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Exploration and Exploitation in Technology-based Alliance Networks

Wim Vanhaverbeke[1], Victor Gilsing[2], Bonnie Beerkens[3] & Geert Duysters[4]

Abstract

Although the literature converges regarding the reasons why and how networks of technology alliances are formed, there is still lack of agreement on what constitutes an optimal network structure, once it has been formed. The aim of this paper is to fill this void and to determine what constitutes an optimal network structure for exploration and exploitation within the context of technological innovation. We differentiate among a firm's direct ties, indirect ties and degree of redundancy and analyze their role in the pharmaceutical, chemical and automotive industry. Regarding the role of direct ties, in combination with indirect ties, we find two alternative alliance network structures that are effective for both exploitation and exploration. We also find that redundancy in a firm's alliance network has a positive effect on exploitation. This is not the case for exploration, however, which seems to reveal a new insight into the role of redundancy when firms explore new technological fields. A final point is that our findings remain largely invariant across the three industries, enhancing the generalisability of our results.

Keywords: Networks, Strategic Alliances, Innovation, Learning
JEL classification: 032, 031

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INTRODUCTION

There is an ongoing debate in the network literature on how network structures facilitate the attainment of desired outcomes for its members. The key question in this debate is whether networks should be sparse or dense, or put differently, whether ties should be redundant or non-redundant. In this discussion Burt (1992a) has claimed that firms can reap rents from the absence of ties among its contacts. According to Burt, there are costs associated with maintaining contacts and efficiency can be created in the network by shedding off redundant ties and selectively maintaining only a limited set of ties that bridge 'structural holes'. This view is clearly at odds with the social capital theory of Coleman (1988, 1990), which claims that firms benefit most from cohesive (or redundant) ties with their alliance partners. According to Coleman, density (or 'closure') facilitates the role of social capital such as the build up of reputation, trust, social norms and social control.

In this debate, the empirical evidence is mixed (McEvily and Zaheer, 1999; Ahuja, 2000 ; Walker, Kogut and Shan, 1997). In view of these apparently inconsistent findings, subsequent studies have investigated the role of different environmental conditions that would favor one view over the other (Podolny and Baron 1997; Rowley, et al., 2000; Podolny 2001; Hagedoorn and Duysters, 2002; Gilsing and Nooteboom, 2005). In line with this, we consider an environmental context of technological innovation and study the role of a firm's network of technology-based alliances. More specifically, the main aim of this paper is to improve our current understanding of the effect of the *structure* of this network on a firm's technological innovation performance in terms of exploration and exploitation (March, 1991). In this study, exploration and exploitation have a specific meaning within the context of the development of *technological inventions*: exploration yields inventions in areas that are novel to the firm, exploitation yields inventions in areas with which the firm is intimately familiar. Here, the literature has paid no attention yet to the role of technology-based alliances with regard to these two tasks. Following Ahuja (2000), we argue that there are three characteristics of a firm's technological alliance network that should be analyzed, i.e. (1) its direct ties, (2) its indirect ties and (3) the degree of redundancy among these ties.

In this way, we contribute to the literature along the following lines. First, we study to what extent a firm's alliance network has an impact on exploration and exploitation and if it contributes differently to both tasks. A better understanding of these issues also has practical relevance because it may inform us in how far a firm can use the same ties for both tasks or that, alternatively, each task puts different (and potentially conflicting) requirements on a firm's alliance network. Furthermore, we contribute by elucidating which role redundancy plays in processes of technological collaboration and hence which view, the structural hole theory or the social capital theory, has (more) validity within the context of technological exploitation and exploration. Furthermore, we contribute to the understanding of the relationship between alliance network characteristics and technological innovativeness by questioning the premise of structural exogeneity. Alliance network characteristics cannot be considered as exogenous variables as they are themselves the outcome of prior strategic managerial choices to improve the innovation performance of the focal firm. A final contribution lies in the fact that we study three different industries, i.e. pharmaceuticals, chemicals and automotive. This enhances possibilities for generalization that importantly complements the literature with its dominant focus on single-industry studies (McEvily and Zaheer 1999; Ahuja 2000; Walker et al., 997; Rowley et al., 2000; Hagedoon and Duysters, 2002; Gulati 1995b).

This paper is structured as follows. First, we elaborate our theoretical argument and formulate a number of hypotheses. Second, we present details about the data, the specification of variables, and the estimation method. Next, we present our main findings and a discussion of the results. Finally, we provide the main conclusions and some indications for further research.

THEORETICAL BACKGROUND AND HYPOTHESES

The distinction between exploration and exploitation goes back to Holland (1975) and was later on further developed by March (1991). Exploitation can be characterized as a process of routinized search, which adds to the existing knowledge base and competence set of firms without changing the nature of activities (March, 1991). Exploration is different. It reflects an entrepreneurial search process for opportunities in areas that are new to the company. In other words, exploitation entails the deepening of a firm's core knowledge base, whereas exploration implies its broadening into non-core areas.

Both for exploration and exploitation, a firm's technology alliance network plays an important role since it represents social capital, i.e. access to resources held by partners that complement its in-house capabilities (Coleman, 1988; Burt, 1992a; Rowley et al., 2000). To study this role of social capital further we suggest, in line with Ahuja (2000), that there are three characteristics of a firm's alliance network that should be analyzed, i.e. (1) its direct ties, (2) its indirect ties and (3) the degree of redundancy among these ties. In this analysis, we abstract from the content of the ties that make up a firm's alliance network (Hansen, 1999)[5]. Instead, our focus entails the differential effect of these three characteristics of a firm's alliance network on the outcome of its technological innovation process, entailing both exploitation and exploration. In this way, we study both activities in joint consideration, which is in contrast to previous studies that have considered both tasks separately, as pertaining to different industries (e.g. Rowley et al., 2000), or sequentially (Rothaermel and Deeds, 2004).

Direct ties

[5] Because we focus on technology alliances, we cannot distinguish between alliances that are intended for exploration or for exploitation like other scholars have done in very different empirical settings (Koza and Lewin, 1998; Rothaermel and Deeds, 2004; Faems et al., 2005).

Technology collaboration with direct ties may provide two important benefits vis-à-vis internal development. One is that they provide access to complementary knowledge and skills. This is important as such complementary knowledge can speed up a firm’s innovation process. In addition, it can serve as a test that enables firms to evaluate the quality and relevance of internally developed expertise (Powell and Brantley, 1992; Dyer and Nobeoka, 2000). A second benefit is that cooperation with direct partners may lead to reduced costs and risks for the firms involved (Ahuja, 2000). 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. In other words, R&D investments by its partner(s) may help to increase or speed up a firm's innovative output.

These benefits related to collaboration with direct ties are relevant for both exploration and exploitation. However, we expect that the impact on the former will be relatively stronger. As argued before, exploitation focuses on existing core technologies and to further improve these, a firm will initially focus on its internal competences. In this case, external knowledge and skills of direct ties will only be beneficial in so far these provide expertise that a firm lacks and that forms a prerequisite to realize such improvements or refinements of its core technologies (Rowley et al., 2000). Exploration, in contrast, reflects a broadening of a firm’s knowledge base. This generally requires access to new and external sources of knowledge (Nelson and Winter, 1982; March, 1991). In this case, direct ties may hold knowledge and skills that are novel to the firm. Or, the existing knowledge of a focal firm and that of its partner(s) may be (re)combined through collaboration, yielding knowledge that is new to the focal firm. In other words, the role of direct ties seems to be more important for exploration relative to exploitation.

However, direct ties may pose a threat as well. Collaboration implies the exchange and sharing of a firm’s proprietary knowledge and that entails a risk of freeridership or of unintended spillovers (Nooteboom, 2000). We anticipate this risk to be higher for exploitation than for exploration. Exploitation deals with a firm's existing knowledge core technologies (Rowley et al., 2000) that may form an important source for competitive advantage (Porter, 1985). Such knowledge is not only valuable to the focal firm but potentially also to its alliance partners. Here, not only collaboration with competitors may possibly erode a firm's competitive position, but also collaboration with other economic actors such as suppliers or customers. The latter may credibly threat to vertically integrate or increase their negotiation power due to the leaked knowledge and expertise (Nooteboom, 2000; Gilsing, 2005). The situation is different for exploration as the outcome of the collaboration in this case is formed by novel knowledge that reflects non-core technology to the focal firm. As a consequence, teaming up with companies in order to create such non-core technologies may pose fewer problems than when dealing with its core technologies. Overall, this implies that the benefits of direct ties seem to be relatively larger for exploration than for exploitation, whereas the risks seem to be relatively smaller.

Although direct ties have an anticipated positive effect on both exploitation and exploration, creating more of them will not always be better. Increasing the number of partners may become counter productive, for three reasons. First, a large alliance portfolio creates a risk of dealing with many unfamiliar streams of knowledge that are increasingly difficult to integrate (Ahuja and Katila, 2004). Second, 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). In other words, a firm can start to suffer from information overload and diseconomies of scale. Third, the risk of freeriders or spillovers tends to grow with an increasing number of alliance partners. More partners implies more potential freeriders or 'recipients' of spillovers while, at the same time, resources and management time to monitor this need to be spread over a larger number of partnerships. Because of these three reasons, marginal benefits of additional alliances will decrease whereas marginal costs of adding new alliances will increase (Ahuja, 2000). As a consequence, we expect an inverted-U shape effect of the number of direct ties on both exploration and exploitation. For exploitation, the risk of information overload is more serious because in this case a firm tends to look for more specific, fine-grained information (Rowley et al., 2000). Such information is generally better obtained from one or a few partners with whom the focal firm maintains an open and durable relation with room for sufficient interaction, i.e. forming a 'strong tie' (Granovetter, 1973; Uzzi, 1996; Gilsing and Nooteboom, 2005; Moran, 2005). After having identified such information, it may still be a time and resource consuming process to understand and apply it successfully (Cohen and Levinthal, 1990). Together, these processes consume considerable resources that can then not be allocated for managing a large portfolio of alliances. In addition, we already argued that the risk of freeriders is more serious for exploitation, relative to exploration. The situation for exploration is different. An innovating firm is generally interested in a wider range of novel technologies in order to keep open its growth options for the future. This requires a less intensive relation with partners, conform Granovetter's weak tie argument (1973). This frees up more time and resources to manage a large(r) number of alliances that enables a focal firm to obtain more of such novel and diverse inputs. Information overload and a (sharp) increase in managerial costs only become a considerable risk at relatively larger numbers of direct ties. Overall, this leads to our first hypothesis:

Hypothesis 1a: *Direct ties are expected to have a curvilinear effect (inverted-U shape) effect on exploration as well on exploitation.*

Hypothesis 1b: *The optimal number of direct ties is expected to be smaller for exploitation than for exploration.*

Indirect ties

Alliances can also be a channel of information between a focal firm and its indirect contacts, i.e. the partners of its partners (Mizruchi, 1989; Gulati, 1995a). Whereas direct ties serve as sources of both resources and information, indirect ties primarily form a source of information (Ahuja, 2000). So, the social capital that a firm derives from its alliance network is not only determined by its direct ties but also by the number of indirect ties it can reach. In general, two kinds of information benefits may be obtained from indirect ties. First, a focal firm's direct partner gains specific knowledge and experience from its collaboration with alliance partners. This may serve as an input into its collaboration with the focal firm which, in this way, benefits from such knowledge and skills held by indirect partners (Gulati and Gargiulo, 1999; Ahuja, 2000). 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, 2000). Here, indirect partners may fulfill a 'radar' function in the sense of bringing more general information on relevant technological developments to the attention of the focal firm (Freeman, 1991; Ahuja, 2000).

Although beneficial for both, we expect the role of indirect ties to be more important for exploration than for exploitation. Information from an indirect tie reaching the focal firm is more likely to contain (some) novel information, which is more important for exploration than it is for exploitation. Moreover, the 'radar' function of indirect ties seems to be rather useful for exploration because in this case, firms search for a broader range of novel information and opportunities (March, 1991). As a consequence, we expect these benefits of indirect ties to be higher for exploration than for exploitation.

On the flip side, however, indirect ties may have disadvantages as well. First, the same mechanism that brings novel knowledge from indirect ties to the attention of the focal firm, also works in the opposite direction (Gulati and Garguilo, 1999). Knowledge that a focal firm develops in collaboration with a direct partner, may also reach this partner's partner(s). In other words, ties to indirect partners may serve as a channel for the (unintended) spillover of knowledge held by the focal firm. For the latter, this may be very hard to monitor, making it difficult to prevent or to enforce sanctions. As a firm's existing knowledge base generally reflects its core competences and main profit engines, this risk may be higher for exploitation than for exploration.

Second, information from indirect ties may not be perfect and may contain ‘noise’. It passes through a common partner, which may interpret and attach meaning to this information in a different way than the focal firm would do. In this process, some of the fine-grained specificities may get lost and not reach the focal firm or lead to misunderstanding on his side. This seems to pose a specific risk for exploitation as this requires more specific and detailed knowledge, which makes it less tolerant for information noise (Rowley et al., 2000; Gilsing and Nooteboom, 2005). For exploration the risk may be less serious as the focus is on gathering broader information on novel issues rather than specific information on familiar issues. Hence, some noise can be tolerated. Overall, the potential benefits of indirect ties seem to be larger for exploration than for exploitation, whereas the risks seem to be relatively lower. This leads to our second hypothesis:

Hypothesis 2a: *Indirect ties are expected to have a positive effect on both exploration and exploitation.*

Hypothesis 2b: *The effect of indirect ties is expected to be larger for exploration than for exploitation.*

Direct and indirect ties combined

By definition, direct ties serve as the bridge between the focal firm and its indirect ties. In other words, both ties operate in combination and should therefore also be considered jointly in assessing their effect on exploration and exploitation. Ahuja (2000) argues that firms with many direct ties are likely to benefit less from their indirect ties than those with fewer direct ties. The main argument is that the more direct ties a firm has, the higher the chance that it has access to a wide range of information and the lower the chance that information from indirect ties forms a significant addition to its knowledge base. In contrast, firms with a limited number of direct ties may miss out on potentially relevant information and may therefore benefit much more from the addition of indirect ties to their alliance network. In other words, with regard to their important role of providing access to complementary knowledge and skills, direct and indirect ties seem to form substitutes.

When considering their disadvantages, we already discussed that both types of ties carry a risk of undesirable spillovers and freeridership (Nooteboom, 2000). In addition, we argued that having many direct ties will consume managerial attention and may lead to information overload. Indirect ties do not have these particular disadvantages but information stemming from indirect ties may be distorted. In other words, when combining many direct ties with many indirect ties, the benefits of each type are largely substituted for, whereas the disadvantages add up. As we have argued in our earlier discussion for hypothesis 1 to 2, we anticipate these disadvantages to be higher for exploitation because in exploitation information overload and distortion are more limited and consequences of spillovers are more severe, compared to exploration. Hence our third hypothesis:

Hypothesis 3a: *The effect of indirect ties on exploration and exploitation is expected to be diminished by a firm's direct ties.*

Hypothesis 3b: *The weakening effect of direct ties on indirect ties is expected to be stronger for exploitation than for exploration.*

Redundancy among ties

In our discussion on the role of direct ties, indirect ties and their combined effect we have abstracted from the degree to which these ties are redundant. As we argued, there is an ongoing debate in the literature about the impact of redundant and non-redundant network ties. To investigate this, we analyze the specific role of redundant and non-redundant ties in technological collaboration, both for exploitation and exploration.

When a focal firm's partners do not have relations among them, they form non-redundant contacts (Burt, 1992a). This enables the firm to access a greater variety of different sources of information. In this way, the firm may hear about emerging opportunities or threats more quickly and may also become informed sooner about the reliability and availability of possible new partners (Burt, 1992a; Powell et al., 1996; Uzzi, 1997). In other words, a non-redundant network structure enables a firm to rapidly locate complementary knowledge and assess it in terms of its quality, relevance and the qualities of the (prospected) partners holding it. This may be beneficial for exploration and exploitation as for both activities, the creation of a technological innovation requires the combined use of various types of skills and knowledge (Nelson and Winter, 1982). A non-redundant network structure provides access to such a broad range of relevant skills and knowledge, and in this way may enhance both exploitation and exploration.

However, accessing such complementary knowledge and information is one issue, understanding, assimilating and applying it to commercials ends another. Put differently, novel knowledge that is accessed through collaboration with external partners may go beyond a firm's absorptive capacity (Cohen and Levinthal, 1990). This is where the benefits of redundant ties come in. Because if one is not able to understand novel information readily from a given source, one may need redundant ties to complement one's absorptive capacity (Nonaka, 1994; Gilsing and Nooteboom, 2005). In other words, even if a tie is known to be redundant for access to sources of information, it may be required to understand and absorb knowledge accessed in another relationship. In addition, even if a firm understands an external knowledge source, it may not be able to judge the reliability of this information. In that case, the firm may need a third party for triangulation. This connects to the argument from information theory that 'noise' is reduced when accessing multiple and redundant contacts (Shannon, 1957; Rowley, 2000). In addition, redundant networks improve the transfer of less tangible resources and tacit knowledge (Nelson and Winter, 1982; Dyer and Nobeoka, 2000; Kogut, 2000). Furthermore, a redundant structure spurs the creation of interorganizational trust that may prevent opportunistic behavior (Coleman, 1988), which is important for this absorption process (Nonaka, 1994; Kogut, 2000; Hansen et al., 2001).

In sum, accessing novel and complementary knowledge and information requires an emphasis on diversity and disintegrated network structures. This is related to Burt's argument

(1992b) stressing the benefits of access to non-redundant contacts to obtain novel information. On the other hand, however, a firm needs to make sure that such novel knowledge, once accessed, is efficiently evaluated, assimilated and applied in order to be valuable (Cohen and Levinthal, 1990). This process favors more redundant network structures in view of integrating the diverse inputs obtained from different partners (Hansen et al., 2001). Therefore, we anticipate that both views may be valid in view of collaboration for technological innovation. These contradictory effects of a non-redundant structure versus a redundant structure prompt us to formulate two competing predictions. Therefore, our final hypothesis:

Hypothesis 4a: *Non-redundancy of a focal firm's network structure is expected to have a positive effect on exploitation and exploration.*

Hypothesis 4b: *Redundancy of a focal firm's network structure is expected to have a positive effect on exploitation and exploration.*

DATA, VARIABLES AND METHODS

Data

We tested the hypotheses on a longitudinal dataset consisting of the alliance and patenting activities of companies that were active during the period 1987-1996 in the chemicals, automotive or pharmaceutical industries[6]. The reason to choose these three industries is that not only R&D-investments and innovations but also technological alliances with different partners are crucial to survive and prosper in these three industries. Moreover, the appropriability regime to protect IP is rather strong in the three industries (Breschi et al., 2000; Ahuja, 2000; Rothaermel and Deeds, 2004). As a result, patents are a good indicator for their technological output. However, the three industries also reveal differences regarding some key characteristics such as the stage of industry development (Walker et al., 1997), the

[6] SIC codes are respectively: 281/282 (281:Industrial Inorganic Chemicals; 282: Plastics Materials and Synthetic Resins); 3711 (Motor Vehicles & Passenger Car Bodies); 2834 (Pharmaceutical Preparations).

importance of exploration vis-à-vis exploitation (Rowley et al., 2000) and the importance of product versus process innovations (Tidd et al., 1997). Pharmaceuticals with its invasion of biotechnologies reflects a younger type of industry that stresses the importance of exploration (Powell et al., 2005), whereas chemicals and automotive form mature industries relying more on exploitation (Coriat and Weinstein, 2004). Moreover, the pharmaceutical industry has a strong focus on product innovations (Powell et al., 1996, Walker et al., 1997), whereas chemicals show a strong focus on process innovations and the automotive industry a mixture of both (Marsili, 2001). Testing our hypotheses in such different industries enables us to assess in how far the role of a firm's alliance network for exploration and exploitation remains invariant across industries, enhancing the generalisability of the results.

The database includes in total 116 focal firms in the three industries for a 12-year period, from 1987 until 1996. The panel is unbalanced because of mergers and acquisitions on the one hand and a few spin-offs and divestments on the other hand. As a result, the number of focal firms slightly varies each year: there were on average 95 companies each year. For 1994, for instance, we have a sample of 94 firms: 27% are car manufacturers, 30% chemical firms and 43% pharmaceutical firms. This sample was selected to include publicly traded companies in these three industries that also established technology-based strategic alliances[7]. Alliance data were retrieved from the MERIT-CATI database, which contains information on nearly 15 thousand cooperative technology agreements and their 'parent' companies, covering the period 1970-1996 (see Hagedoorn and Duysters (2002) for a further description).

In constructing variables based on past alliances, we have made two choices. First, we have not considered different types of alliances separately such as research cooperation, R&D contracting, joint development agreements, joint ventures, and so on. As a consequence, we have not weighted each type of alliance according to the 'strength' of the relationship as some authors did (see Contractor and Lorange, 1988; Gulati 1995b; Nohria and Garcia-Pont, 1991).

[7] Previous studies on inter-firm alliances also focused on the industry leaders (Ahuja, 2000; Gulati, 1995b; Gulati and Garguilo, 1999).

The second choice relates to the length of the period during which the existing alliance portfolio is likely to have an influence on the current technological performance of a company. For most alliances, the MERIT-CATI database does not provide information when they are terminated. For that we have, in line most previous studies on technology alliances, to make an assumption on the average lifespan of alliances. This is usually no more than five years (Kogut, 1988; 1989). Therefore, we choose to use a moving window approach, in which alliances were aggregated over the five years prior to the year of observation, unless the alliance database indicated another lifespan (Gulati, 1995b).

Direct ties, indirect ties and network structure measures were calculated based on the adjacency matrices that were constructed from the MERIT-CATI database about R&D based inter-firm alliances. Since we assume an average lifespan of 5 years for the technology alliances, an alliance matrix was constructed for each year per industry, counting all the technology-based alliances that were established by the firms during the five-year period prior to the year of observation.

The patent data were retrieved from the US Patent Office Database for all the companies in the sample. Working with U.S. patents – the world's largest patent market - for all firms is preferable to the use of several national patent systems "…to maintain consistency, reliability and comparability, as patenting systems across nations differ in the application of standards, system of granting patents, and value of protection granted" (Ahuja, 2000: 434). Especially in industries where companies operate on an international or global scale, U.S. patents may be a good proxy for companies' worldwide innovative performance.

The financial data of the focal firms in the three industries come from a combination of data from Worldscope, Compustat and data published in the companies' annual reports. Alliances are established and patents granted both on subsidiary as well as on parent company level: therefore, we consolidated all data on the parent company level for each firm-year unit of observation, using 'Who Owns Whom' published by Dun & Bradstreet.

An original element in our approach is that the dataset on alliances is constructed independently from whether the firms in this sample have created any innovations. This is in contrast with most prior studies on innovation, in which scholars have been forced to examine only the firms that successfully apllied for patents (Ahuja and Lampert, 2001). The methodology of this paper attempts to overcome this problem of sampling on the dependent variable, with its associated risks to internal and external validity. By combining measures on firms' alliances with a history of all their innovations, radical or not, the project can present a relatively unbiased picture of the relation between a firm's alliance network and the exploration of (radically) new technology.

Variables

Dependent variables. To find out whether new patents in the year of observation have to be categorized as 'exploitative' or 'explorative', we calculated technological profiles of all focal companies. These profiles were created by adding up the number of patents a firm received in each patent class during the five years prior to the year of observation[8]. Classes in which a company received a patent in the year of observation but had not received a patent in the previous five years were considered to be *'explorative'* patent classes[9]. Since knowledge in these unexplored patent classes remains relatively new for the firm immediately after patenting, patent classes kept their 'explorative status' for the next three years, in line with Ahuja and Lampert's (2001) concept of novel and emerging technologies[10]. All classes in which a company had successfully applied for a patent during the previous five years, were

[8] Different scholars have argued that a moving window of 5 years is an appropriate timeframe for assessing the technological impact of prior inventions (Podolny and Stuart, 1995; Stuart and Podolny, 1996; Ahuja, 2000). Studies about R&D depreciation (Griliches, 1979, 1984) suggest that knowledge capital depreciates sharply, losing most of its economic value within 5 years. The USPTO-classes were determined at three-digit level, which resulted in approximately 400 classes.

[9] We 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.

[10] In order to test the robustness of this measure, we also constructed a 'exploration patents'-variable where explorative patents could keep this status for 5 years instead of 3 years. The results in table 3 do not change when the dependent variables are calculated in this way.

labeled as '*exploitative'* patent classes. The dependent variables '*exploration patents'* and '*exploitation patents'* were then constructed by adding up all patents applied for in the year of

observation in the explorative and exploitative patent classes respectively.[11]

Independent variables. The impact of a firm's alliance network on its innovative output has been studied, among others, by Ahuja (2000) and Ahuja and Lampert (2001), Rothaermel and Deeds (2004), Faems et al. (2005) and Schildt et al. (2004). In this paper, innovative output of a company is split up into the exploitation of existing technological capabilities and the exploration of new technological fields. Following our theoretical argument, the impact of a focal firm's alliance network on its explorative and exploitative innovation performance should be decomposed into *direct ties, indirect ties* and the *redundancy of ties* (Ahuja, 2000). These independent variables are calculated based on the alliances that were established during the five-year period prior to the year of observation.

Direct ties[12]: The direct ties represent the first dimension of a firm's alliance network. This variable is proxied by the number of allies to whom the focal firm is directly connected to (i.e., the size of the ego-network)[13]. We also introduce the squared term of the number of alliance partners since hypothesis 1a suggests an inverted U-shaped relationship between innovative performance and the number of direct ties.

Indirect ties: The second dimension of a company's alliance network consists of the number of partners it can reach indirectly. There are different possibilities to operationalize indirect ties. We chose for a variable that measures the impact of indirect ties while taking into account the decline in tie strength of more distant ties. We operationalize this variable

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11 The use of patents as an indicator of learning and innovative output has been criticized on many different grounds (for an overview see Griliches, 1990). Patents are nevertheless generally viewed as the single most appropriate measure of innovative performance at the company level (Ahuja and Katila, 2001; Hagedoorn and Duysters, 2002; Hagedoorn and Cloodt, 2003), in particular in a single industrial sector context (Cohen and Levin, 1989, Ahuja and Katila, 2001). We must acknowledge that although patents are increasingly used as a proxy for learning it does not equate learning. In our view it is a proxy for the output of learning (knowledge stock increase).

12 We calculated all alliance network measures using UCINET 6.0.

13 Another possibility is to use the degree centrality of the focal firm (number of alliances between the focal firm and its alliance partners).

using the 'distance weighted centrality' measure, which is provided by Burt (1991). The variable "… attaches weights of the form 1 – (f_i/(N+1)) to each tie, where f_i is the total number of partners that can be reached up to and including the path distance i, and N is the total number of firms that can be reached by the focal firm in any number of steps" (Ahuja 2000: p. 438). The result is that alliance partners receive smaller weights the longer the path distance to the focal firm. This variable can be calculated by adding up all alliances at several distances weighted by their path distances. Other network centrality measures such as betweenness or Bonacich centrality are valuable alternatives but they do not weigh indirect ties as Burt's measure does. We only report the findings for the distance-weighted centrality measure[14]. We mean-centered the direct and indirect tie variables to reduce the potential threat of collinearity when squared terms and interaction terms are introduced (Aiken & West, 1991).

Redundancy: The third dimension of a firm's alliance network reflects the degree in which its alliances are redundant. The literature offers several possibilities to operationalize (non-)redundancy of alliances (Burt, 1992a; McEvily and Zaheer, 1999; Gulati, 1999; Ahuja, 2000; Baum et al., 2000). We refer to Borgatti et al. (1998) for an extensive analysis of network measures that can be used to formalize the notion of redundancy.

We choose '*network efficiency*' of a firm's ego-network as a measure of non-redundancy (Burt, 1992a: chap. 2) and is calculated by dividing the 'effective size' (a variable measuring the number of non-redundant ties in a firm's ego-network by subtracting the redundancy in the network from the number of partners the focal firm is connected to) by the number of partners in the firm's ego-network. This efficiency ratio ranges "…from a maximum of one, indicating that every contact in the network is non-redundant, down to a

[14] We tested the robustness of the findings with betweenness and Bonacich centrality measures and obtained similar results.

minimum approaching zero, indicating high contact redundancy and therefore low efficiency" (Burt, 1992a: p. 53)[15].

Apart from redundancy based on cohesion, redundancy can also be based on *structural equivalence* as argued by Burt (1992a, b). A variable that captures redundancy by structural equivalence has been provided by Hansen (1999). He analyses the knowledge transfers between divisions within firms, but the idea can be easily transferred to interorganizational networks. Two alliances of the focal firm are structurally equivalent to one another when these two partners are connected to the same other firms in the (overall) alliance network apart from the alliances with the focal firm[16]. Structural equivalence can then be calculated based on Euclidean distance. The Euclidean distance between two alliance partners of the focal firm, i and j, is given by Wasserman and Faust (1994: p. 367)[17]. This measure equals zero when two partners of the focal firm are structurally equivalent. Euclidean distances can be converted into a redundancy measure by taking the average of the Euclidean distances between pairs of direct partners (allies) of the focal company. High values for this variable indicate that the focal firm has alliances with partners that are not structurally equivalent and will give the firm non-redundant information.

Control variables. Although the analysis in this study focuses on the effect of a firm's network structure on exploitation and exploration, there may also be other factors that affect the two dependent variables. We included three types of dummy variables. A first one indicates where the company is headquartered. Following the Triad-concept of the world economy, a company can be headquartered in North America, Asia or Europe - the default is the North America (Ohmae, 1985). Previous studies have shown that firms with headquarters

15 Following Burt we developed different measures for (non)-redundancy. Based on cohesion we also calculated redundancy by 'proportion density' (Burt, 1983; Hansen, 1999) and 'network constraint' (Burt, 1992a). All these variables are highly correlated and substituting network efficiency with these variables does not change the results in table 3.

16 Remark that redundancy measures based on structural equivalence take into account properties of the network structure that go beyond the characteristics of the ego-network of the focal firm.

17 Hansen (1999, p. 96) and Wasserman and Faust (1994, p. 367):

$$d_{ij} = \sqrt{\sum_{k=1}^{g} (x_{ik} - x_{jk})^2} \ for\ i \neq k, j \neq k$$

in different countries have a different propensity to patent (Cockburn and Griliches, 1988). Annual dummy variables were included to capture changes over time in the propensity of companies to patent their innovations. Finally, we included a dummy variable to indicate whether a company is a car manufacturer or a chemical firm (default is the pharmaceutical industry).

Furthermore, we include three organizational variables as controls[18]. The first one is the age of the company. Generally, one would expect older firms to be better at exploitation because of their accumulated experience over the years. In contrast, younger firms with lower stakes and limited habituation in established technologies are expected to be focusing more on exploration (Sorenson and Stuart, 2000).

Next, the natural logarithm of 'corporate revenues' was included to control for the size of the focal firm. Firm size is expected to enhance exploitative learning (Acs and Audretsch, 1991). Large firms have the financial means and vast technological and other resources to invest heavily in R&D. However, they usually experience problems in diversifying into new technological areas, inhibiting experimentation and favoring specialization along existing technological trajectories (Levinthal and March, 1993; March, 1991; Ahuja and Lampert, 2001). As a result, we expect that large firms have an advantage over small ones in exploiting technological dynamics with a cumulative nature, but that they may be at a disadvantage with respect to experimenting and exploring new technological fields.

R&D expenditures, as a ratio of sales, is another control variable. We expect a positive and significant coefficient in both regressions. Assuming that there exists a positive correlation between technological input and output (Pakes and Griliches, 1984) we expect that firms that invest heavily in R&D will have a higher rate of innovation. R&D investments also play a role in the ability of companies to recognize, value and assimilate external knowledge. This constitutes a firm's absorptive capacity, which is crucial to acquire and integrate external knowledge (Cohen and Levinthal, 1990; Kim, 1998; Mowery and Oxley, 1995).

[18] Those variables were calculated for the year prior to the year of observation.

Technological diversity between the firm's partners in the alliance network is another factor that can affect the innovativeness of companies. Ahuja (2000) provides two arguments to include this variable. First, if a firm's allies are active in widely different technological fields, they may remain unconnected, generating structural holes in a focal firm's alliance network. Next, if partners are highly heterogeneous in their technology base, collaboration is unlikely because they do not have the required absorptive capacity to learn from each other (Afuah, 2000; Cohen and Levinthal, 1989; Lane and Lubatkin, 1998). As a result, structural hole measures might reflect the negative impact of technological distance between its allies rather than social structural effects as postulated in hypotheses 4a and 4b.

Yao (2003) provides an interesting way to calculate the technological distance between a focal firm's partners. Following Yao, we take the sum of each dyadic distance between a firm's direct contacts and divide the value by the total number of direct alliances of the firm.

Model estimation

The two dependent variables are count variables and take only nonnegative integer values - i.e. the number of patents a firm filed for in a particular year in patent classes in which it has issued patents during the past 5 years (exploitative learning) and the other ones (explorative learning). A Poisson regression approach provides a natural baseline model for such data (Hausman et al., 1984; Henderson and Cockburn, 1996). A Poisson distribution assumes that the mean and variance of the event count are equal. However, for pooled cross-section count data this assumption is likely to be violated, since count data frequently suffer from overdispersion. A likelihood-ratio test provides strong evidence of overdispersion in the data suggesting that negative binomial models are more appropriate to predict the number of exploitative and explorative patents (Cameron and Trivedi, 1998) [19]. Since we use pooled

[19] The variance exceeds the mean for the dependent variables in Table 2 and is a first indication that the dependent variables suffer from overdispersion. We also tested the presence of overdispersion in exploitation and exploration. For both exploitation and exploration the LR-test for all models in table 3 (pooled data) shows that the negative binomial model is preferred to the Poisson regression model.

cross-section data with several observations on the same firms at different points in time, we modeled the data using a random effects negative binomial estimation[20].

Overdispersion may result from unobserved heterogeneity, i.e. the possibility that firms identical on measured characteristics still differ on unmeasured characteristics. This may be due to differences in underlying innovation capabilities, leading to differences between firms in their propensity or ability to exploit existing technologies and/or explore new technological fields. To control for such unobserved heterogeneity, we include the lagged dependent variable. By incorporating last year's innovation performance as a covariate, firms showing high (low) performance in one year will probably also show high (low) performance the next year. So, if innovation performance is the result of such unobserved factors, controlling via lagged performance should eliminate such spurious effects resulting from endogeneity (Baum et al., 2000).

Differences in patenting behavior between companies or between different years are also captured by the inclusion of dummy variables in the model. First, the propensity to patent may be partly determined by the nationality of the companies or the industry to which they belong. Similarly, we introduced annual dummy variables to account for changes in patenting over time: they may capture the ever-growing importance of intellectual capital or changing macroeconomic conditions.

Another issue is that exploitation and exploration may be mutually related. A firm's existing expertise forms the basis for its absorptive capacity (Cohen and Levinthal, 1990) and may thus affect the way in which novel knowledge is absorbed and integrated within the company. In addition, novel knowledge may possibly also affect the further development of existing expertise, either positively or negatively. In other words, exploration and exploitation are not separate events but may be mutually dependent to some extent. To control for this

20 Hausman tests based on regressions without time invariant regressors show that there is no correlation between the firm specific random effects and the regressors, indicating that random effects negative binomial model would be consistently estimated.

possibility, we introduced the lagged variable of the two dependent variables in each regression.

Finally, the three characteristics of alliance networks (direct ties, indirect ties and redundancy) cannot be considered as fully exogenous variables (Reagans et al., 2005). Network characteristics can be considered as the result of deliberate actions by the focal firm (and its partners). More specifically, such actions may reflect a firm's strategic choice regarding the emphasis it puts on exploration and/or exploitation. This is the classic endogeneity problem: an unobserved (omitted) variable jointly causes both the dependent and independent variable; while both significantly covary, such covariation is spurious (Reagans et al., 2005; Hamilton and Nickerson, 2003). Consequently, there are strong a priori reasons to believe that direct ties, indirect ties and redundancy are (partially) endogenously determined. Direct ties are obviously the outcome of deliberate actions of the innovating firms. They establish new alliances to improve their innovation performance, to seize the business opportunities associated with emerging technologies and to react to actions of their partners (e.g. the establishment of an alliance with a competitor of the focal firm). Firms can also influence the number of indirect contacts by choosing whether they partner with highly centralized firms or isolates. Similarly, the level of redundancy in its (ego-)network can be influenced by (not) choosing partners that have already ties with its existing partners[21].

To address the potential endogeneity problem between innovation performance and these network characteristics, we will adopt a two-step estimation procedure (Cassiman and Veugelers, 2002). In a first step, the three characteristics of the focal firms' alliance portfolio are regressed on all *assumed* exogenous variables. In the second step, the predicted values of the three endogenous variables are included as independent variables in the structural equations (table 3).

RESULTS

21 Controlling redundancy based on 'structural equivalence' is more difficult, especially in the short term.

Table 1 represents the description of the different variables. Table 2 provides the descriptive statistics and the correlations between the variables for the firm-year 603 observations in the sample. The correlation between direct ties and indirect ties is low. Similar low correlations are found between these two independent variables and the different redundancy variables[22]. Correlations between the control variables age, size and R&D intensity are moderate. Size is to some extent positively correlated to the number of direct ties and to the number of exploitation patents in the previous year[23].

Insert table 1 here

Insert table 2 here

Table 3 represents the results of the regression analysis using random-effects negative binomial estimations respectively for exploitation and for exploration. According to the two step approach to correct for endogeneity, we use the predicted values for direct ties, indirect ties and redundancy based on the regressions that included as independent variables overall network characteristics, industry level variables such as industry level R&D, and firm level variables[24].

Insert Table 3 here

Model 1 represents the basic model including only control variables. Model 2 introduces the linear and quadratic term of the direct ties as a regressor to measure the

22 There are very strong correlations between the different redundancy measures we referred to in footnote 15.

23 We did not introduce ‘cumulative patents’ (accumulated over the last 5 years) because it was too strongly correlated with firm size. Therefore, we did not include 'cumulative patents' as independent variable into the regressions in combination with 'firm size'.

24 These regressions can be obtained from the authors.

hypothesized inverted U-shape relationship. The coefficients of these variables have the expected sign and are significant for both exploitation and exploration. This corroborates hypothesis 1a stating that direct ties are beneficial both for exploitation and for exploration, but that with an increasing number of alliances, the consequences of diminishing returns start to dominate.

Moreover, the number of technology alliances at which the innovative performance reaches its maximum is similar for exploitation and for exploration (respectively 74 and 73 direct ties). When we switch to model 3 where the interaction term between direct and indirect ties is included, we see that the these maxima strongly depend on the number of partners a firm can reach indirectly with its portfolio of direct ties[25]. All else equal, firms need many direct ties to reach the maximum value for both exploitation and exploration in case these ties do not connect them indirectly to many other firms in the network. In contrast, an alternative structure that yields a similar positive result for both exploitation and exploration is formed by a limited set of direct ties that provide access to a wide range of indirect ties.

Exploitation and exploration are very much the same on that point: at very low levels of indirect ties the optimal number of direct ties is larger for exploitation, at the mean level these optima are similar and at high levels of indirect ties, the optimal number of direct ties is somewhat larger for exploration. This implies that hypothesis 1b stating that the optimal number of direct ties is smaller for exploitation than for exploration is corroborated for above average levels of indirect ties, but not for below average levels of indirect ties. However, the differences are very small and, therefore, we consider the optimal number of alliances for exploitation and exploration to be similar.

[25] We find the following maxima for the number of direct ties at different levels of indirect ties

- At -1,5 standard deviations from the mean, the optimum is reached at 107 and 102 direct ties resp. for exploitation and exploration
- At the mean: 64 direct ties for both
- At +1,5 standard deviation from the mean: resp. 20 and 27 ties for exploitation and exploration.

Model 3 introduces the indirect ties as an independent variable as well as the interaction term between direct and indirect ties. We have argued – following Ahuja (2000) – that indirect ties have a positive effect on both exploration and exploitation and that the number of direct ties moderates the positive impact of indirect ties. The results of model 3 in table 3 provide strong support for hypothesis 2a. They suggest that innovating firms benefit in a significant way from their indirect ties, both for exploration and exploitation. Hypothesis 2b, on the contrary, is not supported since the coefficients for exploration and exploitation are very similar and not significantly different from each other.

In addition, the interaction term has the expected negative sign and is highly significant in both regressions for exploitation and exploration. This indicates that an increasing number of direct ties diminishes the (eventual) positive effect of indirect ties, which corroborates hypothesis 3a. The coefficients for these interaction terms and marginal effects at the mean are similar: the suggested difference in hypothesis 3b between exploitation and exploration is not corroborated by the data. Figures 1 and 2 visualize how the interaction between direct and indirect ties influences firms' innovativeness, for exploitation and exploration respectively.

Insert Figures 1 and 2 here

The figures show that there are two different optimal strategies. One is that firms can establish alliances with *few* partners that have themselves extensive alliance networks with other firms. In other words, a firm with only a few direct ties is better off when these partners are connected to many others. However, this effect shrivels when the number of direct ties increases and indirect ties even become a burden at a large number of direct alliances (see right hand corner in the back of both figures)[26]. A second optimal strategy is that firms can partner with a large set of companies who only maintain linkages to a few others. As figure 1

[26] The number of direct ties in figures 1 and 2 could be extended to the maximum of 113 alliances (see table 2). This would show a strong increase in innovation performance (both exploration and exploitation) when many direct ties do not lead to many indirect ties (i.e. ties with isolate partners). This strong performance rapidly decreases as the number of indirect ties increases.

shows, this second strategy of a large alliance portfolio with 'peripheral' or isolate partners can yield a similar innovative output as the first strategy.

Figure 1 and 2 show remarkable similarities indicating that both types of optimal strategies are valid for both exploration and exploitation. A focal firm can establish a fairly large number of alliances with partners that themselves have a peripheral position in the overall alliance network or it can team up with a fairly small number of alliance partners that are connected to many other partners in the network. The fact that these two strategies are optimal for both exploration and exploitation has some interesting implications for the management of alliance portfolios. We will discuss a further interpretation of these findings in the discussion section.

Models 4 and 5 test hypotheses 4a and 4b. Model 4 introduces network efficiency, which is a measure for non-redundancy in a focal firm's ego-network. Following our earlier argument, we expect two opposed effects from redundant ties on exploitation and exploration and have formulated two alternative hypotheses, hypothesis 4a and 4b. Model 5 measures the effect of the variable that captures (network wide) redundancy based on structural equivalence, forming a global measure that takes both direct and indirect ties into account. The calculation of structural equivalence is based on the Euclidean distances: higher values represent less redundant information.

For exploitation, both variables have a negative and significant coefficient, supporting hypothesis 4b. As a result, creating redundancy in the alliance network is favorable for exploitation. In contrast, we do not find any significant effect of these two redundancy variables on exploration as we expect from hypotheses 4a or 4b. The interpretation of this surprising finding may be that the two opposed forces of redundancy seem to be at work simultaneously and in this way seem to cancel out in their overall effect on exploration. We come back to this issue in the section on discussion and conclusions.

The lagged dependent variables have a positive and significant effect on exploitation as well as on exploration. This implies that a firm's track record in innovation plays a significant role in explaining its current performance for exploitation and exploitation. Including a lagged dependent variable helps to control for unobserved heterogeneity (Heckman and Borjas, 1980; Jacobson, 1990). The results for exploitation and exploration are reassuring for two reasons. First, they reduce the threat of unobserved heterogeneity and, second, they rule out the alternative explanation that exploitation and exploration might be caused by underlying or unobservable firm characteristics.

Prior experience in exploitation is expected to play a positive role in explaining current exploration. The results show that this is only the case in Model 1 where the control variables are introduced in the regression. This makes sense as in general existing knowledge facilitates the absorption and further development of new knowledge (Katila and Ahuja, 2002). In the remaining models, however, the coefficient remains positive but loses significance. Prior experience in exploration has a clear positive effect on current exploration, whereas it does not have an impact on current exploitation in any of the 5 models. That is also what we expect: exploration implies a broadening into non-core areas that are unrelated to core areas, forming the domain of exploitation.

The coefficients of some control variables also deserve our attention. A company's age has no impact on exploitation or exploration but firm size has a significant positive effect on both types of innovative performance. Since the size measure is the natural logarithm of annual sales, the coefficient measures the elasticity of innovativeness with respect to size. For exploitation, the coefficients in the different models range between 0.31 and 0.35 indicating that the increase in exploitative patents is less than proportional than the sales increase. The same holds for exploration, but the elasticity is even smaller, indicating that smaller firms have an advantage compared to large firms in exploring new technological fields[27]. This finding is in line with the organizational learning literature: large established organizations have relatively more difficulties in diversifying into new technological areas, inhibiting experimentation and favoring specialization along existing technological trajectories

[27] We have to be careful in drawing inferences beyond the data since the sample is restricted to publicly traded firms. We do not observe very small firms in the sample.

(Levinthal and March, 1993; March, 1991; Ahuja and Lampert, 2001). Technological distance between partners has no effect on both exploitation and exploration. This is in contrast with Ahuja's (2000) who found a negative and significant effect on innovative performance.

DISCUSSION AND CONCLUSIONS

The main purpose of this study is to understand how a firm’s network of technology-based alliances affects its innovation performance in terms of exploration and exploitation. To study this we have differentiated between a firm’s direct ties, indirect ties and the redundancy among them. Regarding the role of direct ties, we found that they have a curvilinear effect on both exploration and exploitation. Innovating firms clearly benefit from alliances with their technology partners, however, up to a certain point. When the number of alliances further increases, diminishing returns set in and eventually lead to reduced innovativeness. Both for exploitation and exploration, the optimal number of direct ties strongly depends on the number of indirect firms that a focal firm can reach through this portfolio of direct ties. We have shown that this optimal number of alliances is somewhat larger for exploitation than for exploration, in case the number of indirect ties that a focal firm can reach with these direct ties is limited, whereas the opposite is true in case the number of indirect ties is large. Furthermore, we found that indirect ties mitigate the effect of direct ties, in line with our theoretical argument.

In addition, we found that indirect ties have a positive effect on both exploitation and exploration. This confirms the role of technology alliance networks as information channels and facilitators of knowledge exchange between firms (Powell et al., 1996; Ahuja, 2000) and it shows that being well connected to the rest of the alliance network through (many) indirect ties is advantageous for innovating firms, both for exploitation and exploration.

The negative and significant coefficient of the interaction term indicates that direct and indirect ties have to be considered jointly. The overall impact of direct and indirect ties (as depicted in figures 1 and 2) leads to the conclusion that for both exploitation and exploration there are two different strategies that can yield optimal innovation output: a firm can have the choice between a limited set of direct ties with partners that have extensive alliance networks with other firms throughout the network, or it can partner with a large number of firms who themselves are isolates or are connected to only a few others in the network. This is a new insight that nuances the dominant view in the literature that especially centrally positioned firms will show superior performance (Burt, 1992b; 2000; 2004; Krackhardt, 1990; Gulati, 1999;). In contrast, our findings convey an optimistic message for firms that choose a strategy to team up with partners that have more peripheral positions in the network. Investing in many direct ties with partners that have limited ties themselves – i.e. leading to few indirect ties – can yield an innovation performance that is comparable to a strategy of teaming up with a few centrally positioned partners.

This two-pronged optimal strategy is similar for exploitation and exploration. Innovating firms have the choice to collaborate with a limited number of central players in the network or they can collaborate with a large number of partners that themselves do not have a central position in the overall alliance network. Collaboration with high-status, well-connected partners is sufficiently documented in the literature (Burt, 2004). Teaming up with more peripherally positioned firms deserves further explanation. We explain exploration first. Being at the periphery generally implies that one is outside the immediate sight of dominant and more central players. Because of this, selection forces to comply with dominant designs and existing systems of production, organization, technical standards and so on, may be somewhat less stringent. In this way, deviating from such prevailing ‘industry recipes’ (Spender, 1989) becomes easier (Gilsing and Nooteboom, 2005) so that firms at the periphery may enjoy more freedom to experiment. Collaborating with them may then increase the likelihood that novel information and knowledge is obtained when compared with relatively central firms that tend to operate within more established fields of expertise. The effectiveness of teaming up with peripheral partners for exploitation may be understood as follows. In core areas, forming the domain of exploitation, some firms may choose to cooperate with 'unconnected' partners in order to control outgoing spillovers and to avoid the creation of competitors, through close and extensive cooperation with a limited number of partners. Furthermore, there is the possibility that a focal firm has to team up with several unconnected partners that hold emerging technologies, which need to be integrated in order to strengthen its core technologies further.

These findings on direct ties and on their interaction with indirect ties confirm a key claim of this paper that a firm's network of technology-based alliances has a clear impact on both its explorative and exploitative innovation performance. This is an important finding that also contributes to the literature on exploration and exploitation, with its main focus on the internal organization of firms (March, 1991; Levinthal and March, 1993; Tushman and Anderson, 1986), as it suggests that a firm's external alliance network plays an important role when engaging in exploitation and/or exploration tasks. Furthermore, we may conclude that there is no differential effect of direct ties on exploration relative to exploitation, nor in combination with indirect ties. This is an important result as it implies that a firm's overall alliance network of direct and indirect ties can be instrumental for both tasks. In other words, one does not need an entirely different type of network structure, nor do past investments in building existing ties become obsolete and have to be made anew, for each task separately. Overall this suggests, within the context of technological innovation, that exploration and exploitation can be *combined*, not only at the same time but also by making use of the same network structure of direct and indirect alliances. Reframed in terms of the emerging discussion on 'balancing exploration and exploitation', these findings seem to support the 'ambidexterity hypothesis', i.e. doing both tasks simultaneously, instead of the 'punctuated equilibrium hypothesis', i.e. doing both tasks sequentially (Gupta et al., 2006; Lavie and Rosenkopf, 2006).

Regarding the role of redundancy in technological collaboration, our study has not completely elucidated which role redundancy plays within processes of technological collaboration. We find a significant effect of redundancy on exploitation, which is in line with the idea that exploitation requires more specific and fine-grained information that is better obtained from multiple and redundant contacts (Shannon, 1957; Rowley, et al., 2000). Moreover, redundancy fosters the creation of trust between alliance partners that may prevent opportunistic behavior (Coleman, 1988), which is important when collaborating in the domain of a focal firm's core technologies.

In contrast, we do not find any significant relation between network redundancy and technological exploration. This result may well indicate that both structural holes and closure play a role in a focal firm's alliance network when engaging in the exploration of new technological fields. Collaboration for technological exploration requires, on the one hand, an emphasis on 'casting the net widely' by teaming up with non-redundant partners that offer opportunities for learning, while on the other hand, there is also a need to stay close in order to transfer and absorb novel knowledge fast and reliably through redundant partners with whom one shares familiarity. This is in line with the view, as recently expressed by Burt, that 'brokerage across structural holes seems to be the source of added value, whereas closure can be critical to realizing the value buried in the holes' (2000: 58). Our empirical findings seem to support this idea and we suggest investigating this 'dual face' of the role of redundancy in networks for technological exploration as an issue for future research.

Finally, our findings indicate that the role of a firm's alliance network for exploration and exploitation remains to a large extent invariant across the three industries (only car manufacturers are somewhat less inclined to file for exploitative patents) despite the existence of some considerable industry differences regarding technological innovation. This indicates that our results are not industry specific but may be generalized across different industries. This is an interesting finding that fills an important void in the literature with its dominant focus on single-industry studies (Gulati, 1998; Hagedoorn, 2002).

The current study has several limitations. First, we did not consider the effect of 'tie strength' on exploitation and exploration. Different types of alliances can be weighed according to the ‘strength’ of the relationship as some authors did (see Contractor and Lorange, 1988; Gulati 1995b; Nohria and Garcia-Pont, 1991). We suspect that tie strength will influence the role of direct ties and indirect ties as well as their interaction.

Furthermore, exploration and exploitation have been operationalized in different ways in the literature Our definition of exploration and exploitation comes close to that of Katila (2005) where exploration is determined in terms of entering new patent classes. Other studies define exploitation and exploration in terms of citations to a firm's prior patents in new, successfully applied patents (Katila 2005; Katila and Ahuja 2002; Rosenkopf en Nerkar, 2001; Rothaermel and Deeds, 2004). Both approaches do not measure exploitation and exploration in the same way; Firms may patent in a different patent class while they still cite their prior patents. The opposite is also possible: firms can apply for patents within the range of patent classes in which they are active without any reference to their prior patent stock. Both operationalizations are appropriate to measure firm level exploration ('new to the firm'-innovations). The important point here is that future research should combine the two measures to get a more detailed measurement of exploration: is exploration (no citations to a firm's own patents) within a firm's existing technology classes different than those in new (explorative) classes?

Finally, our exploration measure is only a rough proxy as each patent in a new patent class has the same value: there is no differentiation between different explorative patents. However, the technical jump between classes can be quite different depending on the technological distance between them. Entering a new patent class can be more or less explorative depending on the technological distance between a company's prior patent portfolio and the newly entered patent class(es) (Nooteboom 1999, 2000). In this way, we could transform the current dichotomous approach toward exploration and exploitation into a continuous variable measuring the degree of explorativeness. This qualification may further enrich the analysis of the balance between exploration and exploration.

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TABLE 1
Definitions of dependent and independent variables

Variable name	Variable description	
Exploitation	Number of patents a firm filed for in year t within patent classes in which is has been active in the five years prior to the given year t	dependent variable
Exploration	Number of patents a firm filed for in year t within patent classes in which is has not been active in the five years prior to the given year t	dependent variable
Lagged exploitative learning	Exploitative learning lagged for one year	
Lagged explorative learning	Explorative learning lagged for one year	
Direct ties	Number of partners to whom a focal firm is connected to (standardized variable)	
Indirect ties	'Distance weighted centrality': Number of indirect ties but weighted to account for the decline in tie strength across progressively distant ties (standardized variable)	
Network efficiency	'Effective size' divided by the number of partners in the focal-firm's ego-network (Burt, 1992a, p. 53)	
Structural equival. (corr.)	Average correlation of every pair of profiles of the direct partners of the focal firm (Hansen, 1999)	
Age	The number of years since a company is founded in year t-1	
Size	Natural logaritm of annual sales	
R&D intensity	R&D expenditures as a percentage of sales	
Technological distance between partners	Average technological distance among a focal firms' alliance partners (Yao, 2003)	
Year	Dummy variable indicating a particular year (1987-1997) (1997 is the default)	
Chemical company	Dummy variable set to one if the firm is a chemical company (Pharmaceutical industry is the default)	
Car manufacturer	Dummy variable set to one if the firm is a car manufacturer (Pharmaceutical industry is the default)	
Europe	Dummy variable set to one if the firm is headquartered in Europe (US is the default)	
Asia	Dummy variable set to one if the firm is headquartered in the Asia (US is the default)	
Average geodesic distance	The average of all shortest paths (geodesics) between the different actors in an alliance network.	
Normalized network centralization		
Industry level R&D expenditures	Sum of all R&D spend by the focal firms in an industry in a particular year.	
Industry level patent classes growth	Number of new (explorative) classes firms in an industry have entered during a particular year compared to their existing technology base of the last 5 years.	

Notes: All independent and control variables are lagged 1 year to avoid simultaneity problems.
All network variables are based on alliance network representing all the technology-based alliances that were established in an industry during the five years prior to year t

TABLE 2
Descriptive statistics and correlation matrix

Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13
1 # of exploitative patents	103.51	158.93	0	1136													
2 # of explorative patents	8.88	11.63	0	125	0.27												
3 Direct ties	14.49	15.35	1	113	0.53	0.28											
4 Indirect ties	70.31	32.21	0	177	-0.14	0.01	-0.21										
5 Network efficiency	0.881	0.180	0.1	1	0.15	0.10	0.05	0.15									
6 Structural equival. (corr.)	0.144	0.184	-0.020	1	-0.12	-0.08	0.06	-0.22	-0.92								
7 Age	80.80	46.42	0	237	0.13	-0.02	0.12	0.01	0.07	0.07							
8 Firm size	8.734	1.650	0.29	11.91	0.42	0.24	0.45	-0.27	0.13	0.13	0.38						
9 R&D-intensity	0.128	0.131	0.00	0.72	-0.06	-0.03	-0.05	0.18	-0.05	-0.05	-0.14	-0.40					
10 Techn. distance partners	0.022	0.008	0	0.063	0.01	0.03	-0.12	0.27	-0.22	-0.22	0.08	-0.13	0.02				
11 Lagged # of exploit. pat.	100.80	157.74	0	1136	0.96	0.24	0.54	-0.12	-0.12	-0.12	0.12	0.42	-0.06	0.02			
12 Lagged # of explore. pat.	9.274	12.432	0	125	0.26	0.65	0.26	0.00	-0.05	-0.05	-0.05	0.23	-0.02	-0.00	0.26		
13 Chemical company	0.368	0.483	0	1	0.02	-0.05	-0.04	-0.09	0.07	0.07	0.16	0.09	-0.10	-0.17	0.04	0.01	
14 Car manufacturer	0.278	0.449	0	1	0.05	0.05	0.25	-0.37	0.22	0.22	0.05	0.35	-0.07	-0.20	0.04	0.04	-0.46
15 European firm	0.238	0.427	0	1	-0.16	-0.07	0.00	-0.10	0.15	0.15	-0.00	0.05	0.07	-0.12	-0.16	-0.00	0.17
16 Asian firm	0.330	0.471	0	1	0.11	0.05	0.02	-0.10	0.10	0.10	0.07	0.15	-0.07	-0.09	0.10	0.00	0.00
17 Year 1987	0.093	0.290	0	1	-0.04	-0.01	-0.06	-0.29	0.06	0.06	-0.04	-0.02	-0.02	-0.02	-0.04	-0.03	-0.01
18 Year 1988	0.088	0.283	0	1	-0.00	0.02	-0.04	-0.12	0.07	007	-0.04	-0.05	-0.01	-0.00	-0.02	-0.02	-0.02
19 Year 1989	0.088	0.283	0	1	0.01	0.03	-0.01	-0.06	0.04	0.04	-0.03	-0.04	-0.02	-0.11	-0.01	-0.01	-0.01
20 Year 1990	0.094	0.292	0	1	-0.01	-0.02	0.02	-0.04	0.04	0.04	-0.01	-0.02	-0.02	-0.02	-0.09	0.00	-0.00
21 Year 1991	0.094	0.282	0	1	-0.01	-0.04	-0.01	-0.03	-0.04	-0.04	0.02	-0.01	-0.02	-0.10	-0.00	0.01	-0.00
22 Year 1992	0.089	0.286	0	1	0.01	-0.07	-0.01	-0.00	-0.05	-0.05	0.03	0.01	-0.02	0.01	-0.01	-0.05	-0.00
23 Year 1993	0.093	0.290	0	1	-0.00	-0.07	-0.01	-0.01	-0.03	-0.03	0.04	0.01	-0.02	-0.03	0.00	-0.06	-0.01
24 Year 1994	0.088	0.283	0	1	0.01	-0.04	0.02	0.08	-0.03	-0.03	0.03	0.01	0.01	0.03	0.01	-0.07	-0.00
25 Year 1995	0.088	0.283	0	1	0.06	0.12	0.02	0.07	-0.06	-0.06	0.01	0.03	-0.00	0.07	0.00	0.01	0.01
26 Year 1996	0.091	0.288	0	1	-0.00	0.08	0.04	0.15	-0.01	-0.01	-0.01	0.03	0.13	0.06	0.02	0.15	0.02
27 Avg. geodesic distance	4.017	0.592	3.072	5.495	-0.05	-0.01	-0.11	0.25	0.13	-0.04	0.09	-0.11	-0.01	0.04	-0.00	-0.03	0.79
28 Norm. network central.	0.806	0.214	0.51	1.65	0.05	0.04	0.17	-0.27	-0.18	0.03	-0.02	0.24	-0.01	-0.10	0.05	0.04	-0.56
29 Industry level R&D	13817	6081	5448	2838	0.11	0.05	0.21	0.05	-0.13	0.01	-0.01	0.26	0.05	-0.01	0.05	0.08	-0.57
30 Ind. level patent cl. gr.	0.2011	0.4784	-0.602	2.198	0.13	-0.02	-0.04	0.36	0.13	-0.03	-0.09	-0.20	0.22	0.16	0.01	0.09	-0.17

TABLE 2

Descriptive statistics and correlation matrix (continued)

Variable	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
14 Car manufacturer																
15 European firm	0.11															
16 Asian firm	0.10	-0.39														
17 Year 1987	0.04	0.01	0.01													
18 Year 1988	0.01	-0.01	-0.00	-0.10												
19 Year 1989	-0.01	0.00	-0.00	-0.10	-0.10											
20 Year 1990	0.01	0.00	0.01	-0.10	-0.10	-0.10										
21 Year 1991	0.01	-0.01	0.01	-0.10	-0.10	-0.10	-0.11									
22 Year 1992	0.00	-0.00	0.01	-0.10	-0.10	-0.10	-0.10	-0.10								
23 Year 1993	0.01	-0.01	0.02	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10							
24 Year 1994	-0.00	-0.02	0.00	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10						
25 Year 1995	-0.02	-0.00	-0.01	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.09					
26 Year 1996	-0.02	0.03	-0.03	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10				
27 Avg. geodesic distance	-0.72	0.05	-0.05	-0.11	-0.01	-0.10	-0.17	-0.09	0.07	0.09	0.19	0.06	0.02			
28 Norm. network central.	0.71	0.01	0.06	-0.11	-0.02	-0.01	-0.04	0.01	0.01	-0.05	-0.01	-0.04	0.13	-0.43		
29 Industry level R&D	0.71	-0.00	0.07	-0.17	-0.17	-0.19	-0.11	-0.05	-0.01	0.08	0.06	0.18	0.20	-0.32	0.47	
30 Ind. level patent cl. gr.	-0.23	-0.11	-0.06	0.11	0.08	-0.02	-0.07	-0.11	-0.11	-0.13	-0.09	0.18	0.28	0.02	-0.20	0.02

TABLE 3
Determinants of the patent rate of firms – 1987-1997

Variable	Exploitation Model 1	Model 2	Model 3	Model 4	Model 5	Exploration Model 1	Model 2	Model 3	Model 4	Model 5
Direct ties										
Cumulative alliances		0.2308***	0.2379***	0.2563***	0.2563***		0.2837***	0.2764***	0.3019***	0.3019**
		(0.0484)	(0.0476)	(0.0475)	(0.0476)		(0.0830)	(0.0822)	(0.0851)	(0.0851)
(Cumulative alliances)^2		-0.0296***	-0.0372***	-0.0333***	-0.0333***		-0.0371**	-0.0426***	-0.0405***	-0.0404***
		(0.0069)	(0.0067)	(0.0070)	(0.0070)		(0.0150)	(0.0150)	(0.0153)	(0.0153)
Indirect ties										
Distance weighted centrality			0.3464***	0.7547***	0.3427***			0.3817***	0.8437**	0.3868***
			(0.0871)	(0.2008)	(0.0878)			(0.1339)	(0.3363)	(0.1345)
((Distance weighted centrality)			-0.1406***	-0.1175***	-0.1175***			-0.1391***	-0.1185**	-0.1185**
* (cumulative alliances))			(0.0242)	(0.0260)	(0.0260)			(0.0507)	(0.0538)	(0.0538)
(Non)-redundancy										
Network efficiency				-2.9605**					-3.2834	
				(1.3196)					(2.9843)	
Structural equivalence					-0.3957**					-0.4388
					(0.1764)					(0.3949)
Control variables										
Year dummy variables	included	included	included	included	included	included	included	included	included	included
Car manufacturer	-0.8448***	-0.7440***	-0.5501**	-0.7362***	-0.5158**	-0.2261	-0.1295	0.0999	-0.1152	0.1293
	(0.2475)	(0.2433)	(0.2433)	(0.2589)	(0.2439)	(0.2121)	(0.2100)	(0.2178)	(0.2932)	(0.2199)
Chemical industry	0.0020	0.1613	0.1928	0.009	0.2527	0.1320	0.2043	0.3302*	0.0840	0.3546*
	(0.2283)	(0.2233)	(0.2274)	(0.2389)	(0.2242)	(0.1825)	(0.1820)	(0.1863)	(0.2901)	(0.1878)
Europe	-1.1118***	-1.0978***	-1.0679***	-1.1262***	-1.0791***	-0.7276***	-0.7241***	-0.6753***	-0.7178***	-0.6655***
	(0.2305)	(0.2263)	(0.2281)	(0.2298)	(0.2290)	(0.1954)	(0.1923)	(0.1896)	(0.1936)	(0.1903)

Asia	0.3241	0.2482	0.2140	-0.4249	0.1845	-0.6175***	-0.6038***	-0.4852***	-1.1875**	-0.5117***
	(0.2220)	(0.2165)	(0.2205)	(0.3580)	(0.2184)	(0.1673)	(0.1646)	(0.1678)	(0.6531)	(0.1700)
Age	0.0022	0.0035	0.0030	0.0035	0.0040*	0.0030	0.0031*	0.0023	0.0018	0.0023
	(0.0021)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Firm size,	0.3534***	0.3182***	0.3174***	0.3139***	0.3139***	0.1531***	0.1034*	0.1007*	0.1006*	0.1006*
	(0.0534)	(0.0515)	(0.0503)	(0.0507)	(0.0507)	(0.0552)	(0.0560)	(0.0549)	(0.0551)	(0.0551)
R&D intensity	0.1321***	0.1219**	0.1121**	0.1126**	0.1123**	0.1126**	0.0939**	0.0871*	0.0859*	0.0859*
	(0.0533)	(0.0522)	(0.0520)	(0.0523)	(0.0523)	(0.0450)	(0.0454)	(0.0453)	(0.0454)	(0.0454)
Techn. distance	1.5534	2.9157	2.3148	2.1037	2.1037	-0.6683	-0.1336	-1.5366	-1.6991	-1.6991
between partners	(2.5662)	(2.5257)	(2.4638)	(2.4412)	(2.4412)	(4.2629)	(4.3286)	(4.2934)	(4.2901)	(4.2901)
Exploration (lagged)	-0.0014	-0.0020	-0.0023	-0.0020	-0.0009	0.0157***	0.0149***	0.0154***	0.0152***	0.0152***
	(0.0017)	(0.0017)	(0.0016)	(0.0016)	(0.0017)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Exploitation (lagged)	0.0015***	0.0014***	0.0019***	0.0017***	0.0020***	0.0007**	0.0003	0.0007	0.0006	0.0006
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.0004)	(0.0005)
Constant	-1.1181***	-0.9983**	-1.0746**	2.0030	-0.9713**	-0.6224	-0.2186	-0.4046	3.0540	-0.2448
	(0.4200)	(0.4135)	(0.4179)	(1.4492)	(0.4237)	(0.4378)	(0.4459)	(0.4470)	(3.1448)	(0.4708)
Number of firms	72	72	72	72	72	72	72	72	72	72
Number of firms-years (obs.)	603	603	603	603	603	603	603	603	603	603
Wald chi-squared (d.f.)	338.61 (20)	379.72 (22)	462.64 (24)	481.03 (25)	481.03 (25)	145.69 (20)	163.12 (22)	181.40 (24)	183.57 (25)	183.57 (25)
Log-L	-2551.66	-2540.06	-2523.96	-2521.43	-2521.42	-1730.16	-1724.44	-1719.10	-1718.47	171848
Chi-squared test of random test (d.f. 1)	698.47***	602.46***	576.85***	581.12***	581.11***	137.93***	129.35***	127.32***	126.47***	126.47***

Notes: Standard error between brackets

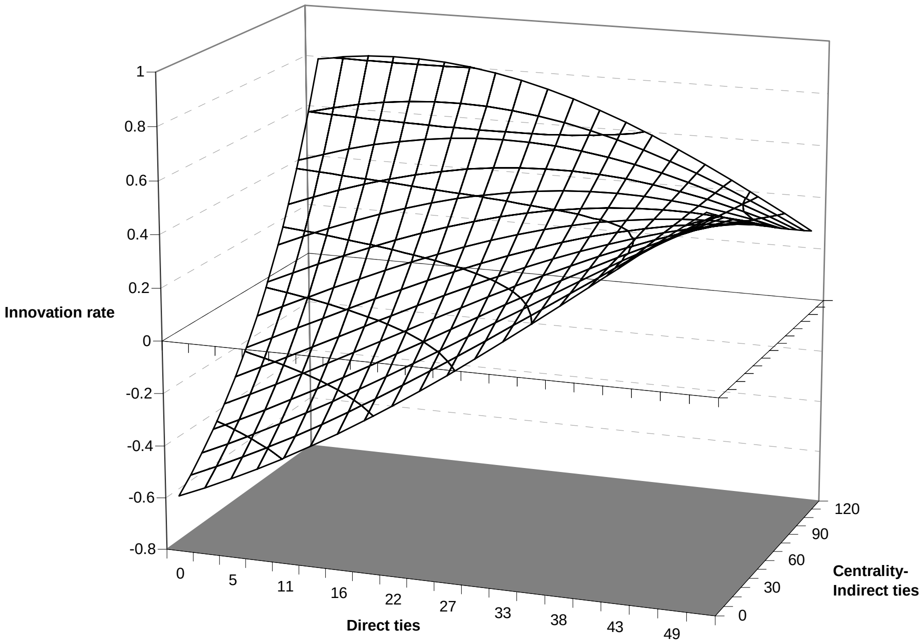
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

'Year dummy variable'-coefficients are not reported in the table.

The models use a random effects negative binomial estimators. The sample is an unbalanced panel.

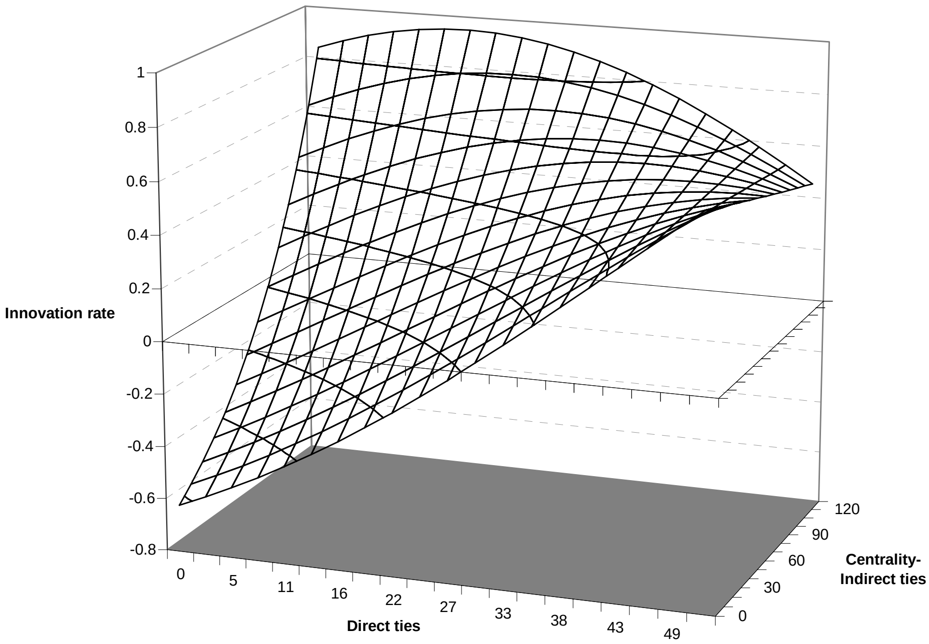
Independent variables are lagged one year to avoid simultaneity problems.

Figure 1: The innovation rate for different levels of direct and indirect ties – exploitation



Note: Edges of the graph are chosen at two times the standard deviation of the 'direct ties' and 'indirect ties' variables

Figure 2: The innovation rate for different levels of direct and indirect ties – exploration



Note: Edges of the graph are chosen at two times the standard deviation of the 'direct ties' and 'indirect ties' variables

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