The exploration of novel technologies in biotechnology through alliance networks

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ABSTRACT

Researchers agree that alliance networks can be an important instrument in a firm's innovation process, but there is limited empirical evidence on actually how they facilitate the creation of new knowledge for exploratory innovation. The research question is what alliance network configuration is optimal for exploratory innovation. To tackle this question this paper regresses the number of exploratory patents filed by 455 dedicated biotechnology firms (DBFs) in 1986-1999, over different measures of DBFs' alliance network configuration. The overall network comprised of 2933 technical alliances over the same period. Network measures included firms' degree centrality, firms' reach centrality, firms' structural holes, overall network density, overall network clustering, as well as control variables. The results show that reach centrality and overall network density affect exploratory innovation in a curvilinear fashion. The results indicate that, in the case of the biotechnology industry, small-world network connectivity is optimal for the circulation of exploratory knowledge that can be recombined into innovative products.

Keywords: alliance network, patents, exploratory innovation, network structure, social capital

Introduction

Exploratory innovation embodies knowledge that differs from knowledge used by the firm in prior innovations and indicates that the firm has broadened its technical competence (Greve, 2007; Rosenkopf & Nerkar, 2001). It requires the creation of technological knowledge that falls outside a firm's existing know-how, even though this knowledge may have been in existence earlier elsewhere. Often, firms enter strategic alliances to access external knowledge that is incapable of being transferred across organizational boundaries through other means (Hagedoorn, 1995; Ahuja, 2000a). As firms in an industry form alliances over time they build up individual alliance portfolios, and collectively these portfolios define the industry alliance network – a set of firms and the alliances between them (Gulati & Gargiulo, 1999). Researchers have posited that firms that have greater access to and understanding of resources through their alliance portfolio should have an advantage in innovation (e.g. Ahuja, 2000b; Oliver, 2001; Zaheer and Bell, 2005). Accordingly, researchers have become increasingly interested in understanding when and how alliances affect firm learning and knowledge creation. Research that examines the influence of networks on innovation has revealed two competing perspectives, each with different causal mechanisms linking network structure to innovation. One view argues that disconnected networks increase creativity and innovation because they provide firms with timely access to diverse information (Burt, 1992; 2004). An alternative view suggests that dense networks are beneficial because they generate trust and reciprocity norms, which increase cooperation and knowledge sharing (Coleman, 1988; Portes, 1998). Research has found support for both views, yielding conflicting results. While studies have found that alliance portfolio closure improves knowledge transfer and innovation (Ahuja, 2000b; Schilling and Phelps, 2007), other research suggests that structural holes in a firm's alliance portfolio structure enhance its knowledge creation (Hargadon and Sutton, 1997; McEvily and Zaheer, 1999).

Moreover, extant research has focused mostly on the amount of innovation produced by firms, and not on the novelty of knowledge created. While some research suggests that firms typically pursue local search and produce exploitative innovations (e.g., Dosi, 1988; Martin & Mitchell, 1998), other research shows that firms vary in the scope of their search and the exploratory content of their innovations (Ahuja & Lampert, 2001; Rosenkopf & Nerkar, 2001). While exploitation improves an organization's short-term performance, exploration increases its long-term adaptability and survival (Levinthal & March, 1993). Moreover, while research often portrays exploration as a process (March, 1991), the manifestation of this process can be observed by examining the exploratory content of a firm's innovations (Benner & Tushman, 2002; Rosenkopf & Nerkar, 2001). A recent paper by Gilsing et al. (2008) investigated the role of an alliance network on exploratory innovation in terms of the technological distance between partners, a firm's network position (centrality) and total network density on a firm's exploratory innovation, but not the effect of other characteristics of a firm's alliance network structure, such as structural holes, number of direct ties, as well as other network macrostructure, such as clustering. There is limited empirical evidence on how alliance networks facilitate the creation of new knowledge for exploratory innovation (Schilling and Phelps, 2007; Lavie and Rosenkopf, 2006). A few studies have examined how organizational design decisions influence exploratory knowledge creation (Jansen et al., 2006; Sigelkow & Rivkin, 2005), but, with the exception of some qualitative case study research (Dittrich, Duysters & de Man, 2007; Gilsing & Noteboom, 2006), research has generally ignored the effects of alliance network structure on exploratory innovation. There is therefore a research opportunity that this paper addresses to test both views on the causal mechanisms linking network structure to exploratory innovation. To this effect, this study uses Walker's (2005) taxonomy of networks as local neighborhood and networks as macrostructure to examine the different theories of how a firm's alliance portfolio structure may influence its exploratory innovation output.

Alliances and exploratory innovation

Innovation is conceptualized as a problem-solving process in which solutions are discovered via local and distant search (Dosi, 1988). It is the broadening of a firm's knowledge base and it requires access to new and external sources of knowledge (Nelson and Winter, 1982; March, 1991). Critical inputs into the search process include access to and familiarity with a variety of knowledge elements, novel problems and insights into their resolution, failed innovation efforts, and successful solutions (Hargadon and Fanelli, 2002). Prior research suggested that search processes that lead to the creation of new knowledge, most often involve the novel recombination of existing elements of knowledge (Fleming, 2001; Nelson and Winter, 1982), or reconfiguring the ways knowledge elements are linked (Henderson and Clark, 1990). Local search, which is synonymous with exploitation, produces recombinations of familiar and well-known knowledge elements, and it is often the preferred mode of search (March, 1991; Stuart & Podolny 1996). In contrast, distant search, or exploration, involves recombinations of novel, unfamiliar knowledge and it involves higher costs and uncertainty (March, 1991). Although distant search can be less efficient and less certain than local search, it increases the variance of search and the potential for highly novel recombinations (Levinthal & March, 1993; Fleming, 2001).

While innovation search research has primarily focused on where firms search for solutions (i.e., local versus distant), the interfirm learning literature has emphasized how firms search. This research argues that strategic alliances are a means of transfer and integration of knowledge that firms do not have (Hamel, 1991). Alliances provide a firm with access to its partners' organizational routines, which reduces its ambiguity about a partner's knowledge and increases the efficacy of its transfer and assimilation (Jensen & Szulanski 2007). Because of the increased social interaction and enhanced incentive alignment and monitoring features they provide, alliances are institutions better suited than market transactions for the repeated exchange of tacit, socially-embedded knowledge (Teece, 1992). Technical innovation, in particular, involves tacit and socially-embedded knowledge (Dosi, 1988), which makes market exchange of that knowledge very problematic (Teece, 1992). To the extent that a firm can increase its access to its partners' knowledge, the motivation of its partners to transfer knowledge, and the efficiency of knowledge exchange and transfer (Inkpen & Tsang, 2005), it will enjoy more fruitfully recombinations (Galunic & Rodan, 1998) and increased potential for innovation (Galunic & Rodan, 1998).

Alliance network as local neighborhood

There is an ongoing debate in the network literature on how network structures facilitate the attainment of desired outcomes for network members. The key question in this debate is whether networks should be sparse (or non-redundant, or open) (Burt, 1992) or dense (or cohesive, or redundant, or closed) (Coleman, 1988). The majority of research on the structure of a firm's local network neighborhood has focused on networks' relative closure (Coleman, 1988). A completely closed network means that all a firm's alliance partners are also partners of each other. A completely open network is one where the partners have no alliances among themselves (Burt, 1992). For most firms, the local neighborhood network structures are somewhere in between these two extremes. To study the role of network structure on exploratory innovation I suggest, in line with Ahuja (2000b), that there are three characteristics of a firm's alliance portfolio that should be analyzed, i.e. (1) its direct ties, (2) its indirect ties, and (3) the degree of redundancy among its ties.

Direct ties

Direct ties may provide two important benefits. Direct ties may hold knowledge that is novel to the firm, or the existing knowledge of a focal firm and that of its partners may be recombined through collaboration, yielding knowledge that is new to the focal firm. In addition, they can serve as a test that enables firms to evaluate the quality and relevance of internally developed expertise (Dyer and Nobeoka, 2000). Alliance partners also provide alternative interpretations of technical problems and solutions, allowing a firm to compare and contrast these perspectives (Nonaka, 1994). A second benefit is that cooperation with direct partners may lead to reduced costs and risks for the firms involved (Ahuja, 2000b). When firms collaborate, the newly created knowledge becomes available to all firms involved. So, when making an investment in R&D a firm can, if collaborating with others, receive more new knowledge in return than in a stand-alone strategy. These benefits are particularly relevant for exploration, i.e. a broadening of a firm's knowledge base that requires access to external sources of knowledge new to the firm (Nelson and Winter, 1982; March, 1991).

Although direct ties have an anticipated positive effect on exploration, increasing the number of direct partners may become counter productive, for two reasons. First, management attention and integration costs may grow exponentially beyond a certain number of alliances (Duysters and de Man, 2003). So, a firm's effectiveness at managing its alliances will decline with the number of alliances it maintains (Deeds and Hill, 1996). Second, one could also argue that collaboration implies the exchange and sharing of a firm's proprietary knowledge, and that it entails risks of free-riding and/or unintended spillovers (Nooteboom, 1999). In this case, the more the partners, the more potential free-riders or spillovers while, at the same time, resources and management time need to be spread over a larger number of ties. Although an exploration strategy is generally interested in novel and diverse inputs in order to keep growth options open, firms in this mode strive to free up time and resources to manage a larger number of alliances to obtain such inputs (Gilsing and Nooteboom, 2005). I thus expect a limit to a firm's effectiveness at managing a large number of alliances that is reflected in the firm's explorative innovation output. Accordingly, I submit that, other things being equal,

> *Hypothesis 1: Exploratory innovation is an inverse-U shaped function of a firm's number of direct ties in its alliance portfolio.*

Indirect ties - Reach

Whereas direct ties serve as sources of both resources and information, indirect ties primarily form a source of information (Ahuja, 2000b), i.e. many indirect ties lead to short average path length (the average number of ties that separates each pair of firms in the network) which increases the speed of information diffusion (Watts, 1999). First, a focal firm's direct partners gain specific knowledge and experience from collaboration with their alliance partners (Gulati and Gargiulo, 1999; Ahuja, 2000b). Second, the focal firm can receive, through indirect ties, information about ongoing innovation projects in different parts of the network, far beyond its direct reach (Ahuja, 2000b). I expect the role of indirect ties to be very important for exploration, as information from an indirect tie reaching the focal firm is more likely to contain novel information. Moreover, the search function of indirect ties seems to be rather useful for exploration because it yields a broader range of novel information and opportunities (March, 1991). However, information from indirect ties may not be perfect as it passes through common partners, who may interpret it in a different way than the focal firm would do. In this process, some of the fine-grained details may be lost and not reach the focal firm or lead to misunderstandings. Thus, costs may occur from the efforts of transfering complex knowledge to recipients (Kogut and Zander, 1993: 629-630). One could also argue that the exchange and sharing of a firm's proprietary knowledge through indirect ties entails a risk of free-riding or unintended spillovers (Nooteboom, 1999). For exploration both these risks may be serious, as the focus is on gathering specific information on novel issues. Accordingly, I submit that, other things being equal, *Hypothesis 2: Exploratory innovation is an inverse-U shaped function of a focal firm's alliance portfolio average path length.*

Structural holes between non-redundant ties

Burt (1992) introduced the structural holes argument, which is concerned with the notion of redundancy, meaning that a firm's network has redundancy to the extent that its partners are connected to each other as well. Firms bridging structural holes act as brokers and it has been frequently shown to perform better than other actors not so positioned (Burt, 1992; McEvily and Zaheer, 1999). The underlying mechanism posited by Burt is that actors in a network rich in structural holes will be able to access novel information from unconnected parts of the network. This promotes diversity, defined as the extent to which a system consists of uniquely different elements, the frequency distribution of these elements, and the degree of difference among the elements (Stirling, 2007). Because exploratory innovations embody relatively novel knowledge, a necessary condition for firm exploratory innovation is access to dissimilar knowledge (Greve 2007, Jansen et al. 2006). As Uzzi and Spiro (2005) noted, bridges between unconnected parts of networks increase the likelihood that different ideas and routines come into contact. Because knowledge is developed partially through firm interaction (Nahapiet and Ghoshal, 1998), actors who bridge structural holes will be able to develop new understandings, not possible to those who do not bridge holes. By searching diverse and novel domains, firms can develop multiple conceptualizations of problems and solutions and apply solutions from one domain to problems in another (Hargadon & Sutton, 1997), thus stimulating intensive experimentation of new combinations, leading to highly novel innovations (Ahuja & Lampert, 2001; Fleming, 2001). This type of networking can also serve as a screening device (Leonard-Barton, 1984) that allows for relevant developments in different technologies to be brought to the firm's attention, in which case the firm has an opportunity to put technologies into novel combinations that enable it to provide unique offerings to the market (Koka and Prescott, 2008). Moreover, because maintaining ties to many other actors is costly, firms can use bridges of structural holes to maximize the efficiency of their overall network ties, thus conserving scarce management attention (Yamaguchi, 1994; Rowley et al., 2000; Gnyawali and Madhavan, 2001; Hagedoorn and Duysters, 2002). These arguments lead to the conclusion that there is probably a positive relationship between a focal firm's ability to span structural holes in the alliance network and exploratory innovation, due to enhanced efficiency, better access to resources and information, and better identification of emerging opportunities.

However, searching through structural holes comes at a price and bears certain risks. Ahuja (2000b) tested the extent to which a firm's innovative output was influenced by the structural holes it spanned and found a negative relationship - spanning structural holes actually resulted in fewer patents. A consequence of having access to many non-redundant ties is that firms have to deal with a higher volume of more diverse information that arrives at faster rates when compared with firms that have fewer structural holes in their alliance portfolio (Gnyawali and Madhavan, 2001). A firm must then expend greater effort and resources to understand and integrate dissimilar knowledge (Cohen and Levinthal, 1990). Attempting to assimilate and integrate highly diverse knowledge can lead to information overload, confusion and diseconomies of scale in innovation effort (Ahuja and Lampert, 2001). Second, a sole focus on searching for novelty through structural holes may result in a random drift so that a firm's knowledge base changes continuously in different and unrelated directions, making the accessed novel knowledge difficult to absorb and integrate (Ahuja and Katila, 2004). This can manifest in costly, excessive and inconclusive experimentation (Ahuja and Lampert, 2001). So, while increasing diversity exponentially increases opportunities for novel recombinations (Fleming, 2001), as knowledge components become more diverse, research shows the chance of their recombination into useful innovations declines, with excessive diversity reducing innovation (Fleming & Sorenson 2001). Accordingly, I submit that, other things being equal,

Hypothesis 3: Exploratory innovation is an inverse-U shaped function of a firm's number of structural holes in its alliance portfolio.

Alliance Network as Macrostructure

Density

A key factor enhancing the firm's ability to utilize and benefit from externally acquired knowledge is its absorptive capacity (Zahra and George, 2002). If a firm is not able to understand novel information from a given source adequately, it may need another partner to complement its absorptive capacity (Gilsing and Nooteboom, 2005). The often noncodifiable and experimental nature of exploration increases the difficulty of firms to recognize and value the knowledge of potential partners, when they are not connected through a common alliance partner. This connects to the argument from information theory that 'noise' is reduced when accessing multiple and redundant contacts (Rowley et al., 2000). In dense networks, firms may be able to develop a richer understanding and a better evaluation and transfer of noncodifiable new knowledge (Rowley et al., 2000), because their ties can enhance their absorptive capacity by acting as a device for screening and interpreting novel information on its potential relevance (Leonard-Barton, 1984; Vanhaverbeke et al., 2008). In addition, a dense network of ties also facilitates the build-up of trust and reputation to constrain opportunism (Burt, 2000; Hagedoorn and Duysters, 2002). Dense networks allow firms to learn about current and prospective partners through common third parties, reducing information asymmetries among firms and increasing their "knowledge-based trust" in one another (Gulati et al., 2000). Network closure also promotes trust by increasing the costs of opportunism (Coleman, 1988), because as a firm's behavior is more visible in a dense network, an act of opportunism can damage its reputation, jeopardizing its existing alliances and reducing future alliance opportunities (Gulati, 1998). As a result, firms would be able to make greater relation-specific investments and enjoy reduced costs involved in monitoring their alters (Zaheer and Venkatraman, 1995). Trust reduces the extent to which alliance partners protect knowledge, increases their willingness to share knowledge, and increases interfirm learning and knowledge creation (Kale et al., 2000). Network density also generates reciprocity exchanges in which partners share privileged resources because they expect recipients will repay them with something of equivalent value (Coleman, 1988). Reciprocity norms reinforce this motivation to share since firms can be confident partners will reciprocate (Dyer & Nobeoka, 2000). As a result, the information and know-how shared will be less distorted, richer and of higher quality (Dyer & Nobeoka, 2000; Uzzi, 1997). Research suggests dense interfirm networks are better for transferring and integrating complex and tacit knowledge than networks with structural holes (Dyer & Nobeoka, 2000; Kogut, 2000). Ahuja (2000b) observed that innovative output – in terms of the number of patents granted to the companies – increased with network closure, and attributed this result to superior cooperation among partners induced by trust and the ability to monitor each other engendered by dense networks.

However, high density can have adverse effects on exploratory innovation. The main argument against high density is that it inhibits the existence and utilization of diversity and the potential for creating novel combinations. Previous research indicated that the rate and extent to which information diffuses in the network increases with density (Yamaguchi, 1994), but density also increases the likelihood that knowledge and information reaching a firm through its alliance network also reaches its partners. Such diffusion of novelty throughout the network can put limits on its appropriation and make it less attractive for firms to search for such novelty (Gilsing and Nooteboom 2005). Another argument against high density is that there are costs associated with establishing and maintaining contacts and that by shedding redundant ties, firms can create efficiency in their network (Burt, 1992). However, in exploration such costs of redundancy play a limited role as the key focus here is on finding and absorbing novelty, making considerations of efficiency less of an issue (Hagedoorn and Duysters, 2002; Gilsing and Nooteboom, 2005). A final argument against high density is that it creates strong behavioral pressures to conform rather than to be radically different (Kraatz, 1998). In this case, firms may also be pre-empted from entering into new, more innovative relationships, as the implicit expectation of loyalty to their existing partners and network may inhibit them from allying with others (Nooteboom, 1999; Gulati et al., 2000). Accordingly, I submit that, other things being equal,

> *Hypothesis 4: Exploratory innovation is an inverse-U shaped function of the overall alliance network density.*

Clustering

As the overall size of a network increases, it is possible that fully connected network subgroups called clusters emerge (e.g. Walker, Kogut and Shan, 1997). Clusters form because firms find it more difficult to interact with every other actor and instead they tend to interact with firms that they perceive to be similar (Brass, Butterfield and Skaggs, 1998). A firm's clustering coefficient can be calculated as the proportion of its partners that are themselves directly linked to each other. The clustering coefficient of the overall network is the average of this measure across all firms in the network. Clustering increases the information transmission capacity of a network. First, the dense connectivity of individual clusters ensures that information introduced into a cluster will quickly reach other firms in the cluster. The multiple pathways between firms within clusters also enhance the fidelity of the information received. Second, clusters within networks are important structures for making information exchange meaningful and useful. The internal density of a cluster can increase the dissemination of alternative interpretations of problems and their potential solutions, deepening the collective's understanding and stimulating collective problem solving (Powell and Smith-Doerr, 1994) and learning (Powell et al., 1996). Third, a focal firm that is embedded in many clusters will have richer reciprocal knowledge with cluster members – that is knowledge of each other's resources, technical know-how, design competencies, and organizational routines, and long-term objectives (Capaldo, 2007). Moreover, trust developed within stable clusters can be high, and previous research suggested that when trust is high partners refrain from instituting controls over knowledge spillovers to competitors (Dyer and Singh, 1998; Inkpen and Tsang, 2005: 158). Dense clustering can then make firms more willing and able to exchange information (Ahuja, 2000a), acquire and exploit resources and knowledge that results in increased efficiency and productivity (Levinthal and March, 1993). In this case, the rationale for teaming up is formed by possibilities to obtain complementary know-how (Burgers, Hill and Kim, 1993) and to reduce the time span of innovation (Hagedoorn, 1995) in an effort to compete more effectively. These arguments apply especially to exploration in view of the uncertainty surrounding it, which limits options for governance by formal contracts (Nooteboom, 1999).

Let us now turn to the arguments against high clustering. One argument is that high clustering entails many redundant paths to the same actors. In this case, the information and knowledge shared within the network become increasingly homogeneous and redundant (Burt, 1992), which inevitably reduces diversity and opportunities for novel combinations (Uzzi and Spiro, 2005). This is a serious constraint when it comes to exploratory innovation. A second argument against clustering is that it can create strong social norms that encourage compliance to local rules and customs leading to a reduced need for formal controls (e.g. Portes, 1998). Norms of adhering to established standards and conventions can facilitate effective suctions and potentially stifle creativity and innovation (Uzzi and Spiro, 2005; Florida, Cushing and Gates, 2004). This however can be a problem when competitive conditions change, and firms need to access new and different information and resources from outside their local network (Granovetter, 1973). Accordingly, I submit that, other things being equal,

> *Hypothesis 5: Exploratory innovation is an inverse-U shaped function of the degree of overall alliance network clustering.*

Research Methodology

Research Setting and Alliance Network Data

I tested the hypotheses using a large sample of strategic alliance agreements by dedicated biotechnology firms (DBFs) in 1986-1999. As I was interested in technical knowledge diffusion I used only alliances with the purpose of technology licensing, research and/or development and/or commercialization, thus excluding marketing and distribution alliances. Alliance data were gathered using the Historical Actions Database by BioAbility.com. I had data on 2933 alliances by 455 DBFs during 1986-1999. I did control for different types of technology-related alliances (e.g. licensing, R&D etc.), by coding the data according to the strength of ties between partners on a 4-point scale, with 1 indicating a licensing deal, 2 a deal mainly focused on research, 3 a deal mainly focused on development, and 4 a deal that included R&D and commercialization. Finally, I constructed alliance networks for each year of observation between 1986 and 1999, resulting in 19 alliance network snapshots. Each network snapshot was constructed as an undirected valued adjacency matrix (Wasserman and Faust, 1994). Where pairs of partners had multiple alliances with each other in a year, I added the individual scores of each alliance to form a composite index. UCINET 6 was used to obtain measures on these networks, as described below (Borgatti et al., 2002).

Measures

Dependent variable. Patent counts have been shown to correlate well with new product introductions and invention counts (Basberg, 1987). Technological profiles of all focal companies were computed to find out whether new patents in a year of observation could be categorized as 'explorative.' These technological profiles were created by adding up the number of patents a firm received in each patent class during the 5 years prior to the year of observation. Classes in which a company receives a patent in the year of observation but had not received a patent in the previous 5 years were considered 'explorative' patent classes. I chose the year when the company filed for the patent rather than the year when it was granted, because the innovation in the company already has been realized when the company files for a patent. Since knowledge remains relatively new and unexplored for a firm immediately after patenting, patent classes kept their explorative 'status' for three consecutive years, parallel to Ahuja and Lampert's (2001) concept of novel and emerging technologies. The dependent variable, *New_Patents,* is a count variable of the number of patents a firm filed for in a particular year in patent classes in which it has not issued patents during the past 5 years. Granted patents were counted in their year of application. I used the Delphion.com database to collect yearly patent counts for each DBF, aggregating subsidiary patents up to the ultimate parent level. Yearly patent counts were created for each firm for the period of 1986 to 1999, enabling the assessment of different lag specifications between alliance network structure and patent output. Moreover, as the propensity to patent may differ due to firm characteristics (Griliches, 1990), I attempted to control for such sources of heterogeneity using the control variable *Presample_Patents* (described below) and firm fixed effects in the estimations.

Direct ties. Social network researchers measure network activity for a node by using the concept of degrees - the number of direct connections a node has. In addition in this case the data is valued so the degrees will consist of the sums of the values of the ties, which constitutes the variable *Degree_C* (Borgatti, Everett and Freeman, 2002). The normalized degree centrality is the degree divided by the maximum possible degree expressed as a percentage but it is inappropriate in our case as it should only be used for binary data.

Indirect ties. I used the measure *Reach_C* which counts the number of nodes each node can reach in k or less steps. The routine Network>Centrality>Reach Centrality in UCINET (Borgatti, Everett and Freeman, 2002) calculates this measure, which reflects how close each actor is to all others. When searching for key individuals who are well positioned to reach many people in a few number of steps, this measure provides a natural metric for assessing each node.

Structural holes. I assessed the presence or absence of structural holes in the overall network of ties among firms. I measured structural holes as constraint using the 'Network> Ego Network> Structural Holes' routine in UCINET (Borgatti, Everett and Freeman, 2002). According to Burt, network constraint effectively measures a firm's lack of access to structural holes (Burt, 1992). I calculated the variable *Hole_Access* as one minus the firm's constraint score (in cases where constraint was non-zero) and zero for all other cases, because a score of zero in the network arose only when the firm was unconnected to others, so had no access to structural holes.

Density. I used the variable *Net_Density* to measure the overall network density, calculated for each time period. This variable measures the ratio of existing links in the network to the number of possible pairwise combinations of firms, with larger values indicating increasing density. For the valued networks used in this analysis it is the total of all values divided by the number of possible ties. In this case the density gives the average value (Borgatti, Everett and Freeman, 2002).

Clustering. The variable *Net_Cluster_Coef* was calculated for each network as the weighted mean of the clustering coefficient of all actors, each weighted by its degree, which gives the density of transitive triples in a network. I used the procedure Network>Properties>Clustering Coefficient in UCINET (Borgatti, Everett and Freeman, 2002).

Control variables. To control for unobserved heterogeneity in firm partnering, I followed the presample information approach of Blundell et al. (1995) and calculated the variable *Presample_Patents* as the sum of patents obtained by a firm in the 5 years prior to its entry into the sample (I had data since 1980). Additionally, the extent to which a network is centralized can also influence its diffusion properties, so the control variable *Net_Centralization* was introduced. A highly centralized network is one in which all ties run through one or a few nodes, thus decreasing the distance between any pair of nodes (Wasserman and Faust, 1994). To control for network centralization, I employed Freeman's (1979) index of group betweeness centralization, calculated for each time period. Finally I introduced the dummy variable *Country* to control for the country of origin of each firm in the sample (although the vast majority were US firms).

Analysis

The dependent variable, *New_Patents*, is a count variable and takes on only nonnegative integer values. A linear regression model would be inadequate for modeling such variables because the distribution of residuals is heteroscedastic nonnormal. A Poisson regression approach provides a natural baseline model for count data (Hausman et al., 1984; Henderson and Cockburn, 1996). A commonly used alternative to the Poisson regression model is the negative binomial model. The negative binomial model is a generalization of the Poisson model and allows for heterogeneity by incorporating an individual, unobserved effect into the conditional mean (Hausman et al., 1984). I used the Hausman et al. (1984) panel data implementation of fixed effects in the context of a negative binomial model to account for unobserved heterogeneity. (Deviance/Degree of Freedom ~ 0.915 was typical of the models, which suggests no evidence of overdispersion). In the present study, unobserved heterogeneity refers to the possibility that unmeasured differences among observationally equivalent firms affect their patenting. Moreover, I ruled out concerns of potential autocorrelations in the data by ensuring that the findings were insensitive to the incorporation of first-order autoregressive errors generated by an AR(1) process. A final estimation issue concerns the appropriate lag structure of the independent variables. Based on prior research that investigates the relationship between interfirm alliances and innovation (e.g. Ahuja, 2000b, Sampson, 2004), I employed one and two year lags of the independent variables relative to the dependent variable, to explore the robustness of the findings. All models were estimated with SAS 8.02.

Results

Table 1 reports descriptive statistics and correlations, and Table 2 reports the results of the analysis of the panel data. Table 1 reveals low correlations amongst variables, except in the case of *Degree_C* and *Hole_Access*. This can be an indication that multicollinearity is present, sometimes resulting in the signs of estimated coefficients to flip (Gujarati, 1995), so I decided to test these variables separately, as well as together in a 'full' model. All the models shown in Table 2 were significant compared to the null model (chi-square test). Models I, II, II report the results using a one-year lag between the independent variables and firm patenting, and Models IV, V, VI report results using a two-year lag. Models II and VI are the complete models, Models I and IV exclude *Reach_C,* and Models II and V exclude *Hole_Access,* in order to check for multicollliniearity effects. In Models II, III, V, VI, the coefficient for *Reach_C* is positive and statistically significant and the coefficient for *Reach_C*^{2} is negative and statistically significant, and together they support Hypothesis 2. In all the models the coefficient for *Net_Density* is positive and statistically significant and the coefficient for *Net_Density*^{2} is negative and statistically significant, and together they support Hypothesis 4. Models I and VI indicate that the coefficient for *Hole_Access* is statistically significant but inconsistent in terms of sign, and inconsistent in terms of significance with the other models. The coefficient for *Net_Cluster_Coef*^{2} is statistically significant in Model I but this result was not confirmed by other models. Thus, Hypotheses 1, 3 and 6 were rejected, as the corresponding coefficients were not consistently statistically significant. The coefficient for control variables *Net_Centralization* and *Presample_Patents* are positive and significant in all models, and the control *Country* is statistically insignificant in all models.

Discussion

Understanding the origins of exploratory innovation is an important endeavor. Because the results of exploration typically take longer to realize, are more variable and produce lower average returns, organizations generally pursue exploitative innovation at the expense of explorative innovation (March, 1991). This presents a fundamental challenge to all organizations: while exploitation improves an organization's short-term performance, exploration increases its long-term adaptability and survival (Levinthal & March, 1993). While research has documented the propensity of firms to pursue local search and exploitative innovation (e.g., Dosi, 1988), we know much less about how and when firms overcome this predisposition and develop exploratory innovations. Explaining how firms develop exploratory innovations *effectively* will provide a better understanding of how organizations are able to thrive and survive. The results indicate that reach centrality is significant for exploratory innovation, i.e. a firm that is connected to a large number of firms by a short average path can reach more information, and can do so quickly and with less risk of information distortion than a firm that is connected to fewer firms or by longer paths. However, information from indirect ties may not be perfect as it passes through a common partner, who may interpret it in a different way than the focal firm would do. In this process, some of the fine-grained details may be lost and not reach the focal firm or lead to misunderstandings. One could also argue that the exchange and sharing of a firm's proprietary knowledge through indirect ties entails a risk of free-riding or of unintended spillovers (Nooteboom, 2000). For exploration both these risks seem to be serious as the focus is on gathering specific information on novel issues.

The concepts of density and centralization were used as complementary measures of 'compactness' of the network. The results also indicate that density seems to have a positive effect on exploratory innovation because it can affect a firm's absorptive capacity - the capability to develop, understand, or use knowledge (Cohen and Levinthal, 1990). This is the case particularly when engaging in exploration, where new and distant knowledge is accessed, dominant designs and standards may be lacking, and formal contracts are a limited option (Nooteboom, 1999). On the other hand, the results suggest that high density can inhibit the existence and utilization of diversity as knowledge diffuses evenly through the network, and thus reduce the potential for creating novel combinations. Such diffusion of novelty throughout the network can put limits on its appropriation and make it less attractive for firms to search for such novelty (Gilsing and Nooteboom, 2005). Moreover, the coefficient for *Net_Centralization* was found to be positive and significant indicating that when the network is organized around its most central points, exploratory innovation is assisted. The control variable, *Presample_Patents,* was also consistently significant and seems to have a positive effect on exploratory innovation. It seems that prior experience in patenting plays a positive role in explaining current exploratory patent output. The results indicate that firms with high exploratory innovation output have short path access to many other firms and operate in dense and centralized technology-based alliance networks, where the rate and extent to knowledge that diffuses is high (Yamaguchi, 1994). These results are consistent Uzzi and Spiro (2005) who argued that the density and connectivity of a small-world network enable the circulation of creative material that can be recombined into new creative products. However, as in Uzzi and Spiro (2005), our networks become sufficiently dense that it leads to excessive cohesion and eventual decline of creative performance (curvilinear effect). The study did not find any significant relation between direct ties or structural holes and exploratory innovation. It seems that the best way for a company to 'cast its net widely' in order to reach new technological fields is through intermediaries, and that the more experience a firm has in patenting the more it will be able to produce exploratory innovation patents.

This study has it limitations that can be explored in future research. Although I take into account the type of alliances themselves (and, implicitly, the associated benefits and costs associated with each type) when building valued network matrices, the findings may be influenced by the fact that I do not make an assumption of average alliance duration. If alliances endure, on average, for three years, then the connectivity of the networks will be biased upwards and this can influence the results. Another limitation is that I cannot make any estimation about the generalizability of the findings outside the field of biotechnology. The only comment I can make is that the results are likely to be limited to industries that make frequent use of alliances, as networks characterized by extreme scarcity may not have a sufficient degree of connectedness to calculate meaningful network measures. Furthermore, exploration has been operationalized in different ways in the literature. The definition used in this study as exploration being determined in terms of entering new patent classes is contrasted with defining it in terms of citations to a firm's prior patents in new, successfully applied patents (Rothaermel and Deeds, 2004). As firms may patent in a different patent class while they still cite their prior patents, or firms may apply for patents within the range of patent classes in which they are active without any reference to their prior patent stock, future research should combine the two measures to get a more detailed measurement of exploration.

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Table 1. Descriptive statistics correlations

		Mean	Std Dev	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	New_Patents	0.741	3.425	0	17	1	0.032**	0.011	0.170**	0.184**	0.159**	0.187**	-0.018	-0.015	0.009	0.006	0.059**	-0.003	0.720**
2	Degree_C	1.212	5.129	0	83		1	0.878**	0.113**	0.121**	0.080**	0.093**	-0.126**	-0.109**	-0.025*	-0.037**	0.234**	-0.033**	-0.002
3	Degree_C^2	27.778	236.49	0	6889			1	0.103**	0.109**	0.072**	0.081**	-0.075**	-0.060**	-0.014	-0.023	0.181**	-0.024*	-0.005
4	Reach_C	0.013	0.043	0	0.377				1	0.942**	0.861**	0.873**	-0.132**	-0.109**	-0.072**	-0.084**	0.329**	-0.010	0.108**
5	Reach_C^2	0.002	0.010	0	0.142					1	0.807**	0.878**	-0.117**	-0.094**	-0.056**	-0.069**	0.333**	-0.008	0.089**
6	Hole_Access	0.031	0.133	-0.531	0.891						1	0.934**	-0.132**	-0.112**	-0.058**	-0.069**	0.254**	-0.007	0.109**
7	Hole_Access^2	0.018	0.085	0	0.793							1	-0.123**	-0.103**	-0.044**	-0.055**	0.258**	-0.002	0.120**
8	Net_Density	0.040	0.022	0.024	0.105								1	0.979**	0.342**	0.385**	-0.358**	0	0
9	Net_Density^2	0.002	0.002	0.001	0.012									1	0.417**	0.467**	-0.300**	0	0
10	Net_Cluster_Coef	1.734	0.363	1.091	2.33										1	0.994**	-0.341**	0	0
11	Net_Cluster_Coef^2	3.139	1.233	1.190	5.428											1	-0.359**	0	0
12	Net_Centralization	0.020	0.031	0	0.106												1	0	0
13	Country	1.270	0.819	1	5													1	-0.002
14	Presample_Patents	0.764	3.332	0	47														1

** - $p < 0.01$; * - $p < 0.05$

Table 2. Panel negative binomial regression models with one- and two-year lag (Number of firms=455; Obs=2113)

Dependent Variable:	***Model I*** ***New_Patents$_{it+1}$***	***Model II*** ***New_Patents$_{it+1}$***	***Mode III*** ***New_Patents$_{it+1}$***	***Model IV*** ***New_Patents$_{it+2}$***	***Model V*** ***New_Patents$_{it+2}$***	***Mode VI*** ***New_Patents$_{it+2}$***
Constant	-2.167** (0.732)	-2.401** (0.735)	-2.850** (0.729)	-2.556** (0.782)	-2.704** (0.783)	-2.7722** (0.783)
Degree_C	0.001 (0.011)	0.003 (0.011)	0.008 (0.010)	-0.017 (0.012)	-0.016 (0.012)	-0.0162 (0.012)
Degree_C^2	0.000 (0.000)	0.000 (0.000)	-0.0001 (0.0002)	0.000 (0.000)	0.000 (0.000)	0.0002 (0.0002)
Reach_C	-	10.971** (1.565)	10.970* (1.907)	-	8.962** (1.668)	10.967** (2.011)
Reach_C^2	-	-33.229** (6.336)	-37.872** (7.711)	-	-29.40** (6.839)	-36.441** (8.129)
Hole_Access	1.420** (0.543)	-	-0.374 (0.589)	0.3628 (0.518)	-	-1.1668* (0.586)
Hole_Access^2	-0.749 (0.846)	-	1.072 (1.010)	0.2162 (0.812)	-	1.5523 (1.028)
Net_Density	44.993** (10.287)	42.309** (10.271)	40.820** (10.159)	51.471** (19.562)	48.92** (19.544)	49.012* (19.54)
Net_Density^2	-428.362** (88.422)	-405.203** (88.292)	-394.870** (87.282)	-668.30** (212.807)	-641.22** (212.60)	-645.12** (212.703)
Net_Cluster_Coef	-1.357 (1.051)	-1.059 (1.051)	-1.110 (1.041)	-0.369 (0.961)	-0.184 (0.961)	-0.091 (0.961)
Net_Cluster_Coef^2	0.642** (0.327)	0.556 (0.327)	0.578 (0.324)	0.313 (0.298)	0.260 (0.297)	0.231 (0.297)
Net_Centralization	8.168** (1.269)	7.747** (1.283)	7.810** (1.272)	3.148** (1.292)	2.766* (1.308)	2.747* (1.310)
Country	-0.035 (0.035)	-0.034 (0.035)	-0.036 (0.034)	-0.039 (0.035)	-0.038 (0.035)	-0.0401 (0.035)
Presample_Patents	0.373** (0.012)	0.367** (0.011)	0.328** (0.010)	0.374** (0.012)	0.368** (0.012)	0.367** (0.012)
Log Likelihood	782.407**	798.823**	799.437**	884.634**	897.382**	890.419**

Standard errors in parentheses
** - p < .01; * - p < .05