NETWORKS AND INNOVATION: A SOCIAL NETWORK ANALYSIS OF BIOTECHNOLOGY COLLABORATION

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ABSTRACT

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In today's fast-paced economy the innovative capability of a company cannot be studied without considering the external organizational relationships that firms maintain. Within inter-organizational networks, firms can learn from one another and benefit from new knowledge developed by other organizations. The ability to access this knowledge is an effective source of competitive advantage. The present study focused on the relationships between organizations in the biotechnology sector. Using network analysis, the study examined the impact of network position on innovation, speed of innovation, access to complementary knowledge, number of R&D projects, and strategic direction. By examining the pattern of network interactions between firms, this research shows that being located in a central position leads to innovation and access to knowledge advantages. Furthermore, it demonstrates that firms that are regularly equivalent and similar in network roles tend to adopt a similar strategic direction.

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INTRODUCTION

At one time, innovation was thought of as merely a product of a firm's autonomous R&D department (Mowery, 1983; Nelson, 1959). Strategy research has generally not looked to place sources of differences in inter-firm innovation in organizational networks. However, in today's fast-paced economy the innovative capability of a company cannot be studied without considering the external organizational relationships that firms maintain. There is a need for understanding further the link between innovation and organizational networks.

Academics argue that one of the reasons behind management theory's interest in networks today is due to 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 and Modena in Italy, and of new industries such as biotechnology and semiconductors. Nohria claims that whereas the old model of organization was the large hierarchical firm, the model of organization that is considered characteristic of the new competition is networks of lateral and horizontal inter-linkages within and among firms (Nohria, 1992). These new organizational forms are appealing due to their greater flexibility and adaptability and their capacity to circulate knowledge. Furthermore, Powell and Smith-Doerr (1994) and Galaskiewicz (1996) see them as facilitating the organizational learning process that emerges through collaboration.

Within inter-organizational networks, firms can learn from one another and benefit from new knowledge developed by other organizations. Knowledge transfer among organizations provides opportunities for collaboration that stimulates the creation of new knowledge and access to R&D projects. However, knowledge is often difficult to spread (Szulanski, 1996; Von Hippel, 1994). This therefore raises the question of how a firm can access useful knowledge from other organizations to gain innovation benefits and R&D collaboration opportunities.

Past research has suggested that organizations not only hold specialized knowledge but also have the opportunity to learn from other actors in the network (Huber, 1991). However, not every organization can learn from all others in the network. A firm may desire to obtain knowledge from other actors but may not be able to gain access. Organizations require external information access to increase the possibility of them learning from their peers. Due to the varying levels of external access, organizations differ in their abilities to leverage and benefit from knowledge developed by other actors. Firms must locate themselves in positions within networks to create access to information opportunities in order to take full advantage of collaborations opportunities.

Although the organizational learning literature has highlighted the importance of the capacity to absorb knowledge by increasing R&D intensity (e.g. Cohen and Levinthal, 1990), much less attention has been focused on the process of gaining knowledge access from external sources. Gaining access to new knowledge requires a collaboration effort that differs from investing in R&D. In organizational networks, firms can access new knowledge through inter-firm linkages (Powell, Kaput, and Smith-Doer, 1996). This research, conceptualizes inter-organizational networks as a natural outgrowth of an interdependent community of organizations belonging to the same industry sector in which organizations have the need to innovate and, at the same time, survive by gaining access to knowledge and skills through collaboration. Furthermore, I argue that this access to external knowledge and skills is an essential ingredient in a larger organizational learning process that unfolds in the network and is important for a firm's innovation. The key thesis tested maintains that a central position allows a firm to access external knowledge developed by other firms in the network and, in turn, enhance innovation.

THEORETICAL FRAMEWORK

INNOVATION

Innovation is a term that is widely used by several scholars in different ways. In its most general sense, innovation is the act of introducing something new. This new element may be a product, process, style of management, scientific discovery, or idea to name a few examples. Innovations can occur in all industries from new industries, such as genetic engineering, electronics, to old industries, such as shipbuilding, and mining. The context of this study is in the biotechnology industry and innovation will be framed as one that is scientific in the form of either patents or licenses. Though patents and licenses are a widely used measure of innovation, it is important to note that there are limitations to their use. Using a number count for determining degree of innovation can be misleading. For example, it is possible for a biotech firm to have only one patented innovation that is more radical and ground breaking than another firm with a high number of less innovative patents. In this case the results could be misleading because the less innovative firm with a larger number of patents will be considered more innovative than the firm with one radically innovative patent. However, despite the apparent flaws in using patents to measure innovation, it is a widely accepted measure of innovation that is directly related to inventiveness and represents an externally validated measure of technological novelty (Griliches, 1990).

Nature of Biotechnology Innovation

It is increasingly recognized that innovation requires the convergence of many sources of knowledge and skill, usually linked in the form of a network. Today, few innovations can be assigned to a single specific technological field or even a specific firm (Powell et al, 1996). Accordingly, firms cannot expect to keep pace with the development of all relevant technologies without drawing on external knowledge sources. 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). Mechanisms of learning and knowledge creation play a decisive role in the emergence of networks. 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. 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.

To understand how innovation might be understood as unfolding in social networks, it is useful to consider different perspective on what organizations and the network of relations between them are, how they come about, and how they function. For this study three main perspectives were used to form the theoretical framework for my model: rational, natural, and open system perspectives.

Rational, Natural, and Open System Perspective

The more traditional rational perspective views organizations as social units (or human collectives) purposely constructed and reconstructed to attain specific goals that are explicit and clearly defined (Etzoni, 1964). Organizations are collectives that exhibit a relatively high degree of formalization. In other words, they have a central coordinating system and high specificity of structure and coordination (March and Simon, 1958).

Rational system theorists stress goal specificity and formalization. Each of these elements makes an important contribution to the rationality of organizational action (Scott, 1998). Examples of this can be seen in formal alliances where relationships between companies involve long-term financial relationships and/or contracts. These financial contractual ties formalize, specify, and rationalize important terms of the relationship. However, in the context of my research, relationships involve a social interaction factor. This social interaction is what makes inter-organizational networks emergent and more informal rather than goal specific and formalized. Biotechnology, a fast-paced industry, does not have the luxury of being predictable. Competition is fierce and the ability for firms to continue to exist depends on their ability to quickly adapt and succeed in the race to innovate.

In contrast to the machine-like description of organizations adopted by the rational system perspective, the metaphor that best describes the natural system perspective is that of an organism (Scott, 1998). Under the natural system, organizations are organic systems instilled with a strong drive to survive. According to Scott, natural systems are "collectives whose participants are pursuing multiple interests, both disparate and common, but recognize the value of perpetuation and consider the organization as an important resource." (Scott, 1998: 26) Here, the behavior of participants is not guided by the formal roles and written rules that have been stated by the organization but rather by their own interests, although they do consider the organization as important to fulfill their needs and interests.

Unlike the rational system, natural system analysts are more concerned with the complex interactions between the normative and the behavioral structures of organizations. In this case, the development of informal structures and distinctive cultures is an important means of survival. These structures emerge out of the natural abilities and interests of participating firms and enable the collective to benefit from its memberships, resulting in a distinct structure for each organization (Mayo, 1945; Selznick, 1957). This is best seen in the emergence of innovation networks in the biotechnology industry. Informal collaborations are maintained to gain access to strategic resources such as financing, knowledge and skills essential for survival. However, despite the apparent fit of this model to the industry context of this study, one essential factor the natural perspective fails to consider is the environment.

Unlike the rational and natural system perspectives, the open system considers the environment when studying organizations. The open system perspective views organizations as a combination of parts whose relations make them interdependent. This perspective views the environment as a source of system maintenance, diversity, and variety. Scott (1998) describes this perspective as a system of interdependent activities linking shifting coalitions of participants. These coalitions of participants have varying interests that are highly influenced by their environment. Therefore, external forces shape internal arrangements and vice versa. According to Powell (1996), sources of innovation do not reside solely inside firms but instead are often found outside the organization in the intricacies between firms, universities, research laboratories, suppliers, and customers (Powell, 1996).

Therefore, to clarify the industry setting and actor characteristics, both the natural and open systems can be integrated. The two perspectives are, at times, viewed as competing explanations, however, they need not be. Each actor, especially a smaller firm, is constantly striving to survive and innovate. Moreover, one essential means of doing so is through the development and maintenance of external and open collaborative agreements.

Firms in biotechnology fields rely on collaborative relationships to access, survey, and exploit emerging technological opportunities (Powell, 1996). Therefore, it can be proposed that these network relationships are a natural outgrowth of a socially interacting community in which organizations have the need to consistently innovate and, at the same time, are structured as loosely coupled systems that are highly dependent on the environment for self-maintenance. Social network analysis allows for the analysis of this social environment and expresses it as patterns or regularities in relationships among interacting firms. Therefore, the aim of using social network analysis in the Biotechnology network is to convey network relationships as patterns of interaction among interacting firms. To understand how social network analysis applies to the context of this study it is useful to give a brief introduction to what social network analysis is all about.

SOCIAL NETWORK ANALYSIS

Introduction to Social Network Analysis

Social network analysis has attracted considerable interest and intrigue from social behavioral scientists in recent decades. This interest can be strongly attributed to the alluring focus of social network analysis on relationships among social entities, and on the patterns and implications of these relationships. Social network analysis views the social environment as patterns or regularities in relationships among interacting units. These units are referred to as *actors*, and any regular patterns in relationships are referred to as *structure*. The relational structure of a social network system consists of the pattern of relationships among the collection of actors.

Along with the growing interest and adoption of network analysis techniques has come a consensus about the focal principles underlying the network perspective. These principles differentiate social network analysis from other research approaches (Wellman, 1988). In addition to the use of relational concepts, the following ideas are important:

- Actors and their actions are viewed as interdependent rather than independent.
- Relational ties (also called linkages) between actors are channels or conduits for the flow of resources (material and non-material, financing and knowledge)
- Network models view the network structural environment as providing opportunities for or constraint on individual action.

In social network analysis, the observed attributes of social actors (such as innovation, productivity of firms, and motivation of employees) are interpreted as a function of their location in the network.

Fundamental Concepts in Network Analysis

To comprehend the heart of this research, readers must have a basic knowledge of key network analysis concepts. These concepts are actor, tie content, dyad, indirect ties and network position.

Actor

Social network analysis focuses on understanding the relations or linkages among social entities and the implication of these linkages. These social entities are referred to as actors. Actors are individuals, corporations, or collective social units. Examples of actors are firms in an alliance, people in a group, departments within a corporation, or nation-states part of a world system. The use of the term "actor" does not imply that these entities necessarily have the ability or desire to "act" (Wasserman and Faust, 1994).

Tie Content

As one may have already imagined, actors are linked to one another through social ties. The defining feature of a tie is that it establishes a linkage between a pair of actors. Some of the most common types of *ties* employed in network analysis are:

- Transfers of material or non-material resources (for e.g., Information sharing, financing, or lending)
- Association or affiliation (for example jointly attending a social event, or belonging to the same social club)
- Physical connection (e.g. road, river, corporate building connecting actors)

- Formal relations (e.g., authority)

This study conceptualizes network ties as involving the transfer of both material and non-material resources, specifically information. Biotech firms are involved with venture capital firms, public research labs, universities and manufacturers. Through these ties there is a transfer of resources such as information and financing. In addition, this study assumes a tie to exist if two firms are associated or affiliated to one another. For example, when two firms associate with the same public research laboratory this study assumes that they are tied to one another by virtue of being affiliated to the same third party. These types of ties are called indirect ties and will be explained in greater depth later in this study.

Dyad

A linkage or relationship immediately establishes a tie between two actors. An important concept to understand is that the *tie* is inherently a property of the pair and does not belong simply to an individual (Wasserman and Faust, 1994). Various network analysis researchers are concerned with understanding the ties among pairs. The approaches they use take the *dyad* as the unit of analysis. A dyad is made up of a pair of actors and the linkages between them. The dyad is frequently used as the basic unit of analysis for the statistical analysis of social networks. There can be two kinds of dyadic relations, direct ties and indirect ties.

Indirect Ties

Two important aspects to conceptualizing a firm's network structure are direct and indirect ties. Both direct and indirect ties can influence a firm's innovation (Ahuja, 2001). In order to visualize the concept of direct and indirect ties in the context of this study, Figure 1 in Appendix I identifies ties between two biotech firms and a university. In Figure 1, BioFirm A and BioFirm B each have one direct tie to a University X. BioFirm A and BioFirm B also have an indirect tie by virtue of their common partnership to the University X. In the network being studied, it is important to note that the presence of direct ties between biotech firms was minimal and thus not sufficient for analysis. However, there were numerous indirect ties between firms found through their common partnerships with universities, public research labs, venture capitalists, and manufacturers.

It is important to highlight that formal direct agreements can be interpreted through a rational system perspective, but the focus of this research is on the natural system, which is created through the indirect links between firms. Collaborations in high-tech industries typically reflect more than just a formal contractual exchange. As Powell et al (1996) explain, beneath most direct ties lies a sea of informal indirect relations and when knowledge is broadly distributed, the locus of innovation is found in a network of external partners such as universities and research labs. 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 affiliated to one another largely through indirect linkages.

These indirect linkages act as a channel of information between the firm and many indirect contacts (Mizruchi, 1989; Davis, 1991; Gulati, 1995). In this study, knowledge is critical and Biotech firms must be expert in cooperating with external partners such as universities, public labs, venture capitalists and manufacturing companies. According to Powell (1991), sources of innovation do not reside exclusively inside firms; instead they are commonly found in the ties between firms, universities, research labs, manufacturers, and other partners in the network. 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).

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 benefits in two forms. First, these indirect network ties can serve as an information collection mechanism (Freeman, 1991). In this case 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 a 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. Thus firms should strategically locate themselves in network positions that allow them access to various types of useful information. The concept of network position is key to understanding the motivation behind this research.

Network Position

Network position is an outcome of the relationships between actors and is considered a key variable in social network analysis. The goal of positional analysis is to represent patterns of complex social network data in a simplified form in order to reveal subsets of actors who are similarly embedded in networks of relations (Wasserman and Faust, 1994).

The analysis of actors and their relative positions in the network can be accomplished using several levels. The level of analysis refers to the subset of actors being examined in the network structure and the interactions between these actors. For the purpose of this study, the focus will be on only two levels of analysis, namely the individual level and the dyadic level.

One of the most commonly used levels of analysis is the individual level. In this case, the individual actor is the unit of analysis. In terms of networks, this implies that each actor is studied in terms of the relationships that connect him/her to all other actors in the network. On the other hand, at the dyadic level the focus is on the similarity in the way pairs of actors are connected to all other actors in the overall network. This study analyzes the ties among pairs of Biotechnology firms in a network. Furthermore, this research focuses on two independent variables, namely Centrality and Structural equivalence. To examine each of these variables, different levels of analysis are required.

INDIVIDUAL LEVEL OF ANALYSIS / Centrality

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 the biotechnology network and then related to each individual actor's innovation. A very useful method that attempts to describe and measure properties of "actor location" in a social network is *centrality*.

The degree to which an individual actor is connected to others in a network is called network centrality. In the extreme case, an actor's position is central to the extent that all relations in the network involve him/her (Burt, 1980). This is the structural property most commonly related to beneficial outcomes including power (Brass, 1984), influence in decision-making (Friedkin, 1993), and individual innovation (Ibarra, 1993). An actor's centrality captures the extent of an actor's access to resources, such as information (Sparrow, Liden, Wayne, Kraimer, 2001)

Central actors are those that are extensively involved in relationships with other actors. This involvement makes them more visible to the others. Indeed, there are different kinds of centrality that measure different aspects of being a central actor involved in many ties.

Degree centrality

One of the most often used measures of centrality is degree centrality. In this case, the actor with the most 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 2 in Appendix II, we can see that in the case of the star network that 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 on Figure 2, and we can see that a circle has no actor more active than any other actor. In this case all actors are interchangeable, thus all actors should have the same degree centrality. Therefore, degree centrality illuminates the most visible actors in the network. 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.

Betweeness Centrality

Betweeness centrality refers to the rate at which an organization falls between other firms. Particularly, betweeness 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 2, you can see that the actor in the middle (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). Assuming these actors are Biotech firms, then from looking at the line network 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. The main idea is that an actor is central if it lies linked between other actors, and thus in order to have a large betweeness centrality the actor must be linked between many other actors.

For example, if a Biotech firm needs to go through two other firms in order to reach an actor with needed information, then the middle actors may have control over the interaction since they block the direct path to the information-rich firm. One could state that the actors in the middle have more access to diverse knowledge than other firms who are low in betweeness centrality (Freeman 1979; Freidkin, 1991).

Closeness Centrality

This measure pertains to the closeness of an actor in relation to all the other actors in the network. Firms are considered to have high levels of closeness when they can quickly react with others. Closeness has been related to the idea of minimum distance such that individuals with high levels of closeness will have the shortest path between themselves and all others. Closeness is inversely related to distance: the greater the distance, the lower the closeness centrality (Wasserman and Faust, 1994). From the star network in Figure 2, we can see that in comparison to actors B through G, actor A is high in closeness centrality because there is one path separating him/her from all the other actors.

In other words, the suggestion is that an actor is central if it can quickly interact with all the others. If a firm has a high level of closeness centrality, then there is less dependence on others to relay information (Freeman, 1979).

This is specifically relevant in the context of this study where actors rely on other actors for the relaying of knowledge and skills. The actors that are centrally located with respect to closeness centrality can be very productive in obtaining information from other actors. If the actors in the network are engaged in problem solving, which is often the case in a science intensive field such as biotech, efficient solutions often occur when one actor has very short communication paths to the other.

Eigenvector centrality

Eigenvector centrality refers to the extent to which an actor is central due to the centrality of the actors to which it has ties. Therefore, a biotech firm can be central through association because it is connected to another actor that is highly central. 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.

Each of the above mentioned centrality variables capture the extent of an actor's access to resources, such as skills and knowledge (Sparrow, Liden, Wayne, Kraimer, 2001). For innovation to occur, actors need to be located in central positions in order to gain access to external knowledge that can be used for learning. Within Biotech networks, a social process referred to as organizational learning unfolds as firms become increasingly interdependent on their external collaborations for complementary knowledge.

Centrality and Organizational Learning

According to Brown and Duguid (1991), organizational learning is a social construction process that unfolds in and between network positions. An organization's network position reveals its ability to access external information and knowledge. By occupying a central position in the network, an actor is likely to access desired strategic resources, such as information and skills, which can be assumed to enhance innovation and organizational learning. Gaining access to information and skills may increase the probability of a firm learning because firms can use these resources to develop new knowledge by integrating them with existing stocks of knowledge. Therefore, organizational learning requires (1) access to information and skills as well as (2) an ability to integrate them into the organization's routines, but the particular focus in this study is only on the first of these two components

Knowledge is an essential ingredient for *fuelling* organizational learning. Knowledge creation occurs more readily in the context of a community that is fluid and evolving rather than tightly bound or static. Sources of innovation do not reside solely inside firms.

Instead, they are often located in the relationships between firms, universities, research laboratories, suppliers, and customers (Powell, 1996). In other words, as Von Hippel (1988) points out, the trading of know-how often requires the establishment of relationships in which exchange occurs within a learned and shared code.

Centrality and access to complementary knowledge

As mentioned above, inter-firm networks represent a fast means of gaining access to knowledge that cannot be produced internally. The network like configurations that have evolved in advanced technology markets can process information in multiple directions. Furthermore, they create intricate webs of communication and mutual dependence: "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). Hence, it is generally assumed that inter-organizational networks foster the conditions for innovation by allowing information sharing and knowledge transfer. Different network positions represent different opportunities for an actor to access new knowledge that is critical to developing new products or innovation ideas.

An organization's network position reveals its ability to access external information and knowledge. By occupying a central position in the network, an actor is likely to access desired strategic resources, such as knowledge and skills. Such resources will fuel the actor's innovative activities by providing the external information necessary to generate new ideas. Equally, the innovative work of actors will benefit from access to the new knowledge necessary to resolve design and manufacturing problems (e.g. Dougherty and

Hardy, 1996; Ibarra, 1993; Van de Ven, 1986). However, such knowledge is usually distributed unevenly between organizations. As Szulanski (1996) argued, knowledge is difficult to spread across different actors within a network. For this reason, it is important for companies to locate themselves in a central position in order to gain access to knowledge benefits from their network alliances. Hence, the following hypothesis is proposed:

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

Centrality and Innovation

With respect to the production of technological innovations, Cohen and Levinthal (1990) showed that the accumulation of knowledge enhances organizations' ability to recognize and assimilate new ideas, as well as their ability to convert this knowledge into further innovations. Actors that are more centrally located *accumulate* greater knowledge and, thus we assume, will be in a better position to convert this knowledge into further innovations.

Similarly, Tushman and Anderson (1986) and Henderson (1993) have argued that established firms possess information-processing routines that facilitate incremental innovation along existing technological trajectories. According to Cohen and Levinthal (1990), the background knowledge required for innovative activity is cumulative, where new ideas are more efficiently assimilated if a solid base of knowledge has been established (Nelson and Winter, 1982; March, 1991). Moreover, the cycle between innovation and the accumulation of knowledge within the organization tends to be self-reinforcing, such that organizations with a larger knowledge base are more likely to pursue the innovative opportunities that further contribute to the accumulation of knowledge (Cohen and Levinthal, 1990). These firms that are more central accumulate more knowledge.

Studies show that a network serves as a locus of innovation because it provides favorable access to knowledge and resources that are otherwise unobtainable (Powell, Koput, Smith-Doer, 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 do weak-performing firms. Centrally located firms with access to a greater variety of activities are better able to locate themselves in information rich positions. Thus, differential location in a network of partnerships results in firms having divergent capabilities for benefiting from collaboration. 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.

Bearing this in mind, it is assumed that centrally located firms within an organizational network 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). Therefore, this access to knowledge allows for the assumption that firms that are more centrally located will have greater access to innovation enhancing knowledge thus yielding greater probability of innovation. An organization occupying a more central position in an inter-organizational network is likely to produce more innovations. Hence, the following hypothesis:

Hypothesis 2: *The centrality of an organization's network position is positively related to its innovation.*

According to Powell (1998), inter-firm cooperation accelerates the rate of technological innovation. The organizational learning process involves inter-firm collaboration where network linkages act as channels of information. Therefore, assuming that the centrality of an organization's network position is positively related to its innovation, this study proposes:

Hypothesis 3: *"A firm's network centrality is positively related to the likelihood of it increasing its rate of innovation as a result of collaboration."*

Centrality and R&D projects

The position an organization occupies in the emerging network can influence its ability to access fine-grained information about potential partners, as well as its visibility and attractiveness for other organizations throughout the network, even if it is not directly tied to them. The information advantages resulting from network centrality have been a recurrent theme in network analysis (Freeman, 1979). According to some social cognition studies, central actors have a more accurate representation of the existing network (Krackhardt, 1990). Furthermore, it is believed that central organizations have a larger "intelligence web" through which they can learn about collaborative opportunities, thus lowering their level of uncertainty about collaboration (Gulati 1999; Powell et al. 1996). Therefore, the more central an organization's network position, the more likely it is to have better information about a larger pool of potential partners in the network (Gulati and Gargiulo, 1999). Thus, this allows, more "important," central firms to have a higher probability of accessing innovation-enhancing opportunities from other central actors in organizational networks.

Rather than monopolizing the returns from innovative activity and forming exclusive partnerships with only a narrow set of organizations, successful firms positioned themselves as the hubs at the center of overlapping networks, stimulating rewarding research collaborations among the various organizations to which they are aligned, and profiting from having multiple research projects. Therefore, this study proposes the following.

Hypothesis 4: *"A firm's centrality will be positively related to the number of R&D projects it has."*

All four of the above hypotheses focused on the individual firm's location and its relation to innovation, access to complementary knowledge, increased speed of innovation, and number of R&D projects. However, another useful level of analysis is the dyadic level. Dyadic level analysis is especially useful for analyzing firm similarity in a network.

DYADIC LEVEL OF ANALYSIS/ Regular Equivalence

At the dyadic level, the focus is on similarity between pairs of actors. A method widely used by network analysts for describing similarity in network position and differentiating members in a dyad is regular equivalence. Regular equivalence is an indicator of firms that occupy the same social position in the social structure and so are alike to the extent that they have the same pattern of relations with occupants of other positions. Position refers to a structural pattern of interactions in the same sense as centrality. For example, two firms that have many ties (i.e. high degree centrality) to other firms that themselves have few ties to other firms (i.e. low degree centrality) would be regularly equivalent. Actors occupying the same position need not be in direct, or even indirect, contact with one another. For example, doctors in different hospitals occupy the position of "doctor" by virtue of similar pattern of interactions with nurses and patients, though individual doctors may not know each other, work with the same nurses, or see the same patients.

The idea behind regular equivalence is simply represented graphically. Let us assume that firm A and D are firms with high degree centrality, firms B, C, E, F, and G have low firm centrality, and that firm H and I are not central at all. In Figure 3 in Appendix III, we can see that firms A and D who both have high degree centrality are both regularly equivalent. Firm A is connected to B and C which both have low degree centrality. Similarly, Firm D is connected to firms E, F, and G who also have low degree centrality. Thus, because of both firm A and D's similarity in degree centrality and their connection to low degree centrality firms they are regularly equivalent. In the same way, it can be said that C, D, E, F and G are regularly equivalently because they all are low in degree centrality and at the same time each of them are connected to a firm with high degree centrality. It must be noted that a firm does not require ties between actors to be regularly equivalent. From the figure we can see that firms H and I have no ties at all and are thus considered isolates. Firms H and I are also considered regularly equivalent because they both have no ties to any other actors. Thus both X and Y occupy the same social position and are alike in the sense that they have no relation with occupants of other positions. Therefore, regular equivalence calculates the similarity of a pair of actors by seeing if they are connected to other actors who are themselves similar.

Researchers use regular equivalence to accurately capture the idea of social roles (White and Reitz, 1983). The idea of social roles indicates that those who have a similar role share a *structurally similar* social world instead of having exactly the same social world (Faust, 1988). Rather than relying on attributes of actors to define similarity, regular equivalence analysis seeks to identify similar actors by identifying regularities in the patterns of network ties.

A social role is communicated through social influence. It provides firms with an understanding of how they should behave (DiMaggio and Powell, 1983). Firms then look to other actors in regularly equivalent positions to evaluate what their social role should be. Johanson (2000) postulates that actors, who occupy similar social positions (roles), are socially influenced by similar mechanisms. In this study, social influence refers to the process whereby firms come to adopt a similar strategic direction.

Social Influence

According to Johanson (2000), regular equivalence is a rather pure social influence mechanism because it reflects only one type of social influence process called adaptation. By adaptation, Johansen refers to the process in which firms that occupy similar positions in the network are likely to have to *adapt* to the same type of social demands and expectations in their social network environment. It is through this process of adaptation that this study assumes biotech firms end up adopting a similar strategic direction.

Social Influence Processes that Unfold in Biotech

According to both institutional and resource dependence perspectives, *strategic direction* is limited by a variety of external pressures and biotech firms must be responsive to external demands and expectations in order to adapt and survive (Meyer and Rowman, 1977;Pfeffer and Salancik, 1978). This study conceptualizes that regularly equivalent biotech firms that occupy similar roles are subject to similar external demands and expectations and therefore adopt similar strategic directions. All these organizations have a strong need to adapt to environmental uncertainty (Oliver, 1991). According to DiMaggio and Powell (1983), forms of homogeneity come about when firms try to adapt to this uncertainty. Thus, in the process of adapting to uncertainty, social influence processes unfold in the biotechnology network that may lead regularly equivalent biotech firms to adopt a similar strategic direction.

This mechanism of influence is referred to as isomorphism. DiMaggio and Powell (1983) describe this concept as an influence mechanism that forces one actor to resemble other actors that face the same set of environmental conditions. This study assumes that regularly equivalent actors are isomorphic as a result of external demands and expectations and the need to adapt to the uncertainty of the biotech environment.

Demands and Expectations

Institutional theory focuses on the isomorphism of organizational strategies in response to external demands and expectations (Oliver, 1991). External pressures from powerful firms in the network may induce an organization to conform to its peers by requiring it to perform a particular task and specifying the role responsibities for its performance. This form of isomorphism results from both formal and informal demands and expectations exerted on organizations by other more powerful and influential organizations, upon which they are dependent. In this study, the existence of a common interdependent biotech network environment may affect many aspects of an organizations strategy. As a result, organizations that are regularly equivalent may take on similar roles and in turn adopt a similar strategic direction as a consequence of pressures to conform.

According to institutional theory, conformity is useful to organizations in terms of enhancing organizations' likelihood of survival (Oliver, 1991). The advantages of compliance with external demands and expectations are revealed in the variety of rewards to which organizational conformity has been related to the literature, for example access to resources, attracting personnel, and acceptance by other organizations (DiMaggio and Powell, 1983). In the context of this study, conformity may reduce the organization's vulnerability to negative assessment of its strategic direction. One very common reaction to external demands and pressures is imitation of other organizations that play a similar role, especially successful organizations that firms are connected to. Thus, as a reaction to external demands and expectations, regularly equivalent biotech firms will begin to assume similar roles and as a result of pressures to conform may imitate one another and adopt a similar strategic direction.

Imitation

Uncertainty encourages imitation. This form of isomorphism is referred to as modeling. Imitation or modeling, as DiMaggio and Powell (1983) use the term, is a standard response resulting from uncertainty. They hypothesized that, when organizational technologies are poorly understood, when goals are ambiguous, or when the environment is uncertain, organizations tend to model themselves on other organizations. They observed that once different organizations in the same line of business are structured into an organizational field, such as biotechnology, powerful forces emerge that leads them to become more similar to one another. This study assumes that firms become more similar because as firms begin to imitate one another they take on the social role of other actors who are regularly equivalent to them.

In respect to strategic direction, much of this modeling stems from the fact that despite considerable searching for diverse business models, there is relatively little variation to be selected from (DiMaggio and Powell, 1983). Models may be borrowed from firms without them being aware or may be diffused unintentionally. When firms intentionally imitate other organizations they tend to model their strategic direction after similar organizations in their field that they perceive to be more legitimate and successful in an effort to reduce environmental uncertainty and possibly reap similar rewards (DiMaggio and Powell, 1983). As Aldrich (1979: 265) argues, "the major forces that organizations must take into account are other organizations." Frequent or empathic communication is not necessary for two biotech firms to be aware of one another. Organizations involved in relations with the same firms are likely to have direct and indirect awareness of each other: direct by meeting when interacting with their mutual acquaintances and indirect by hearing about each other through mutual acquaintances. When speaking of regular equivalence and competition actors usually compete by using one another to evaluate relative adequacy (Burt, 1987). Thus it is largely through this social comparison that biotech firms compete and adapt to uncertainty. In turn, these firms intentionally mimic the strategic direction of other biotech firms in similar roles that they perceive as being legitimate and successful in hopes of gaining similar rewards.

Thus this study proposes that in the struggle to adapt to uncertainty, external demands and expectations, biotechnology firms that are regularly equivalent adapt through imitation of one another. In the process of trying to adapt to uncertainty and the pressure of network demands and expectations, biotech firms may look to other regularly equivalent biotech firms in evaluating their own strategic direction.

In other words, biotech firms that occupy similar positions in the network share a *structurally similar* environment and are highly likely to take on similar social roles because they adapt to the same type of social demands and expectations in their social network environment. Furthermore, when adapting to uncertainty, this study assumes that regularly equivalent biotech firms may mimic firms that play similar social roles and in turn adopt a similar strategic direction. Therefore, this paper proposes the following:

Hypothesis 5: "Firms who are regularly equivalent will adopt a similar strategic direction."

METHODOLOGY

SAMPLE

The data used for this study came from a pre-existing data set that was part of a larger study for UQAM conducted by Dr. Anne-Laure Saives between October 2001 and

January 2002. The data were collected from Biotechnology firms involved in the human and animal nutrition sector in Quebec, Canada.

The sample consists of 40 different firms. Each firm is involved in a combination of different alliances with universities, venture capitalists, manufacturing firms, public labs, consultants, and private labs. Of the 40 firms interviewed only 38 returned complete and usable data, which results in a response rate of 95%. The sample was composed of mainly young firms, 50% being less than 5 years old. Additionally, the average age of the firms in the sample is 12.4 years. The average number of employees per firm was 94 and 45% of the sample had less than 10 employees.

DATA COLLECTION

Data were collected on network linkages, number of patents, number of R&D projects, strategic direction, R&D capabilities, and demographic variables. The data collection started in October 2001 and finished in January 2002. Network data and all other variables were collected through the interviewing of high-level managers within each firm. Each interview lasted on average one and a half hours. The interviewers spoke, when possible, with the president of each company (25). When it was not possible, they interviewed the person (one person per company) who was designated by the company as the one to be able to answer to "strategic management" issues: R&D director (5), CEO (often the R&D manager also in smaller firms) (3), COO (2), Marketing director (4), and Human Resources director (1). A representative from each firm was asked questions on the number of patents and the number of licenses they have. Network affiliation data was collected through questioning each firm for the name of their partner and his/her activity. Then a follow up question was asked about the results from these alliances: whether the firm saw access to complementary knowledge and/or increased speed of innovation.

DEVELOPING MEASURES FOR INDIVIDUAL LEVEL ANALYSIS

Independent Variables

Network centrality

The first four Hypotheses required analyzing firm centrality within the network. In order to measure these hypothesis, centrality variables for Degree centrality, Closeness centrality, Betweeness centrality, and Eigenvector centrality were calculated using UCINET (Borgatti, Everett, and Freeman, 2002). UCINET is 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 partner.

Firstly, the analysis began by creating 2 mode data sets of firm by alliance partner data. Then adjacency matrices for each category of coilaboration partner were created. These matrices were of Universities, Venture Capitalists, Public Labs, Biotech Firms, Consultants, Private Labs, Equipment Suppliers, Trader, Public Development Organization, Distributor, Raw Materials Supplier and Manufacturers. Binary adjacency arrays were created where values of "1" signified a relation present and "0" a relation absent. These matrices were manually created using excel and then transferred to UCINET. This data was then converted into a firm-by-firm adjacency matrix by creating ties if firms had alliances with the same third parties.

Out of these matrices only four had sufficient information on network ties. These four matrices (Universities, Venture Capital Firms, Manufacturers, and Public Labs) were added together to form one combined matrix. This was done by adding each of the corresponding cells of the four matrices to form a new adjacency matrix of the overall links that individual Biotech firms contain.

With UCINET, this combined matrix was used to calculate Degree Centrality, Betweeness Centrality, Closeness Centrality, and Eigenvector Centrality. UCINET has a function for each of the centralities mentioned, which yield centrality scores for each individual in the network, as well as a network level measure of "centralization". In order to compute regression analysis of hypotheses 1 through 4, the centrality scores of each firm were imported into SPSS to be used for linear regression analysis.

Dependent Variables

Innovation

Hypothesis two 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 of technological novelty (Griliches, 1990). Number of patents data was input into SPSS to perform linear regression analysis on the centrality variables (Degree, Betweeness, Closeness, and Eigenvector centrality).

Number of R&D projects

In this study the number of R&D projects variable is the number of research and development projects individual firms are currently working on and have all ready completed. This information was also obtained through interviews given to managers. To statistically test Hypothesis 4, this data was then transferred into SPSS and used to perform regression analysis with the independent centrality variable.

Results from alliances

The hypotheses 1 and 3 required analyzing whether firms who are more central in a network were more likely to see *Access to complementary knowledge* and/or *Increased speed of innovation* as a result of alliances. This data was measured by taking yes/ no answers from interviews and converted into two datasets, one representing access to complementary knowledge and the other increased speed of innovation. In this case a value of "1" represents Yes they did see the above mentioned results from alliances, and 0 signifying the individual firm did not see results from alliances. For both of these variables only twenty eight of the thirty eight companies in the sample provided usable data. The raw datasets were then input in to SPSS and used for analyzing the relationship between the centrality variables (Independent variable) and Access to complementary knowledge, and increased speed of innovation as a result from alliances.

Hypotheses 1 and 3 propose that more centrally located biotech firms have a greater likelihood of seeing increased speed of innovation or access to complementary knowledge as a result of alliances. These hypotheses were both tested using logistic regression. Binary logistic regression is a type of regression analysis where the dependent variable is a dummy variable (coded 0, 1). In other words, a value of 1 if the event happens, and 0 if event doesn't happen. The logistic regression model is simply a non-linear transformation of the linear regression. It produces a formula that predicts the probability of the occurrence as a function of the independent variables. Logistic regression also produces *Odds Ratios* (O.R.) associated with each predictor value. The odds of an event is defined as the probability of the outcome event *occurring* divided by the probability of the event *not occurring*. The odds ratio for a predictor tells the relative amount by which the odds of the outcome increase (O.R. greater than 1.0) or decrease (O.R. less than 1.0) when the value of the predictor value is increased by 1.0 units.

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. Size was measure by the number of employees each firm had. The variable whether a firm has permanent R&D facilities was categorical, hence, it was only relevant to determine whether a difference existed. A data set was created were the value "1" was assigned to firms who had permanent R&D facilities and 0 for firms where R&D facilities were absent.

DEVELOPING MEASURES FOR DYADIC LEVEL ANALYSIS

Independent Variable

Regular equivalence

Hypothesis 5 focused on the concept of regular equivalence. This hypothesis measures the similarity of positions between two individuals. In order to develop variables to measure this hypothesis, regular equivalence was computed for the actors in the network using UCINET. Using the initial firm-by-firm adjacency matrix of firms that had alliances with the same third parties, a matrix of regular equivalent actors was created. The regular equivalence function is an iterative algorithm; within each iteration a search is implemented to find a similar partner. A measure of similar values is based upon the absolute difference of magnitudes of ties.

Dependent Variable

Strategic direction

The dependent variable was collected through a guided interview in which executive managers of each company were asked where they intend to guide their firm within a five-year time horizon. There were 6 initial strategic direction responses: 1) IPO, 2) To be Acquired, 3) Independent Commercialization of New Products, 4) Commercialization of New products through alliances, 5) R&D of new products, and 6) Impartation.

Since the independent variables were in the form of a matrices regression needed to be computed in UCINET. The 6 categories of strategic direction were converted into a matrix using the exact match rule. Exact match gives a value of 1 if a vector value matches and a 0 if it does not. There fore when two companies have the same strategic direction it would give a value of 1 and if they differ a value of 0 would be assigned.

In order to examine the relationship between the regular equivalence matrix and strategic direction matrix, Quadratic Assignment Procedures (QAP) was used. This permutation procedure generates all correlations that result form permuting the rows and columns of one of the structural matrices, and thus allows us to determine the distribution of all possible correlations given the structure of the two matrices. Thus it builds into the test statistic the kind of row/column interdependence that is assumed in the network data.

Control Variables

The control variables included age, size, and whether each firm had permanent R&D facilities. Since both the dependent and independent variables were in the form of matrices each of the control variables had to be converted into UCINET actor by attribute matrices. The variables age and size were converted into two separate matrices using the absolute difference rule. Absolute difference gives the degree of difference that exists between two firms such that if the two firms have the same age the value given 0. The greater the age difference between two firms the greater the number was. On the other hand the control variable permanent R&D facilities required the use of the exact match rule to distinguish between firms that "both have" R&D facilities and required the absolute difference rule to determine whether "both don't" have facilities. Each of these matrices was then correlated with the dependent variable through QAP.

RESULTS

Individual Level Data

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, number of R&D projects, likelihood of increased speed of innovation from alliances, and likelihood of access to complementary knowledge from alliances.

In order to test hypothesis 2, which proposes a positive relationship between centrality and innovation, regression analysis had to be performed using the dependent variable innovation and independent variable centrality. 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

Appendix IV) 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, Betweeness, and Eigenvector centrality 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 network, the more innovative they it is likely to be.

Furthermore, some interesting findings regarding the control variables were found (refer to Appendix IV). 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 that the greater the age of a firm, the greater the innovation. However, size (number of employees) was found not to be significant to innovation.

It is important to highlight that centrality variables tend to be correlated to one another and it is important to see if these variables have independent effects. After conducting a test for collinearity of all four centrality variables, Degree centrality and Eigenvector centrality proved to have major problems with multi-collinearity. Even after removing each variable separately, results still showed that Degree and Eigenvector centrality were highly collinear (Appendix VIII). Thus, Betweeness and Closeness centrality have independent effects in this statistical model.

Hypothesis 4, which stated that a firm's network centrality is positively related to the number of R&D projects it has, was tested in a similar manner as hypothesis 1. In this case, degree centrality, closeness centrality, betweeness centrality, and eigenvector centrality were not significantly related to number of projects (Appendix IV). Therefore, Hypothesis 4 was not supported. Furthermore, no relation was found with any of the control variables. Hence, the number of R&D projects that a firm has is not related to its network centrality.

Hypothesis 1 and 3 were both tested using binary logistic regression. Hierarchical logistic regression analysis was performed using the control variables on each access to complementary knowledge and increased speed of innovation and then another logistic regression was performed with the focal centrality variables. Due to incomplete data on the dependent variable, only twenty-eight out of the thirty-eight biotech firms could be used for this analysis. Results from the logistic regression illustrated in Appendix V, indicated that Hypothesis 1 was supported, while hypothesis 3 was not. Furthermore, no significant relationship was found for the control variables in both Hypothesis 1 and 3.

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 Appendix V we 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 did increase the likelihood of a firm seeing access to complementary knowledge as a result of alliances, but no relationship was found between the centrality variables and likelihood of seeing increased speed of innovation.

Dyadic Level Data

Hypothesis 5 was supported. From the Quadratic Assignment Procedure (QAP) regression results (Refer to Appendix VI), we can see that regular equivalence had a significant effect on strategic direction. The control variables age, permanent R&D facilities and size did not have a significant effect on strategic direction. Thus, regularly equivalence is positively related in similarity of strategic direction. Firms who are regularly equivalent tend to have a similar strategic direction.

DISCUSSION

How can a firm gain useful knowledge from other firms in a network in order to enhance its innovation? This research suggests that a firm's external knowledge access in a network is useful in answering this question. A firm's external knowledge access is characterized by its network position. By occupying a central network position, a firm is likely to access useful knowledge from other firms. The first major finding of this research indicates that a firm's innovation is significantly increased by its centrality in the network, which provides opportunity for shared learning, knowledge transfer, and information exchange.

However, of the four centrality variables used only three showed a significant relationship to innovation. Closeness centrality was not significantly related to innovation. As previously mentioned, closeness centrality measures how close a biotech firm is to others within the network, such that high levels of closeness indicate firms can interact quickly with others. The non-significant relationship may be explained by problems with the network data. When closeness centrality was computed, UCINET indicated that the network was not connected and that, technically, closeness cannot be calculated as there are infinite distances. Thus, in the case of closeness centrality actors in the network were not sufficiently connected to one other to be able to appropriately calculate closeness centrality. Perhaps, if the network were more highly connected there would have been a significant relationship between closeness and innovation.

In the case of degree, betweeness, and eigenvector centrality the network centralization index indicated that firms were sufficiently connected to one another. By looking at the results (Appendix IV) one can see that degree centrality was most significant followed by eigenvector and betweeness. This variation in significance may be explained by the network centralization index that showed results of around 77%, 40%, and 9% for degree, eigenvector, and betweeness centrality respectively. This indicates that the more central the network was in each of the three centrality variables, the more significant its relationship was to innovation.

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 a firm's innovative capability is significantly increased by its degree centrality. As Freeman (1979) argued, degree centrality is the most suitable centrality measure for capturing an individual actor's access to information or knowledge. The higher a biotech firm's degree centrality the more knowledge sources the firm has. This external knowledge is necessary to generate new ideas and produce innovations. Knowledge transfer occurs in a shared social context in which highly central biotech firms may have greater access to knowledge and in turn generate more innovation.

A significant relationship was also found between eigenvector centrality and innovation. Eigenvector centrality refers to the extent to which an actor is central because of the centrality of the actors to which it has ties. 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. Betweeness centrality, on the other hand, measures the rate at which an organization falls between other firms. If a firm is high in betweeness centrality, this means that many other firms must go through the central firm in order to reach others. This in turn implies that firms high in betweeness have access to a variety of different types of information and skills from different areas of the network. As Freeman (1979) and Friedkin (1991) explain, the biotech firm that is high in betweeness centrality has more control over information and has access to diverse knowledge and skills. In this case network ties can serve as conduits through which information about technical break-throughs, new insights to problems and failed approaches can be accessed from various areas of the network. Thus, this access to diverse information and skills, coupled with the potential to control the information flow, may lead a biotech firm to enhance its innovation.

An interesting finding in this research is the significance of the control variables on innovation. It was found that both age and permanent R&D facilities had an effect on innovation. These findings are interesting because they add on to the academic literature that supports the relationship of each of these control variables and innovation.

First, this study found a significant relationship between internal R&D facilities and innovation. The idea of firms having internal R&D capabilities relates to the notion of absorptive capacity. Organizational learning in networks is both a function of access to knowledge (network centrality) and the capabilities for utilizing and building on such knowledge (absorptive capacity). Drawing on a network perspective on organizational learning, there are two important concepts, network position and absorptive capacity, that determine the effectiveness of inter-organizational learning and knowledge transfer (Powell et al, 1996).

Cohen and Levinthal (1990) described the importance of a firm's ability to assimilate and replicate new knowledge gained from external sources. They labeled such ability as "absorptive capacity." Absorptive capacity results from a prolonged process of investment and knowledge accumulation. Investment in R&D facilities is a necessary condition for the creation of absorptive capacity. 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.

Second, this study shows that the control variable age was significantly related to innovation. In the same way, Sorensen and Stuart (2000) conducted a study on the Biotechnology industry and found that as organizational age increases, so does innovation (measured by the number of patents).

According to Stinchcombe (1965) older firms may be more efficient than younger firms because they have more cumulative information processing experience, stronger network relationships, and a more experienced workforce. Organizational learning theorists also have argued that age leads to experience with a set of routines and in turn enhances an organization's capabilities partly by improving the reliability with which routines are implemented (March, 1991). Innovation at the organizational level is governed by collections of organizational routines and search strategies (Cyert and March, 1963;Nelson and Winter, 1982). Thus the age of a firm is useful in understanding individual firm innovation. As March (1988) put it, routines are repositories of organizational knowledge, and it is through the combination of these routines that innovation is generated.

In respect to innovation generation, as illustrated in the theoretical portion of this study, accumulation of knowledge enhances an organization's ability to recognize and assimilate new ideas, as well as to convert this knowledge into further innovations (Cohen and Levinthal, 1990). Similarly, Tushman and Anderson (1986), and Henderson (1993) have claimed that established firms posses information processing routines that facilitate incremental innovation across existing technological trajectories. Thus, if the passage of time leads to an accumulation of foundational knowledge, organizational innovation will increase with age.

Despite the significant relationship found between age and innovation, and the literature that supports these results, it is important to note that though older firms tended to demonstrate a higher level of innovation, the average age of a firm in this study was 12.4 years and is still considered relatively young in comparison to "old age" firms.

This research also examined the relationship between centrality and the likelihood of a firm gaining access to complimentary knowledge. Though no significant relationship was found for all four centrality variables, a significant relationship appeared between degree and eigenvector centrality with regards to access to complementary knowledge resulting from alliances. This finding highlights the idea that different network positions represent different opportunities for an actor to access complementary knowledge.

The results of this study show that when a biotech firm is highly involved in the network, they are more likely gain access to complementary knowledge through alliances. Theoretically, biotech firms with high degree centrality should have access to more information 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. As Freeman (1979) argued, degree centrality is the most suitable measure for capturing a firm's access to knowledge. An alternative 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 collection and processing benefits can influence a firm's ability to access useful and complementary knowledge.

The significant relationship found between eigenvector centrality and innovation may largely be attributed to its strong relation to degree centrality. In terms of information flow, the results imply that biotech firms who were most connected to highly central actors in the biotech 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 many other firms who are themselves connected to highly central firms, thus multiplying the possibility of gaining access to useful information (Wasserman and Faust, 1994).

Neither betweeness, nor closeness centrality proved to be significant to access to complementary knowledge. The reason as to why closeness centrality was not significant may largely be attributed to the fact that the network under study was not closely connected and thus could not output sufficient usable results. It is interesting to note that the effect of centrality variables on innovation was similar to their effect on access to knowledge except in the case of betweeness centrality. In both cases, degree and eigenvector centrality were significant to innovation and access to complementary knowledge and closeness was not. Indeed, the interesting difference is in the non-significance of betweeness centrality on access to complementary knowledge.

These results indicate that a biotech firm's betweeness in the network is not significantly related to its access to complementary knowledge. Betweeness centrality is different than other centrality variables in that it does not directly measure an actor's access to complementary knowledge. Rather, it measures an actor's access to diverse knowledge and its potential to control this diverse knowledge within a network. The term *diverse knowledge* should not be confused with *complementary knowledge*. In this study, complementary knowledge refers to knowledge that can be used for learning. In contrast the term diverse knowledge implies that it is non-repetitive and comes from different areas of the network. The type of access that middle actors have is access to a wider variety of knowledge. Thus it is possible that actors that are between many other actors may have very little access to knowledge, while actors with many ties may be low in betweeness. The significance of betweeness centrality on innovation and not on access to complementary knowledge may partly be attributed to the requirements for innovation. In the case of innovation, betweeness centrality may have been significant because innovation requires not only the access to external knowledge, but also the transfer of *complementary expertise and skills* as well (Powell et al, 1996). The importance of gaining complementary skills and expertise should not be discounted in the generation of innovation (Henderson and Clark, 1990). Thus the reason betweeness was significant to innovation and not to gaining access to complementary knowledge may be because access to knowledge alone is not sufficient for innovation generation. Another explanation to why betweeness centrality was not significant to access to complementary knowledge may be in the individual firm's capabilities to filter complementary knowledge. According to Henderson and Clark (1990), an organization is constantly barraged with information. Thus, organizations must be able to develop filters that allow it to immediately identify what is most crucial in its information stream. As research efforts evolve, the ability to identify complementary knowledge helps scientists to work efficiently. Hence, these results may imply that firms who were in between many other firms may have been bombarded with many different kinds of information, but possibly did not have the capabilities to decipher what knowledge was complementary.

It is also useful to add that data problems may have played a part in the non-significance of betweeness centrality on innovation. First, due to incomplete data only 28 out of the 38 biotech firms could be used, which makes the sample size less than 30 and not an ideal size for statistical analysis. Second, in the case of betweeness centrality only 8.3 % of the network was centralized, which means that a very small portion of the sample exhibited betweeness and thus decreased the probability of finding a significant relationship. Third, the criteria used to measure whether a firm gained access to complementary knowledge was a "Yes" or "No" answer thus making it impossible to measure the differences in access to complementary knowledge. All of these factors may have affected the accuracy of the results.

Providing further evidence that networks play an important role in shaping business strategy, another finding of this research was the significant relationship found between firms who are regularly equivalent and their similarity in strategic direction. These results illustrate that similarity in network roles of biotech firms is related to the similarity in their strategic direction. This in turn implies that biotech firms that have similar roles in the network are likely to have a similar strategic direction because they adapt to the same type of social demands and expectations in their social network environment. These results may indicate that biotech firms that play similar network roles mimic one another's strategic direction in an attempt to adapt to the uncertainty of their similar social environment.

The results of this study have provided interesting groundwork for further investigation of organizational learning processes, innovation, regular equivalence and especially the affect of network roles on firm strategy. However, this study failed to find a significant relationship between centrality and number of R&D projects, or increased speed of innovation.

The non-significant relationship between centrality and number of R&D projects means that a firm's network position is not significantly related to the number of R&D projects it has. This could probably be explained by the fact that there were no direct ties between biotech firms. As Powell et al (1996) pointed out, for a firm to expand its awareness of additional research and development projects it should expand its formal R&D collaborations with other biotech firms. This expanding of formal R&D collaboration requires that biotech firms have direct ties to one another. Thus the lack of direct collaboration between biotech firms may have influenced the non-significance of centrality on number of R&D projects. As Brown and Duguid (1991) claimed, "learning about R&D projects is about becoming a practitioner, not learning about a practice." (Brown and Duguid, 1991) It is also possible that the number of projects is not related to information transfer, but rather is a function of each firm's competencies and the demand for those competencies at that period of time. There is no apparent main stream literature that empirically shows a relationship between number of projects and centrality, but it would be interesting to further research what variables may be related to number of projects.

There was also no significant relationship found between centrality and increased speed of innovation. This means that a biotech firm's network position has no effect on its speed of innovation. Increase in a firm's innovation is a result of more than just being central in a network. Clark et al. (1987) found that the speed of innovation is strongly influenced by direct personal interaction between organizations. This direct interaction between firms greatly facilitates communication, coordination, and allows for quick movement of products from the research phase through to development and manufacturing (Henderson and Clark, 1990). Thus the non-significance of network position on the likelihood of seeing an increased speed of innovation is in part due to the lack of direct interaction between biotech firms in this study. Second, perhaps centrality is not useful in measuring speed of innovation because speed has more to do with the individual firm's capabilities. Firms may have access to knowledge however, seeing increased speed of innovation requires a firm's specific capabilities to rapidly turn this knowledge into innovation. According to academics (Abernathy and Utterback, 1978; Teece, 1987), the rate of innovation is a function of a firm's researchers, ability to learn across projects, technological capabilities, and research processes rather than solely position in inter-firm networks. Thus, it is likely that where a firm is located in the network does not have any effect on how fast it generates innovation.

It is also important to note the limitations of this study. First, the data used in this research were not collected for the specific hypotheses developed in this thesis. While the use of network data rich in indirect ties is useful to understanding organizational networks, there was little data on direct ties between biotechnology firms. Essentially, the network in this regard is comprised of biotech firms affiliated to one another through third party ties rather than directly interacting with other biotech firms. Perhaps, a Biotech sector more rich in direct ties may have provided a better representation of the biotech industry and provided greater insight into the effect of network position on innovation, access to knowledge, increased speed of innovation, and strategic direction.

In addition, a replication of certain aspects of this study using a newly structured interview, with more than simply one person per firm may give the researcher a more accurate representation of a firm's network environment. Furthermore, perhaps abstaining from using categorical "Yes/No" answers for the variables' access to complementary knowledge, increased speed of innovation, and permanent R&D facilities would have aloud for more precise measurement of the effects of each variable.

Although previous research has elaborated the concept of organizational learning, this research adds little systematic understanding of the social processes that underlie how firm's learn from each other. Critical insights and ideas reside in collaboration networks. Knowledge and ideas are shared and common meanings are developed through interactions. Knowledge is socially constructed, and organizational learning involves a complex social process in which different firms interact with each other (Berger and Luckman, 1996, Huber; 1991). More research is needed to investigate these social learning processes that unfold in a network position and result in innovation.

In conclusion, the results of this research highlight the importance of collaboration between organizations. A network may be compared to a database of diverse knowledge. The ability to access this knowledge is an effective source of competitive advantage. By examining the pattern of network interactions between firms, this research shows that being located in a central position leads to innovation and access to knowledge advantages. Furthermore, it demonstrates that firms that are regularly equivalent and similar in network roles tend to adopt a similar strategic direction. A firms network position should not be discounted as a source of competitive advantage.

From this study it is evident that network location has the potential of shaping the nature of competition. In particular, the results (Appendix VII) of this study demonstrate the dominant effect of degree centrality on innovation. These findings on degree centrality suggest that biotech firms that keep a high number of alliances are more likely to be innovative. Indeed, it is not enough to simply have many ties in the network to produce innovations. Innovation requires many factors such as human intellect, R&D financing, learning across projects and absorptive capacity. However, from this study it may be proposed that by being highly connected and interacting with many different organizations such as manufacturers, public laboratories, venture capitalists, and universities, a biotech firm can increase its access to external knowledge and in turn enhance its potential to innovate. Therefore having a large number of ties is important for innovativeness.

This then brings us back to the question of whether innovation in biotech networks is the outcome of a formal rational design or a more informal natural process. There is a general consensus that the biotechnology environment is a relatively uncertain and unstable one. However, this lack of stability may actually lead firms to do things in a more formal and goal specific fashion as an attempt to control their environment.

In many cases biotech firms begin by forming contractual ties that formalize, specify, and rationalize important terms of the relationship. Thus it can be proposed that there is a structural design behind the shape of the biotech 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 the emergence of 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 biotech combine both rational and natural elements of organization to produce innovation outcomes.

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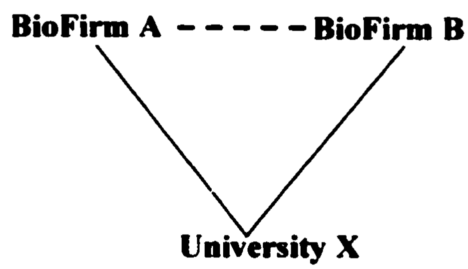
Appendix I- Direct and Indirect Ties

FIGURE 1

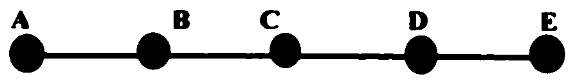


\- - - Indirect Tie

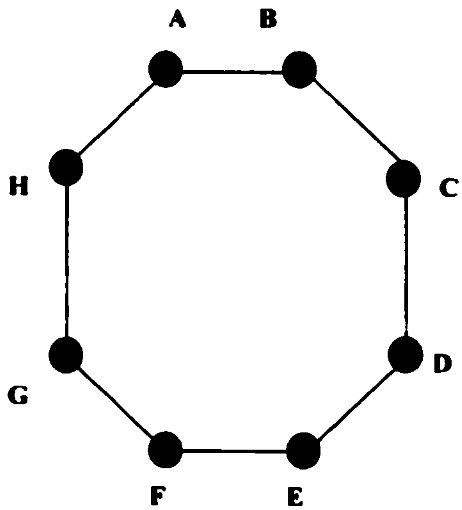
—— Direct Tie

Appendix II

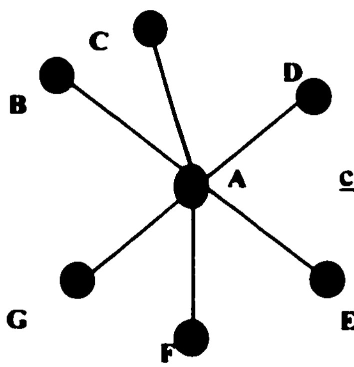
Figure 2: Centrality Diagrams



a) Line Network



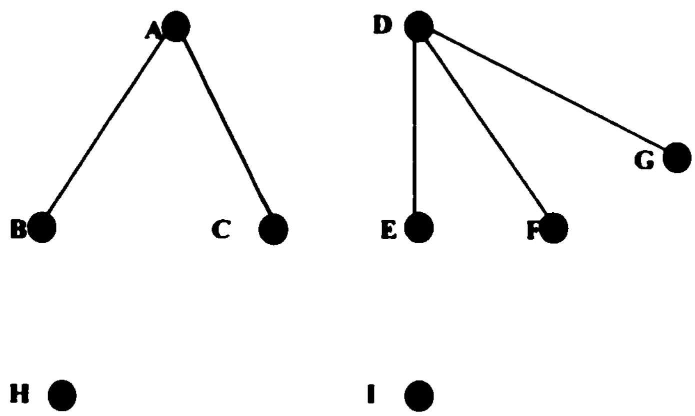
b) Circle Network



c) Star Network

Appendinx III

FIGURE 3: REGULAR EQUIVALENCE



Appendix IV

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		
Betweeness 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**
n=38					
*p<.05					
**p<.01					

Number of R&D projects					
Variable	1	2	3	4	5
Age	-0.245	-0.265	-0.251	-0.233	-0.271
Size	0.161	0.21	0.171	0.158	0.209
Permanent R&D	0.05	0.162	0.077	0.078	0.165
Degree Centrality		-0.298			
Closeness Centrality			-0.103		
Betweeness Centrality				-0.166	
Eigenvector Centrality					-0.31
R^2	0.036	0.11	0.046	0.063	0.117
ΔR^2		0.074	0.01	0.027	0.08
ΔF		2.738	0.339	0.934	3.003
n=38					
*p<.05					
**p<.01					

Appendix V

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		
Betweeness 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
n=28					
*p<.05					
**p<.01					
^p<.06					

Likelihood of Increased Speed of Innovation					
Variable	1	2	3	4	5
Age	-0.014	-0.035	-0.009	-0.016	-0.043
Size	0.015	0.031	0.02	0.016	0.037
Permanent R&D	-0.769	-0.144	-0.715	-0.731	-0.025
Degree Centrality		0.025			
Closeness Centrality			0.792		
Betweeness Centrality				0.031	
Eigenvector Centrality					0.067
Nagelkerke R^2	0.146	0.258	0.447	0.147	0.278
ΔR^2		0.112	0.301	0.001	0.132
-2 Log Likelihood	32.077	29.46	24.379	32.051	28.96
n=28					
*p<.05					
**p<.01					

Appendix VI

Results of Hierarchical QAP Regression: Effect of Regular Equivalence

Strategic Direction		
Variable	1	2
Age	0.051	0.048
Size	0.076	0.069
Permanent R&D	.088	0.041
Both Don't R&D	.107	0.079
Regular Equivalence		0.132*
R^2	0.013	0.03
ΔR^2		0.017
n=38		
*p<.05		
**p<.01		

Appendix VII

Multi-Collinearity of Centrality Variables

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-6.165E-02	.307		-.201	.842					
	Age	2.832E-02	.012	.442	2.356	.024	.436	.375	.335	.573	1.744
	NoEmpl.	-2.475E-04	.001	-.073	-.386	.702	.271	-.066	-.055	.567	1.762
	InternalRD	.886	.359	.355	2.471	.019	.396	.390	.351	.975	1.025
2	(Constant)	-.422	.544		-.775	.445					
	Age	3.071E-02	.011	.479	2.758	.010	.436	.450	.357	.554	1.805
	NoEmpl.	-6.703E-04	.001	-.197	-1.084	.287	.271	-.194	-.140	.505	1.982
	InternalRD	.377	.371	.151	1.016	.318	.396	.182	.131	.756	1.323
	Degree	7.531E-02	.050	2.059	1.503	.143	.528	.265	.194	.009	112.207
	Closeness	-1.390E-02	.049	-.052	-.286	.777	.328	-.052	-.037	.505	1.982
	Betweeness	-.150	.178	-.254	-.845	.405	.397	-.152	-.109	.184	5.425
	Eigenvector	-.117	.098	-1.375	-1.186	.245	.499	-.212	-.153	.012	80.353

a Dependent Variable: Innovation

APPENDIX VIII

Bivariate Correlations of Linear Regression Variables											
Variable	Mean	s.d.	1	2	3	4	5	6	7	8	9
1. Degree	43.10	32.11									
2. Closeness	13.72	4.40	.612**								
3. Betweeness	1.21	1.99	.794**	0.314							
4. Eigenvector	18.44	13.83	.990**	.607**	.743**						
5. Innovation	0.84	1.17	.528**	.328*	.397*	.499**					
6. No.Projects	3.26	2.68	-0.22	-0.07	-0.162	-0.229	-0.218				
7. Age	11.33	18.33	0.083	0.027	0.077	0.06	.436**	-0.1			
8. NoEmpl.	94.72	345.98	0.177	0.092	0.05	0.157	0.271	0.01	.653**		
9. InternalRD	0.68	0.47	.393*	0.269	0.172	.387*	.396*	0.05	0.12	0.155	
10. Strategic Intent	3.47	1.22	0.046	-0.14	0.043	0.045	-0.191	0.11	-0.2	-0.094	0.13
n=38											
*p<.05											
**p<.01											

Bivariate Correlations of Logistic Regression Variables										
Variable	Mean	s.d.	1	2	3	4	5	6	7	8
1. Degree	45.37	33.41								
2. Closeness	14.06	4.06	0.575**							
3. Betweeness	1.44	2.25	0.880**	0.31						
4. Eigenvector	19.23	14.10	0.990**	0.567**	.773**					
5. Age	12.86	20.77	0.12	0.08	0.07	0.10				
6. Size	121.93	401.00	0.19	0.12	0.03	0.18	0.653**			
7. Internal R&D	0.71	0.46	0.32	0.07	0.15	0.32	0.14	0.18		
8. Increased speed	0.68	0.48	0.33	0.520**	0.05	0.35	0.17	0.19	0.24	
9. Access to Know	0.82	0.39	0.44	0.742**	0.14	0.439*	0.14	0.13	0.32	0.478*
n=28										
*p<.05										
**p<.01										

Appendix IX

Bivariate Correlations of Dyadic Level Variables							
Variable	Mean	s.d.	1	2	3	4	5
1. Regular Equiv.	0.69	0.39					
2 .Age	14.46	21.49	0.065				
3. Size	168.59	459.3	0.077*	0.612**			
4. Internal R&D	0.56	0.50	0.149*	0.07	0.071		
5. Both Don't R&D	0.25	0.46	-0.149*	-0.07	-0.071	-1	
6. Strategic Direct	0.44	0.50	0.135*	0.096	0.106	0.267	0.011
n=38							
*p<.05							
**p<.01							