the broader network structure within which a tie is embedded are all likely to influence the value of a tie. Although, in this study, indirect ties provided relatively less significant benefits than direct ties, that conclusion is unlikely to be universally true. For instance, in Bian's (1997) analysis of job searches in China, direct ties provide only an intermediation benefit by connecting potential employees with job-granting officials, while the indirect tie in the form of the job-granting official provides the more substantive benefit of an actual job.

The arguments and findings on structural holes further reinforce the basic conclusion that the impact of different network attributes and positions can only be understood relative to a particular context. The strategy of matching the type of benefit (resource sharing versus information spillovers) with the form of social structure (a closed versus an open network) by itself draws attention to the contradictory effects of network structure on innovation output. The results of the statistical analyses further contribute to illuminating the debate on the appropriate form of facilitative social structures. In interorganizational collaborations, it appears that the benefits of increasing trust, developing and improving collaboration routines, and reducing opportunism that are provided by a group of cohesive interconnected partners outweigh the disadvantages of not having the informational diversity that is provided by having many structural holes in a firm's network. Reconciling this result with that of an earlier study on structural holes and innovation is useful. In an interesting process study of innovation, Hargadon and Sutton (1997) demonstrated how a firm exploits its position as the spanner of structural holes to develop new products. On the surface, the results of that study appear to conflict with the findings reported here, but a key difference between the network context they depict and the one studied here is relevant. In Hargadon and Sutton's (1997) study, the focal firm is a product-development consulting firm that bridges structural holes between clients in different industries. Here, the network consists of collaborative linkages between firms in the same industry. Thus, the nature of ties between firms varies significantly for the two networks. Collaboration and resource sharing between competitors, two salient features of this network, are not the issue in Hargadon and Sutton's network. Rather, the key principle there is brokerage. By contrast, in the collaboration between competitors that is studied here, developing norms of cooperation is likely to be especially important, hence the benefits of interconnected, closed networks. Again, the basic conclusion that emerges from the above comparison of results between this study and Hargadon and Sutton's (1997) study is that whether structural holes are good, bad, or irrelevant is liable to be a function of the context. When developing a collaborative milieu and overcoming opportunism are essential to success, closed networks are likely to be more beneficial. When speedy access to diverse information is essential, structural holes are likely to be advantageous.

My final point concerns the implications of the contingency arguments highlighted above for the broader, developing literature on network resources and social capital (Adler and Kwon, 1999). Although the facilitative role of networks has led to their identification as network resources or social capital (Burt, 1997; Gulati, 1999), and network attributes have been associated with several distinct benefits, such as trust, information, and power, scholars have been unable to agree on the form of social structures that constitute social capital or network resources. For instance, cohesion theorists have presented densely interconnected networks as the normative ideal (Coleman, 1988). Conversely, others have emphasized the benefits of structural-hole-rich networks (Burt, 1992). Scholars in a third tradition have argued that a network of partners exclusively tied to a focal actor is to be preferred to one in which the focal actor's partners have many other partners (Cook and Emerson, 1978; Brass and Burkhardt, 1992). For the actor seeking to develop social capital, these positions suggest a confusing panoply of choices. At one level, the arguments of this paper add further complexity to this problem by highlighting the fact that each of these social structural choices in fact entails a significant trade-off between two potentially beneficial network outcomes. Densely interconnected networks enable trust but limit the inflow of diverse and fresh insights. Structural-hole-rich networks provide informational benefits but inhibit trust development. Partners exclusively tied to an actor provide power benefits, but it is partners with many other partners that provide the indirect ties that enhance his or her informational reach within the network. At another level, however, the conclusions of this study suggest a path out of this dilemma.

The arguments and results from this study suggest that the debate about the appropriate form of social capital may be profitably informed by the extension of an established principle of organization design to the network arena: the optimal structural design is contingent on the actions that the structure seeks to facilitate (Lawrence and Lorsch, 1967). What constitutes an enabling social structure for one set of actions may well be disabling for others (Podolny and Baron, 1997). Thus, the form taken by social capital is likely to be contingent on what actors seek to enable through it. Under the appropriate circumstances, exclusive, cohesive, and nonredundant connections can all constitute social capital. A network composed of relationships with partners with few ties to others would facilitate control over exchange partners (Cook and Emerson, 1978; Brass and Burkhardt, 1992). Such a network might be the objective for a firm seeking power over its buyers or suppliers (Porter, 1980). A network composed of partners with many interlocking and redundant ties would facilitate the development of trust and cooperation (Granovetter, 1985; Coleman, 1988; Portes and Sensenbrenner, 1993). Such a network may be useful from the firm's perspective when it and its partners are faced with a common external threat, for instance, adverse political or legislative actions, or in the context of standard setting in high-technology industries (Oliver, 1990; Kogut, Walker, and Kim, 1995). Finally, a network of many non-overlapping ties would provide information benefits (Burt, 1992). Such a network would be ideal for an organization whose primary business entails the brokerage of information or technology (Hargadon and Sutton, 1997). Identifying the benefit sought from a social structure is therefore likely to be critical in identifying the form of social structure that is most likely to be facilitative. What this study has shown is that there is no simple, universal answer.

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