Indirect networks: an intangible resource for biotechnology innovation

Nader Salman[1] and Anne-Laure Saives[2]

[1]PlusFunds Group Inc., New York, nsalman@plusfunds.com
[2]Department of Management and Technology, School of Management, University of Quebec at Montreal, 315 Sainte Catherine East, Montreal, Canada QC H2X 3X2. saives.anne-laure@uqam.ca

In the context of the emergence of new modular organizational forms, especially in high-tech sectors such as the biotechnology sector, this article proposes that while a firm observes benefits from direct alliances, it also benefits from indirect linkages. First, a theoretical framework revolving around indirect ties is built on the basis of social network and innovation management literature. It ends with the proposition of two research hypotheses linking the indirect network position of a firm to its innovation capacities. To test those hypotheses, data on strategic partnerships and collaborations were collected through 40 interviews with biotech firms from the nutrition sector in the biotech clusters of Quebec (Canada). Using network analysis, centrality measures and hierarchical regressions, results of this study indicate that by occupying a central position in a network of indirect ties, a firm is more likely to access useful knowledge from its direct partners and increase innovation. We suggest, as a conclusion, that indirect network position could be considered as an intangible strategic resource for biotech firms.

1. Introduction

Innovation was once thought of as merely a product of a firm's autonomous research and development (R&D) department (Nelson, 1959; Mowery, 1983). However, in today's fast-paced advanced technology industries, especially the biotechnology sectors, the innovative capability of a company cannot be studied without considering the external organizational relationships that firms maintain with numerous kinds of partners such as universities, public laboratories, investors, etc. (Powell et al., 1996). Academics argue that one of the reasons behind management theory's interest in network today is because of the emergence of 'the new competition' (Nohria, 1992). This concept alludes to the competitive rise over the last two decades of small entrepreneurial firms, of regional districts such as Silicon Valley in California and Prato or Modena in Italy, and of new industries such as biotechnology and semiconductors. Whereas the old model of organizational form was the large hierarchical firm, the model of organization that is considered characteristic of the new competition is networks of direct and indirect linkages among firms (Nohria and Garcia-Pont, 1991; Nohria, 1992; Schilling and Steensma, 2001, Verspagen and Duysters, 2004). These new organizational forms are appealing because of their greater flexibility, adaptability, and their capacity to circulate intangible strategic resources such as information, knowledge, and skills. However, knowledge is often difficult to spread (Von Hippel, 1994; Szulanski, 1996). This therefore raises the question that is studied here of how a firm can position itself to access useful knowledge from other organizations to gain innovation benefits and collaboration opportunities.

Network position is an outcome of the relationships between actors and is considered a key variable in social network analysis. Social network analysis views the social environment as patterns or regularities in relationships among interacting units. In social network analysis, the observed attributes of social actors (such as innovation, access to resources, and strategy) are interpreted as a function of their location in the network (Wasserman and Faust, 1994). The goal of positional analysis is to represent patterns of complex social network data in a simplified form in order to reveal access to information and innovation benefits from being centrally embedded in networks of indirect relations.

According to Powell (1998), sources of innovation do not reside exclusively inside firms; instead they are also commonly found in the indirect links between firms. Similarly, Ahuja (2000) found that indirect ties had a positive effect on innovation. In an attempt to measure differences in the magnitude of tie contribution to innovation output, Ahuja found that the magnitude of indirect tie contribution was much smaller than that of direct ties. Unlike most network studies on the biotechnology sector, the research presented in this article examines specifically the effect of being located in a network of indirect ties on innovation output and access to knowledge from direct ties. Thus, for the purpose of clarification, it should be noted that the network under study is one that is rich in indirect ties where biotech firms are not directly linked to one another but rather affiliated to one another through their common direct partnerships. This article proposes that while a firm observes benefits from direct alliances, it also benefits from indirect linkages. In this respect, the indirect network position of a firm (or the position of the firm within its network of indirect ties) could be considered as one of its intangible strategic resources.

In the first portion of this research paper, a theoretical framework revolving around indirect ties is built on the basis of social network and innovation management literature. The theoretical framework then ends with the proposition of two research hypotheses. The second part of this research proceeds to explain methodological issues. Third, a discussion suggests that by occupying a central position in a network of indirect ties, a firm is more likely to access useful knowledge from its direct partners and increase innovation. A conclusion considering that indirect network position could be considered as an intangible resource follows.

2. Theoretical perspective

2.1. *Nature of biotechnology innovation*

Biotechnology is an industry that is knowledge based and predominantly composed of small firms involved in R&D (Audretsch and Stephan, 1996). In this field, the formation of alliances is a key factor explaining the survival and growth of smaller biotech firms (Niosi, 2003). Few innovations can be assigned to a single specific technological field or even a specific firm (Powell et al., 1996), as it is increasingly recognized that innovation requires the convergence of many sources of knowledge and skills, usually linked in the form of a network. In this respect, innovation networks are widely considered as an effective means of industrial organization of complex R&D processes. In most of the recent research on industrial economics and innovation theory, the increasing complexity of knowledge, the accelerating pace of the creation of knowledge and the shortening of industry life cycles are considered responsible for the rising importance of innovation networks (Ahrweiler, 1999). Additionally, mechanisms of learning and knowledge creation play a decisive role in the emergence of networks. In the knowledge-based society, not only is the quantity of knowledge used greater, but also the mechanisms of knowledge creation and utilization change constantly. In this light, networks are to be considered as a component of the emerging knowledge-based society, in which knowledge is crucial for economic growth and competitiveness (Grant, 1996).

2.2. *Indirect networks and the transfer of information*

Two important aspects to conceptualizing a biotech firm's access to information are its direct and indirect ties in the network. Both direct and indirect ties can influence a firm's innovation (Ahuja, 2000). Figure 1a illustrates the concept of direct and indirect ties in the context of this study. In this figure, BioFirms A and B for example each have one direct tie to a University X. BioFirms A and B also have an indirect tie together by virtue of their common partnership to the University X.

One important aspect to studying indirect ties is their information collection and processing benefits. These indirect linkages act as a channel of information between the firm and many indirect contacts (Mizruchi, 1989; Davis, 1991; Gulati,

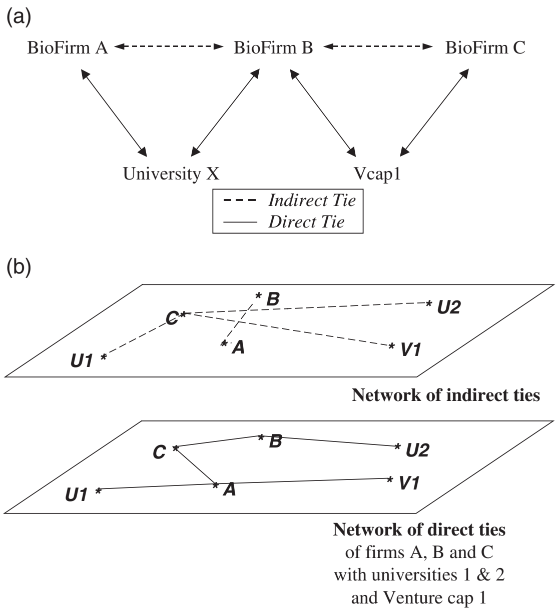


Figure 1. Direct and indirect ties.

1995). In the biotech industry, cooperating with external partners is critical to gaining access to information. A firm's partners bring the knowledge and experience they gained from their interactions with their other partners to their interactions with the focal firm and vice versa (Gulati and Garguilo, 1999). If we refer to Figure 1a, BioFirm B's direct linkages to University X and VCap 1 may provide it with access not just to knowledge held by its partners (University X or VCap 1) but also to the information held by its partner's partner (BioFirms A and C). In the context of this study, the partner's partners are solely other biotech firms in the network. It is important to note that the focus of this research is not on the relational content of the indirect ties but rather the outcome of being centrally located within them. Thus, we assume that indirect ties may potentially lead to access to a combination of non-mutually exclusive intangible resources such as information, knowledge, and skills that flow through the network.

Granovetter (1973) argued in his classic article that weak tie relations (indirect and informal) give greater access to new information and opportunities. He claims that strong ties (direct) restrict information flows from outside sources. Granovetter proposes that weak relations (indirect ties) serve as bridges to other social groupings holding information and resources unavailable within ones direct social circle. Thus, firms with many weak or indirect relations gain speedy advantages in learning about and taking advantage of new opportunities. Hence, a major benefit of weak ties is that they provide a strong form of social capital for access to knowledge and skills (Granovetter, 1973; Walker et al., 1997).

Individual firms can pursue only a limited number of technologies and lines of research, but indirect network ties can increase a firm's pool of information and provide important benefits in two forms. First, indirect network ties can serve as an information collection mechanism (Freeman, 1991). In the case of high-tech sectors, firms can receive information on the success or failure of many simultaneous research efforts (Rogers and Larsen, 1984), and in turn technological dead ends or promising technological trajectories can be detected early. Second, indirect network ties can serve as screening device (Leonard-Barton, 1984), where each additional partner a firm has can serve as an information filter, absorbing, sifting, and classifying new technical developments in a manner that goes beyond the information-processing capabilities of a single firm. These information collection and processing benefits can influence a firm's innovation capacity. Thus, firms should strategically locate themselves in network positions that allow them access to various types of useful information.

2.3. Network position

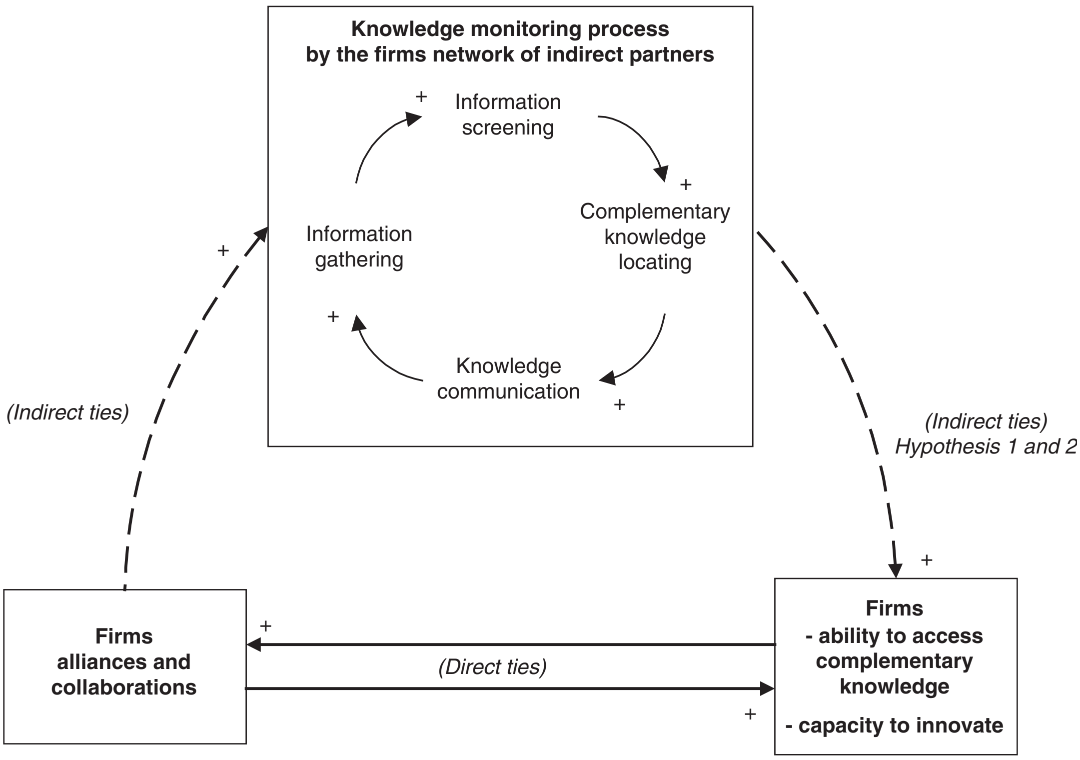
At the individual level of analysis, position describes the pattern of relationships in which an individual actor is involved and that characterizes his/her location relative to other actors in the network. In this research, the positions of biotech firms are examined within a network of indirect ties and then related to each individual actor's innovation and access to complementary knowledge. A very useful method that attempts to describe and measure properties of 'actor location' in a social network is *centrality*.

Being centrally located refers to the position of an individual actor in the network and represents the extent to which the focal actor occupies a strategic position in the network by virtue of being involved in many significant ties. Centrality is the structural property most commonly related to beneficial outcomes including access to resources (Sparrowe et al., 2001), influence (Friedkin, 1993), and innovation (Ibarra, 1993). Indeed, there are different kinds of centrality that measure different aspects of being a central actor involved in many ties. Thus, in the context of this study, as can be seen on Figure 1b, centrality refers to those actors who are central in respect to their indirect ties to one another and thus within a network of indirect relations. This indirect network is a result of each firm's affiliation with the same direct ties. Though most studies incorporating centrality measures focus on networks of direct ties, we propose that indirect networks are equally as important to understanding the *social structure* of the biotech industry.

2.4. Centrality and access to complementary knowledge within indirect networks

Indirect networks represent a fast means of gaining access to knowledge that cannot be produced internally (Powell et al., 1996). Being in between a larger number of information sources through indirect ties, central actors are likely to receive new information sooner than less central actors, as well as to enjoy earlier access to important new developments (Rogers and Larsen, 1984). Thus, in the context of this study, an actor's centrality within an indirect network represents different opportunities for locating stocks of complementary knowledge. It is important to indicate that we use the term 'complementary knowledge' loosely to refer to information, skills, and knowledge that the biotech firm considers as useful or adding value. Hence, we propose that being centrally located within a network of indirect ties situates firms in a better position to locate a combination of possible information, knowledge, and skills that flow through network ties.

Figure 2 illustrates that indirect ties may be equated to channels of communication that facilitate the flow of information by connecting firms to an intangible indirect knowledge monitoring process. Through their indirect ties firms are able



Direct Ties	*Indirect Ties*
Tangible	Less Tangible
Strong Ties	Weak Ties
Transfer of Knowledge	Flow of Information
Transfer of Resources	Monitoring for Resources

Figure 2. Theoretical model of the impact of its indirect ties on a firm's innovation capacities.

to gather large quantities of information about successes and failures of research efforts. Each potential link a firm is indirectly tied to can serve as an information-screening mechanism, absorbing, and classifying new technical developments in a manner that goes far beyond the information-processing capabilities of a single firm. Therefore, firms that are centrally located within a network of indirect ties are privy to more information, and potentially have a greater capacity of indirectly monitoring their external environment and locating information, knowledge, and skills. Hence, the following hypothesis is proposed:

Hypothesis 1: *A firm's centrality within a network of indirect ties is positively related to the likelihood of it gaining access to complementary knowledge as a result of its alliances.*

2.5. Centrality and innovation

With respect to the production of technological innovations, Cohen and Levinthal (1990) showed that the accumulation of knowledge enhances organizations' abilities to recognize and assimilate new ideas, as well as their ability to convert this knowledge into further innovations. According to their absorptive capacity, we assume that actors that are more centrally located *accumulate* greater knowledge and, thus, will be in a better position to convert this knowledge into further innovations. Studies show that a network serves as a locus of innovation because it provides favourable access to knowledge and resources that are otherwise unobtainable (Powell et al., 1996). In a study of the biotechnology industry, Powell et al. (1996) attempt to test empirically the claim that when the knowledge of an industry is broadly distributed and rapidly changing, the locus of innovation will be found in inter-organizational networks of learning, rather than in individual firms. They found that strong-performing biotechnology firms have larger, more diverse alliance networks than weak-performing firms.

Centrally located firms, specially within indirect networks, have access to a greater variety of activities and are better able to locate themselves in information-rich positions. The information that passes through networks is influenced by each participant's position in the network structure (Powell et al., 1996). Network centrality measures which organizations are key in the flow of information and exchange of knowledge within the network structure. Bearing this in mind, it is assumed that from the information advantages that central biotech firms possess they will gain collaboration benefits related to innovation output. Furthermore, innovation is viewed as an information-intensive activity in terms of the information collection and information processing involved (Ahuja, 2000). Hence, it is generally assumed that indirect networks foster the conditions for innovation by allowing information sharing and knowledge transfer. '*By enhancing the spread of information, they sustain the conditions for further innovation by bringing together differing logics and novel combinations of information*' (Powell, 1998). Therefore, this access to knowledge through indirect networks allows for the assumption that firms that are more centrally located will have greater access to innovation enhancing knowledge and skills, thus yielding greater probability of innovation output. Hence, the following hypothesis:

Hypothesis 2: *The centrality of a firm's network position within an indirect network is positively related to its innovation.*

3. Methodology

3.1. Data collection

To test those hypotheses, data from 40 face-to-face semi-oriented interviews with biotech firms from the nutrition sector in Quebec were analysed. The data used for this study came from a larger data set collected from the biotechnology health, nutrition, agricultural, and environmental sectors in Quebec between October 2001 and January 2002 (Saives, and Cloutier 2002). Of the estimated 69 firms in the specific nutrition sector, 40 high-level managers familiar with the strategic management issues within each firm accepted face-to-face interview and 38 reported complete and usable data. Data were collected on strategic partnerships and collaboration, intellectual property strategy, number of patents and licences, strategic direction, R&D capabilities and projects, and demographic variables. Network affiliation data were collected by questioning each firm for their strategic partnerships and collaborations (with universities, venture capitalists, manufacturing firms, public and private labs, consultants, equipment suppliers, distributors). Additionally, follow-up questions were asked about the results expected and obtained from these strategic alliances: mainly whether the firm saw access to complementary knowledge and/or increased speed of innovation.

3.2. Independent variables

3.2.1. Degree centrality. One of the most often used measures of centrality is degree centrality. In this case, the actor with the most indirect connections, i.e. the highest degree, is the most central. Degree centrality refers to a count of the number of ties an actor has, meaning the number of organizations the actor is in contact with. As Wasserman and Faust (1994) put it, an actor with a high centrality level, as measured by its degree, is where 'the action is' in the network. From Figure 3, one can see that in the case of the *star network*, actor A is clearly the most active and thus has a large amount of degree centrality. Contrast the *star network* with the *circle network* shown in Figure 3, and one can see that all actors in a circle are interchangeable; thus, all actors should have the same degree centrality. With regard to indirect networks, as shown in Figure 1b, we see that C is the highest in degree centrality because it has the most indirect ties by affiliation with the same third party. Therefore, degree centrality illuminates the most visible actors in the network, who, in the case of this study, are those who have the most indirect ties by affiliation with the same direct tie. This actor should be recognized as a major channel of relational information and as a crucial component in the transfer and collection of information throughout the network.

3.2.2. Betweenness centrality. Betweenness centrality refers to the rate at which an organization falls between other firms. Particularly, it refers to how often an organization serves as the shortest path linking other actors together. This means that many other firms must go through the central firm in order to reach others. A path delineates the sequence of organizations linked to one another in the network and allows researchers to calculate the distance between firms in the network. From the *star network* in Figure 3, one can see that actor A, the one between the others, has control over the paths in the graph. These actors are said to have the potential to act as brokers or gatekeepers of information within the network (Freeman, 1979). One could state that the actors in the middle have more access to diverse knowledge than other firms who are low in betweenness centrality (Freeman, 1979; Friedkin, 1991). Assuming these actors are biotech firms, then from looking at the line network in Figure 3 it can be said that the actors in the middle might have the potential to control information transfer while those at the edge do not. Thus, in relation to this study, the main idea is that an actor is central if he/she lies indirectly linked between other actors, and thus in order to have a large betweenness centrality the actor must be linked between many other actors in a network of indirect ties.

3.2.3 Closeness centrality. This pertains to the closeness of an actor in relation to all other actors in the network. Firms are considered to have high levels of closeness when they can quickly react to others. Closeness has been related to the idea of minimum distance such that firms with high levels of closeness will have the shortest path between themselves and all others. Closeness is thus inversely related to distance: the greater the distance the lower the closeness centrality (Wasserman and Faust, 1994). From the star network in Figure 3, one can see that in comparison with actors B through G, actor A is high in closeness centrality because there is one path separating him/her from

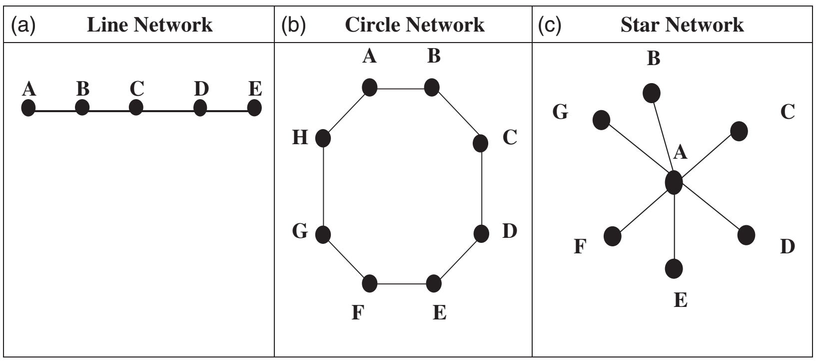


Figure 3. Different kinds of networks.

all other actors. In other words, the suggestion is that a biotech firm is central if it can quickly interact with all the others, and thus is less dependent on others to relay information (Freeman, 1979).

3.2.2. Eigenvector centrality. Eigenvector centrality refers to the extent to which an actor is central because of the centrality of the actors to which he/she has ties. Therefore, a biotech firm can be central through association because it is indirectly connected to another actor that is highly central in the indirect network. Indeed, firms can be highly central with only a few ties if the firms with whom they associate with are highly central within the network. Relating this to access to innovative information, an actor who is high on eigenvector centrality is connected to many actors who are themselves connected to many actors, thus multiplying the possibility of gaining access to important information. Furthermore, the rate at which a highly central biotech firm receives new information may be higher than that of a less central firm. Thus, by being located in a central position, firms can potentially accelerate the rate at which they receive information and in turn access information about breakthroughs or developments earlier than firms who are less central in the network.

The hypotheses required analysing firm centrality within the indirect network (Salman, 2002). In order to measure the hypotheses, centrality variables for Degree Centrality, Closeness Centrality, Betweenness Centrality, and Eigenvector Centrality were calculated using UCINET (Borgatti et al., 2002), a network analysis program that computes network variables using dyadic data. Dyads were measured using the raw data collected about organizational ties between each biotech firm and its partners. Firstly, the analysis began by creating two mode data sets of the firm by alliance partner data. Then binary adjacency matrices were manually created for each category of collaboration partner (universities, venture capitalists, public labs, biotech firms, consultants, private labs, equipment suppliers, trader, public development organization, distributor, raw materials supplier and manufacturers). Transferred to UCINET, these data were converted into a firm-by-firm adjacency matrix by creating ties if firms had alliances with the same third parties. Interestingly, out of these matrices, four had significant information on network ties revealing the main actors of the biotech firms' direct networks in the nutrition sector. These four matrices (Universities, Venture Capital Firms, Manufacturers, and Public Labs) were added together to form one combined matrix. With UCINET, this combined matrix was used to calculate Degree Centrality, Betweenness Centrality, Closeness Centrality, and Eigenvector Centrality at the individual level, as well as a network measure of 'centralization'. In order to compute regression analysis of Hypotheses 1 and 2, the centrality scores of each firm were imported into SPSS to be used for linear regression analysis.

3.3. Dependent variables

3.3.1. Access to complementary knowledge. Hypothesis 1 required analysing whether firms who are more central in a network were more likely to see *Access to complementary knowledge as a result of alliances*. These data were measured by taking Boolean variables. The questions came in the form of: 'what results did your company expect and obtain from its strategic alliances? Complementary knowledge (Y/N)'. Other Boolean variables (obtained results from alliances) taken, but not included in this study because partly correlated, were acceleration of innovation, new product on the market, financing, R&D diversification, and access to larger projects. Twenty-eight companies building alliances in the sample provided usable data. Hypothesis 1 (which proposes that more centrally located biotech firms have a greater likelihood of seeing access to complementary knowledge as a result of alliances) was tested using binary logistic regression.

3.3.2. Innovation. Hypothesis 2 required the linear regression between centrality and the dependent variable innovation. This variable was obtained by collecting data on the number of patent and/or license counts through interviewing executive managers in each biotech firm. Patents are a meaningful measure in this industry because they are directly related to inventiveness and they represent an externally validated measure, even if not perfect, of technological novelty (Gilfillan, 1952; Griliches, 1990).

3.3.3. Control variables. The control variables included age, size, and whether each firm had permanent R&D facilities. *Age* was measured by the number of years the firm has been in existence until January 2001. Because of the relative youth of the emerging biotech sector in Quebec, the variable '*size*' was measured by using the number of employees each firm had. The variable whether a firm has permanent R&D facilities was Boolean.

3.4. Results

For each of the following regressions performed, the independent variable was Centrality and the control variables were *age*, *size*, and *whether or not firms had permanent R&D facilities*. In addition, the dependent variables were *innovation* (measured by number of patents and licenses) and *likelihood of access to complementary knowledge from alliances* (Saives and Cloutier, 2002).

Hypothesis 1 was tested using binary logistic regression. Hierarchical logistic regression analysis was performed using the control variables on the access to complementary knowledge variable and then another logistic regression was performed with the focal centrality variables. Results from the logistic regression illustrated in Table A1 (Appendix A) indicated that Hypothesis 1 was supported. The results from the logistic regression of access to complementary knowledge on centrality show that eigenvector centrality had a significant relationship and that degree centrality was marginally significant. From Table A1 (Appendix A), one can see that inclusion of the control variables alone show that Age, Size, and Internal R&D only explain 15% of the variance in the dependent variable. Including eigenvector centrality separately explained 34% and degree centrality explained 30% of the additional variance in likelihood of seeing access to complementary knowledge. Thus, a firm's eigenvector centrality within a network of indirect ties did increase the likelihood of a firm seeing access to complementary knowledge as a result of alliances.

In order to test Hypothesis 2, hierarchical regression analysis was performed using the control variables on the Innovation and then another regression was performed with the focal centrality variables. Results from Hypothesis 2 (refer to Table A2 in Appendix A) reveal a positive relationship between innovation and all four centrality variables. Inclusion of control variables alone show that Age, Size, and Internal R&D only explain 31% of the variance in the dependent variable. Including Degree, Closeness, Betweenness, and Eigenvector Centralities separately explained 16%, 6%, 10%, and 15% of the additional variance in innovation, respectively. Therefore, Hypothesis 2 is supported and the results demonstrate that there is a significant relationship between a firm's centrality and its innovation. In other words, the more central a firm in the biotech indirect network, the more innovative it is likely to be.

Furthermore, some findings worth noting regarding the control variables were found (refer to Table A2 in Appendix A). Firstly, when regression was performed between the control variables and innovation, *having permanent R&D facilities* was the control variable that had the most significant relationship with innovation for all centrality variables. *Age* also had a significant relationship with innovation implying that the greater the age of a firm, the greater the innovation. However, *size* was found not to be significant to innovation.

It is important to highlight that centrality variables tend to be correlated to one another. After conducting a test for co-linearity of all four centrality variables, and even after removing each variable separately, results showed that Degree and Eigenvector Centralities were highly collinear (Table A3, Appendix A). Thus, Betweenness and Closeness Centralities have independent effects in this statistical model.

4. Discussion

This research proposed that while a firm observes benefits from direct alliances it also benefits from indirect linkages. Though the concept of an indirect network is relatively intangible at first glance, one must not discount the benefits that it can provide. This study sought to evaluate the idea that maintaining a network with large numbers of indirect ties may be an effective means for actors to enjoy information benefits of network size without adopting the costs of network maintenance associated with direct ties (Burt, 1992).

The results of this study suggest that by occupying a central position in an indirect network, a firm is more likely to access complementary knowledge (scientific and technological expertise) from its direct partners and increase innovation (Saives and Cloutier, 2002). The theoretical framework suggested that indirect networks play a significant role in the innovation process. According to this framework, indirect ties serve primarily as a potential channel of communication and interaction between the focal firm and many other firms in the network. Furthermore, according to Hansen et al. (1999) and Granovetter (1982), indirect ties can be seen as a tool for monitoring the external environment for complementary knowledge and new opportunities. Indeed, indirect relations in the scientific community may facilitate mutual monitoring between biotech firms, both in the process of planned environment scanning and accidental observations (e.g. gossip). Thus, information stemming from monitoring of competitors' research efforts and technologies may be an important input to a firm's own knowledge production (Lorenzen and Mahnke, 2002). Whereas direct relations between firms (at least, in the successful cases) allow for in-depth transfer of knowledge, indirect relations hence allow firms to monitor a wide and flexible range of information (Granovetter 1973; 1982). This information also includes what is not expected nor searched for, which may have a greater potential for inspiring change and innovation in firms (Granovetter 1982). This may be the case in the context of our sample, located in the renowned biotech clusters of Montreal and Quebec (Saives and Cloutier, 2003), where monitoring is facilitated in local clusters because indirect relations between actors, planned as well as coincidental, are more frequent with geographical and organizational proximities (Sierra, 1997).

This research demonstrated that different aspects of being centrally located increased the innovation of a firm. Firms that are high in degree centrality simply have the highest number of connections in the network. Thus, the significant relationship between degree centrality and innovation shows that the number of indirect ties significantly increases a firm's innovative capability. As Freeman (1979) argued, degree centrality is the most suitable centrality measure for capturing an individual actor's access to information. The higher a biotech firm's degree centrality the more potential knowledge sources the firm has. This external information and knowledge is necessary to generate new ideas and produce innovations. Since innovation is an information-intensive activity, highly central biotech firms may generate more innovation.

A significant relationship was also found between eigenvector centrality and innovation. The significance of eigenvector centrality may partly be attributed to its close relation to degree centrality. This measure calculates the extent to which a biotech firm is connected to many other firms who are themselves connected to highly central firms, thus increasing the potential for innovation by multiplying the possibility of gaining access to important information and the rate at which that information is received. Betweenness centrality, on the other hand, measures the rate at which an organization falls between other firms. As Freeman (1979) and Friedkin (1991) explain, the biotech firm that is high in betweenness centrality has greater access to diverse information and skills. In this case, the indirect network ties can serve as conduits through which information about technical breakthroughs, new insights to problems and failed approaches can be accessed from various areas of the network. Thus, in the context of this study, the access to diverse information and skills may lead a biotech firm to enhance its innovation.

An interesting finding in this research is the significance of internal R&D capabilities on innovation. The idea of firms having internal R&D capabilities relates to the notion of absorptive capacity. Cohen and Levinthal (1990) described the importance of this firm's ability to assimilate and replicate new knowledge gained from external sources. Investment in R&D facilities is a necessary condition for the creation of absorptive capacity. Absorptive capacity results from a prolonged process of investment and knowledge accumulation. As Cohen and Levinthal (1990) alluded to, the capability to utilize external knowledge is often a by-product of investment in R&D facilities. Organizations with a high level of absorptive capacity invest more in their own R&D facilities and have the ability to produce more innovation (Cohen and Levinthal, 1990). Similarly, the results of this research show that firms who had permanent R&D facilities were more likely to be innovative. However, organizational learning in networks is not only a function of access to knowledge (network centrality) but also of the capabilities for utilizing and building on such knowledge (absorptive capacity). Both concepts determine the effectiveness of inter-organizational learning and knowledge transfer (Powell et al., 1996).

This paper also demonstrates the potential influence indirect ties have on a firm's access to complementary knowledge from direct partnerships. The results of this study show that the centrality of a focal firm in the indirect network is positively related to the likelihood of that firm gaining access to complementary knowledge from its direct alliances (direct network benefits). Similar to Ahuja's (2000) idea of the interacting effect of direct and indirect ties on innovation, we assumed that centrality in a network of indirect ties will positively influence the likelihood of a firm gaining access to complementary knowledge from its direct ties. However, unlike Ahuja, we did not have enough data to measure the magnitude of this effect. We stress that indirect ties are not a substitute for direct ties. However, in the absence of multiple direct ties, different aspects of a firm's centrality may provide strategic competitiveness in gaining access to complementary knowledge.

Theoretically, biotech firms with high degree centrality should have access to more knowledge than other actors (Wasserman and Faust, 1994). This means that biotech firms, who are most active in the network in the sense that they have the most ties to other firms, are more likely to gain access to complementary knowledge. In our case, a possible explanation of the results could be that a focal firm's direct partners bring the knowledge and experience from their interactions with their other partners (Jaffe, 1986, Jaffe et al., 1993). Another explanation to the significance of degree centrality might be that indirect network ties can serve as a screening device (Leonard-Barton, 1984), where each additional partner a firm has can serve as an information filter, absorbing, sifting, and classifying complementary knowledge in a manner that goes beyond the information-processing capabilities of a single firm. These information-monitoring capabilities may influence a firm's ability to quickly locate and access complementary knowledge from its direct partners (Figure 2).

Similarly, the significant relationship found between eigenvector centrality and innovation may largely be attributed to its strong relation to degree centrality. These results imply that biotech firms who were most connected to highly central actors in the indirect network gained access to complementary knowledge. The reasons as to why eigenvector centrality proved to be significant to access to complementary knowledge may perhaps be that this measure calculates the extent to which a biotech firm is connected to firms that are most likely to gain access to useful information and locate stocks of knowledge (Wasserman and Faust, 1994).

5. Conclusion

An indirect network may be compared with a 'shadow' database of diverse information. The ability to access this information is an effective source of competitive advantage. By examining the pattern of indirect network interactions between firms, this research shows that being located in a central position leads to innovation and access to knowledge advantages. Therefore, a firm's indirect network position should not be discounted as an intangible strategic source of competitive advantage.

But, although previous research has elaborated the concept of organizational learning, this research adds little systematic understanding of the social processes that underlie how firms learn from each other and how firms activate this intangible resource of being centrally but indirectly linked to strategic sources of knowledge. Because knowledge and ideas are shared and common meanings developed through interactions, critical insights reside in collaboration networks and social capital. Knowledge is socially constructed, and organizational learning involves a complex social process in which different firms interact with each other (Berger and Luckman, 1966; Huber, 1991) under specific conditions of proximities (Sierra, 1997). More research is needed to investigate these embedded social learning processes that unfold in a network position and result in innovation.

This then brings us back to the basic question of whether innovation in biotech networks is the outcome of a formal network or a more informal natural process. It can be proposed that there is a structural design behind the shape of the biotech value network and that a rational process, in which firms set up many alliances in order to achieve innovation, created this design. However, the way in which innovation ultimately comes about may not be entirely rational and formal but rather informal and unpredictable. Innovation also requires the development of informal structures such as indirect ties to other firms, which create access to information and skills beyond those available from the immediate alliance partner. All together then networks in the biotechnology sector combine rational and natural elements of organization to produce innovation outcomes.

Furthermore, more in-depth longitudinal research needs to be done on the dynamic effect of indirect ties in the context of the emergence of flexible, modular organizational forms or 'strategic configurations' (Nohria and Garcia-Pont, 1991; Schilling and Steensma, 2001). In a study of alliances over a 20-year period, Gulati (1995) examined the main factors that led firms to enter into alliance with one another. His results provided evidence that indirect ties lead to useful information benefits. Gulati (1995) found that firms who were directly unconnected where more likely to enter into an alliance if they had a common partner or were less distant from each other in the indirect network. Thus, indirect ties create a dynamic system for the formation of alliances. In this case, previous indirect ties may become direct ties and open the door to more indirect partners for further alliance opportunities. It is direct ties that can bind firms tightly; however, it is indirect ties that weakly knit firms into a larger dynamic community.

References

Ahrweiler, P. (1999) Towards a general description of innovation networks: commonalities and differences in the SEIN case studies. SEIN Working Paper, #3.

Ahuja, G. (2000) Collaboration networks, structural holes, and innovation: a longitudinal study. *Administrative Science Quarterly*, **45**, 425–455.

Audretsch, D.B. and Stephan, P.E. (1996) Company–scientist locational links: the case of biotechnology. *The American Economic Review*, **86**, 3, 641–653.

Berger, P. and Luckman, T. (1966) *The Social Construction of Reality: A Treatise in the Sociology of Knowledge*. Garden City, NY: Anchor Books.

Borgatti, S.P., Everett, M.G. and Freeman, L.C. (2002) *Ucinet 6 for Windows*. Harvard: Analytic Technologies.

Burt, R.S. (1992) *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press.

Cohen, W. and Levinthal, D. (1990) Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*, **35**, 128–152.

Davis, G.F. (1991) Agents without principles? The spread of the poison pill through the intercorporate network. *Administrative Science Quarterly*, **36**, 583–613.

Freeman, C. (1991) Networks of innovators: a synthesis of research issues. *Research Policy*, **20**, 499–514.

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

Friedkin, N.E. (1991) Theoretical foundations for centrality measures. *American Journal of Sociology*, **96**, 1478–1504.

Friedkin, N.E. (1993) Structural bases of interpersonal influence in groups: a longitudinal case study. *American Sociological Review*, **58**, 861–872.

Gilfillan, S.C. (1952) The prediction of technical change. *The Review of Economics and Statistics*, **34**, 4, 368–385.

Granovetter, M.S. (1973) The strength of weak ties. *American Journal of Sociology*, **78**, 1360–1380.

Granovetter, M. (1982) The Strength of Weak Ties: A Network Theory Revisited. In Marsden, P.V. and Lin, N. (eds.), *Social Structure and Network Analysis*, Beverly Hills, CA: Sage, pp. 105–130.

Grant, R.M. (1996) Toward a knowledge-based theory of the firm. *Strategic Management Journal*, **17**, Winter, 109–122.

Griliches, Z. (1990) Patent statistics as economic indicators: a survey. *Journal of Economic Literature*, **27**, 1661–1707.

Gulati, R. (1995) Sociological structure and alliance formation patterns: a longitudinal analysis. *Administrative Science Quarterly*, **40**, 619–652.

Gulati, R. and Garguilo, M. (1999) Where do networks come from? *American Journal of Sociology*, **104**, 1439–1493.

Hansen, M., Nohria, N. and Tierney, T. (1999) What's your strategy for managing knowledge? *Harvard Business Review*, **77**, 2, 106–116.

Huber, G.P. (1991) Organizational learning: the contributing processes and the literatures. *Organization Science*, **3**, 501–521.

Ibarra, H. (1993) Network centrality, power, and innovation involvement: determinants of technical and administrative roles. *Academy of Management Journal*, **36**, 471–501.

Jaffe, A.B. (1986) Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. *The American Economic Review*, **76**, 5, 984–1002.

Jaffe, A.B., Trajtenberg, M. and Henderson, R. (1993) Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, **108**, 3, 577–598.

Leonard-Barton, D. (1984) Inter-personal communication patterns among Swedish and Boston-area entrepreneurs. *Research Policy*, **13**, 101–114.

Lohrenzen, M. and Mahnke, V. (2002) Global strategy and the acquisition of local knowledge: How MNCs enter regional knowledge clusters. *DRUID Summer Conference* on *Industrial Dynamics of the New and Old Economy–Who is Embracing Whom?*, Copenhagen/Elsinore, 6–8 June 2002.

Mizruchi, M.S. (1989) Similarity of political behavior among large American corporations. *American Journal of Sociology*, **95**, 401–424.

Mowery, D.C. (1983) The relationship between intra-firm and contractual forms of industrial research in American manufacturing, 1900–1940. *Explorations in Economic History*, **20**, 351–374.

Nelson, R.R. (1959) The simple economics of basic research. *Journal of Political Economy*, **67**, 297–306.

Niosi, J. (2003) Alliances are not enough explaining rapid growth in biotechnology firms. *Research Policy*, **32**, 737–750.

Nohria, N. (1992) Networks and organizations. In Nohria, N. and Eccles, R.G. (eds.), *Networks and Organizations: Structure, Form, and Action*. Boston: Harvard Business School Press, pp. 1–35.

Nohria, N. and Garcia-Pont, C. (1991) Global strategic linkages and industry structure. *Strategic Management Journal*, **12**, 105–124.

Powell, W.W. (1998) Learning from collaboration: knowledge networks in the biotechnology and pharmaceutical industries. *California Management Review*, **40**, 3, 224–240.

Powell, W.W., Koput, K.W. and Smith-Doerr, L. (1996) Inter-organizational collaboration and the locus of innovation: networks of learning in biotechnology. *Administrative Science Quarterly*, **41**, 116–145.

Rogers, E.M. and Larsen, J.K. (1984) *Silicon Valley Fever: Growth of High Technology Culture*. New York: Basic Books.

Saives, A.-L. and Cloutier, L.M. (2002) La biotechnologie et la nutrition humaine au Québec. In Niosi, J., Cloutier, L.M. and Lejeune, A. (eds.), *Biotechnologie et industrie au Québec*, Montréal: Éditions Transcontinental, pp. 79–123.

Saives, A.-L. and Cloutier, L.M. (2003) Une analyse des mécanismes de coordination des activités d'affaires de valorisation des biotechnologies dans le systéme bioalimentaire du Québec. *Gestion*, **28**, 1, 52–63.

Salman, N. (2002) Networks and innovation: a social network analysis of biotechnology collaboration, *MSc. Thesis*, John Molson School of Business, Concordia University, Montreal, Canada, 70p.

Schilling, M.E. and Steensma, H.K. (2001) The use of modular organizational forms: an industry-level analysis. *Academy of Management Journal*, **44**, 6, 1149–1168.

Sierra, C. (1997) Proximité(s), interactions technologiques et territoriales: Une revue. *Revue d'Économie Industrielle*, **82**, 7–38.

Sparrowe, R.T., Liden, R.C., Wayne, S.J. and Kraimer, M.L. (2001) Social networks and the performance of individuals and groups. *Academy of Management Journal*, **44**, 316–325.

Szulanski, G. (1996) Exploring internal stickiness: impediments to the transfer of best practice within the firm. *Strategic Management Journal*, **17**, 27–34.

Verspagen, B. and Duysters, G. (2004) The small worlds of strategic technology alliances. *Technovation*, **24**, 563–571.

Von Hippel, E. (1994) "Sticky information" and the locus of problem solving: implications for innovation. *Management Science*, **32**, 590–607.

Walker, G., Kogut, B. and Shan, W. (1997) Social capital, structural holes and the formation of an industry network. *Organization Science*, **8**, 109–125.

Wasserman, S. and Faust, K. (1994) *Social Network Analysis: Methods and Applications*. New York: Cambridge University Press.

Appendix A

Table A1. Results of hierarchical logistic regression: effects of network centrality.

Likelihood of gaining access to complementary knowledge					
Variable	1	2	3	4	5
Age	0.008	0.051	0.769	0.017	0.043
Size	0.014	0.046	−0.024	0.02	0.059
Permanent R&D	−1.44	−0.716	−7.722	−1.34	−0.683
Degree Centrality		0.072***			
Closeness Centrality			1.678		
Betweenness Centrality				0.225	
Eigenvector Centrality					0.196*
Nagelkerke R^2	0.192	0.489	0.865	0.219	0.536
ΔR^2		0.297	0.67	0.027	0.344
−2 Log likelihood	22.793	16.383	5.344	22.268	15.228

*$P<0.05$; **$P<0.01$; ***$P<0.06$. $N=28$. R&D, research and development.

Table A2. Results of hierarchical regression analysis: effects of network centrality.

Innovation					
Variable	1	2	3	4	5
Age	0.442*	0.472**	0.458*	0.419*	0.447**
Size	−0.073	−0.145	−0.096	−0.066	−0.137
Permanent R&D	0.355*	0.19	0.291*	0.303*	0.201
Degree Centrality		0.44**			
Closeness Centrality			0.247		
Betweenness Centrality				0.316*	
Eigenvector Centrality					0.414**
R^2	0.314	0.474	0.37	0.41	0.457
ΔR^2		0.16	0.056	0.096	0.144
ΔF		10.054**	2.935	5.388*	8.738**

*$P<0.05$; **$P<0.01$. $n=38$. R&D, research and development.

Table A3. Multi-co-linearity of centrality variables.

Coefficients[1]

	Unstandardized coefficients		Standardized coefficients	*t*	Sig.	Correlations			Co-linearity statistics	
	B	Standard error	β			Zero-order	Partial	Part	Tolerance	VIF
Model 1										
(Constant)	−6.165E–02	0.307		−0.201	0.842					
Age	2.832E–02	0.012	0.442	2.356	0.024	0.436	0.375	0.335	0.573	1.744
NoEmpl.	−2.475E–04	0.001	−0.073	−0.386	0.702	0.271	−0.066	−0.055	0.567	1.762
	0.886	0.359	0.355	2.471	0.019	0.396	0.390	0.351	0.975	1.025
Model 2										
(Constant)	−0.422	0.544		−0.775	0.445					
Age	3.071E–02	0.011	0.479	2.758	0.010	0.436	0.450	0.357	0.554	1.805
NoEmpl.	−6.703E–04	0.001	−0.197	−1.084	0.287	0.271	−0.194	−0.140	0.505	1.982
InternalRD	0.377	0.371	0.151	1.016	0.318	0.396	0.182	0.131	0.756	1.323
Degree	7.531E–02	0.050	2.059	1.503	0.143	0.528	0.265	0.194	0.009	112.207
Closeness	−1.390E–02	0.049	−0.052	−0.286	0.777	0.328	−0.052	−0.037	0.505	1.982
Betweenness	−0.150	0.178	−0.254	−0.845	0.405	0.397	−0.152	−0.109	0.184	5.425
Eigenvector	−0.117	0.098	−1.375	−1.186	0.245	0.499	−0.212	−0.153	0.012	80.353

[1]Dependent variable: Innovation.Sig., significance; VIF, Variance inflation factor.