Exploration and Exploitation in Technology-based Alliance Networks

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Acknowledgements
We are grateful to Bart Nooteboom and Bart Verspagen for comments on earlier versions of this paper. We thank Ad Van den Oord for his expert help with data collection and coding.
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. With regard to the role of redundancy, we found no effect of redundancy for exploration. In contrast, we find that structural holes in the overall network and redundancy at the ego-network level in a firm’s alliance network both have a positive effect on exploitation. This points to an interesting insight, indicating that both structural holes and closure in a focal firm’s alliance network have an effect on the generation of technological inventions in familiar technology areas.
INTRODUCTION

As competition becomes increasingly knowledge-based, firms have become aware of the need to manage their intellectual resources and technological capabilities on an ongoing basis (Kogut and Zander, 1992; Grant, 1996; Zack, 2003). This is not an easy task, however, as innovating companies have to stay competitive in their existing markets in the short term and develop the required knowledge about technologies and product development in the long term. March (1991) examined this tension between an innovating firm's short and long term objectives by making a distinction between exploitative and explorative learning. Exploitation is associated with the refinement and extension of existing technologies, whereas ‘exploration’ consists of experimentation with new alternatives. March (1991) argues that each company needs to balance both types of learning to stay competitive both in the short and the long run.

Shorter product life cycles, technological convergence, rising R&D costs and the growing role of emerging technologies are a few of the determinants explaining why incumbents face considerable problems to develop all the required knowledge capabilities internally (Gomes-Casseres, 1996; Mowery, 1988; Mytelka, 1991; Teece, 1992; Hagedoorn and Duysters, 2002). Consequently, innovating companies are increasingly forced to tap into external sources of knowledge (e.g. Cohen and Levinthal, 1990). Managers are gradually replacing the traditional inward R&D-focus by a more outward-looking approach that draws heavily on technologies from networks of universities, startups, suppliers, and competitors (Chesbrough, 2003). Hence, technological learning is increasingly based on a combination of internal and external learning: internal learning based on a firm’s own R&D efforts, external learning on the technology acquired from alliance partners.

Prior research suggests that a variety of mechanisms may be used to access externally developed knowledge such as, among others, informal networking, hiring employees,
strategic alliances, M&As, external corporate venturing, etc... (Van de Vrande et al, 2006). In this study, we focus on the role of strategic alliances as one of these mechanisms to acquire externally developed technology (Hagedoorn, 1996; Mowery and Oxley., 1995; Powell et al., 1996; Rosenkopf and Almeida, 2003; Vanhaverbeke and Noorderhaven, 2001). We investigate how the alliance portfolio of an innovating company influences both its exploitative as explorative learning. Although a few studies have considered the role of strategic alliances in relation to exploration and exploitation (Koza and Lewin, 1998; Rothaermel and Deeds, 2004; Schildt et al., 2005), the literature has not analyzed yet to what extent a firm’s alliance network has an impact on exploration and exploitation. Since exploration and exploitation are profoundly different (March, 1991), we anticipate that there may be considerable differences in how a firm’s network of strategic alliances influences both tasks. In order to understand this differential effect, we focus on the role of the structure of this network and study how it affects a firm’s technological output in terms of exploration and exploitation.

This focus on the role of structure is related to an ongoing debate in the network literature on how network structures facilitate network members to attain their desired outcomes. 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. Burt (1992a) claims that firms can reap rents from the absence of alliances among its alliance partners. 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 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 taken on a contingency approach and studied how the validity of each view may vary with different environmental settings or with different tasks or purposes (Podolny and Baron 1997; Burt 1998; Rowley, et al., 2000; Ahuja 2000b; Podolny 2001; Hagedoorn and Duysters, 2002; Gilsing and Nooteboom, 2005). In line with this, we consider the two tasks of exploration versus exploitation and study in how far this distinction explains the differential value of redundant versus non-redundant ties. Following Ahuja (2000), we argue that there are three structural elements 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.

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 such a differential effect may indicate 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. Next, 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 innovation. Finally, we contribute to the understanding of the relationship between alliance network characteristics and technological innovativeness by questioning the premise of structural exogeneity. Although we investigate the effect of alliance network characteristics on exploitative and explorative innovative performance, these 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 firm.

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 as it reflects an entrepreneurial search process for opportunities in areas that are new to the company. In this paper, we consider both activities within the context of technological innovation and study the effect of network structure on the resulting output of each activity. In other words, exploitation entails the deepening of a firm’s core technologies and yields inventions in areas with which the firm is intimately familiar. In contrast, exploration entails the broadening into non-core technologies and yields inventions in areas that are novel to the firm.

For the generation of both types of technological inventions, 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). Instead, our focus entails the differential effect of these three characteristics of a firm’s alliance network on its exploitative and explorative innovation performance. In

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1 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).
this way, we study exploration and exploitation that are performed simultaneously by companies in contrast to previous studies that have considered both activities as attributes of different industries (e.g. Rowley et al., 2000), as sequential activities (Rothaermel and Deeds, 2004) or as characteristics of different alliances depending on the type of alliance partner” (Faems et al., 2005).

Direct ties

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; Das and Teng, 2001). 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 also 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; Klein Woolthuis et al., 2005). 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, 1997; Gilsing and Nootenboom, 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) 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 the collaboration with its 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 (Nootenboom, 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; Mitsuhashi, 2003). 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; If one is not able to understand novel information readily from a given source, he 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 et al., 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; Muthusamy and White, 2005).

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\(^2\). 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 three industries favor the use of patents in view of appropriability (Breschi et al., 2000; Ahuja, 2000; Rotheamrl and Deeds, 2004). As a result, patents can be considered as a good indicator for a firm’s technological innovation output. However, the three industries also reveal differences regarding some key characteristics such as the stage of industry development (Walker et al., 1997), the 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

\(^2\) 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).
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 10-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. 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). 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

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3 Previous studies on inter-firm alliances also focused on the industry leaders (Ahuja, 2000; Gulati, 1995b; Gulati and Garguilo, 1999).
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 only examined firms that successfully applied for patents (Ahuja and Lampert, 2001). The methodology of this paper attempts to overcome this problem of sampling on the dependent variable. By combining measures on firms’ alliances with a history of all their inventions, the empirical
analysis can present a relatively unbiased picture of the relation between a firm’s alliance network and its explorative and exploitative innovation performance.

**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. 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. 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. All classes in which a company had successfully applied for a patent during the previous five years, were 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.

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4 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.

5 Most patents are assigned multiple patent classes. To split up patents into being either exploitative or explorative we have only used a patent’s main class designation ignoring the additional class designations. Relying on the main class designation is of course a simplification. In most instances, patents are assigned to a combination of old and new patent classes, which allows for different grades of exploration, instead of a dichotomous division between exploitation and exploration. This is a possible way for extending the current research on exploration and exploitation but goes beyond the scope of the current paper.

6 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.

7 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.

8 The use of patents as an indicator of learning and innovative output has been criticized on many different
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. (2005). 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\textsuperscript{10}: 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)\textsuperscript{11}. 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 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).

\textsuperscript{9}Technology alliances are not tagged as explorative or explorative as other scholars (Rothaermel and Deeds, 2004; and Faems et al, 2005) have done in a different context. There are both theoretical and practical reasons not to do this. First, there is no clear distinction between so called 'explorative' and 'exploitative' alliances. Grant and Baden-Fuller (2004) analyze the distinction between knowledge accessing (exploration) and knowledge acquisition (exploitation) in strategic alliances, but they admit (p. 79) that a clear-cut dichotomy between two types of alliances is not possible because knowledge transfer always requires a common knowledge overlap between the two alliances partners (Grant, 1996; Nooteboom 2004; Nooteboom et al. 2007). Second, a quick survey among alliance managers shows that they do not establish alliances for 'exploitative' or 'explorative' reasons. There are many reasons to establish alliances and the objectives are multidimensional.

\textsuperscript{10}We calculated all alliance network measures using UCINET 6.0.

\textsuperscript{11}Another possibility is to use the degree centrality of the focal firm (number of alliances between the focal firm and its alliance partners).
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 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\(^\text{12}\). 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

\(^\text{12}\) 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).13

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 firm14. 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)15. 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

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13 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.

14 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.


\[
d_{ij} = \sqrt{\sum_{k=1}^{g} (x_{ik} - x_{jk})^2} \text{ for } i \neq k, j \neq k
\]
the North America (Ohmae, 1985). Previous studies have shown that firms with headquarters 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. 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; Audretsch and Acs, 1991; Damanpour, 1992). 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

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16 Those variables were calculated for the year prior to the year of observation.
17 For an overview of the relation between firm size and innovativeness see Camisón-Zornoza (2004).
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).

Technological diversity between the firm’s partners in the alliance network is another factor that can affect the innovativeness of companies. There are 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 (Ahuja, 2000). 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)\textsuperscript{18}. Since we use pooled 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\textsuperscript{19}.

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

\textsuperscript{18} 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.

\textsuperscript{19} 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.
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 activities but may be mutually dependent to some extent. To control for this 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.

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

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20 Controlling redundancy based on 'structural equivalence' is more difficult, especially in the short term.
the three endogenous variables are included as independent variables in the structural equations (table 3).

RESULTS

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. Similarly, low correlations are found between these two independent variables and the different redundancy variables\textsuperscript{21}. 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\textsuperscript{22}.

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Insert table 1 here
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Insert table 2 here
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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\textsuperscript{23}.

\textsuperscript{21} There are very strong correlations between the different redundancy measures we referred to in footnote 13.

\textsuperscript{22} 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’.

\textsuperscript{23} These regressions can be obtained from the authors.
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 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 these maxima strongly depend on the number of partners a firm can reach indirectly with its portfolio of direct ties. 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

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24 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.
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.

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.

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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). 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 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 who 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 that specify two opposed effects from redundant ties on exploitation and exploration. Model 4 introduces network efficiency, which is a measure for non-redundancy in a focal firm’s ego-network. Model 5 measures the effect of the variable that captures 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 correlation: higher values represent more redundant information. Here, the results show that for exploitation network efficiency has a negative effect whereas structural equivalence also has a negative and significant coefficient. In other words, boosting one’s exploitative innovation performance is best served by local redundancy and global non-redundancy. These findings provide support for both hypotheses 4a as 4b. This surprising finding points to a new insight in the role of redundancy. It indicates that the two different effects of redundancy seem to operate in combination and should not be seen as mutually

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25 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.
exclusive in their effect. In contrast, we do not find any significant effect of these two redundancy variables on exploration as we expect from hypotheses 4a or 4b. We come back to these findings on both exploitation and exploration in the section on discussion and conclusions.

When considering the control variables, we see some interesting results from the lagged dependent variables. First, 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 exploitation plays a significant role in explaining its current performance for exploitation. The same holds for exploration. Including a lagged dependent variable also helps to control for unobserved heterogeneity (Heckman and Borjas, 1980; Jacobson, 1990)26. Second, 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). The results show that this is only the case in Model 1 where the control variables are introduced in the regression. In the remaining models, however, the coefficient remains positive but is no longer significant indicating that the effect of existing knowledge on the absorption of new knowledge is partly captured by the alliance network variables. Finally, prior experience in exploration has no effect 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 of the other control variables also deserve our attention. A company’s age has no impact on exploitation or exploration but firm size has a significant

26 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.
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. 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 (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

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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.
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 of an alliance network 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 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; Gupta et al., 2006), as it suggests that a firm’s external alliance network also 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 shown that exploitative innovation performance is enhanced by both local redundancy as global non-redundancy. This indicates that both structural holes and closure in a focal firm’s alliance network have an effect on its exploitative innovation performance, which is in contrast with our theoretical argument and points to a new insight. The two different effects of redundancy should not be considered as mutually exclusive but instead can be seen as operating in combination. In other words, collaboration for the generation of technological inventions in core areas requires, on the one hand, an emphasis on ‘casting the net widely’ by teaming up with partners that provide access to non-redundant indirect ties. This offers opportunities for the access to diverse information and hence for learning, which is in line with Burt’s view (1992). On the other hand, there is also a need to stay close in order to transfer and absorb novel knowledge fast and reliably through partners that are connected to each other, within one’s ego-network, with whom one shares familiarity. This 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). And with the idea
that 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. Overall, this implies support for the argument 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’ (Burt, 2000: 58).

In contrast, we do not find any significant relation between network redundancy and explorative innovation performance. Although we do not have an immediate explanation for this finding, it at least indicates that the ‘dual face’ of redundancy, as outlined above, does not operate similarly for the creation of technology in non-core areas, or that it operates in more subtle and complex ways that cannot be captured by standard network measures such as network efficiency and structural equivalence. Or it might even provide food for a more provocative thought that redundancy does not have an effect on a firm’s explorative innovation performance. This suggests that direct ties, indirect ties and their interaction clearly matter for boosting one’s explorative innovation performance, whereas redundancy does not. At this point, we suggest that the investigation of this ‘dual face’ of the role of redundancy in the creation of non-core technologies is an issue for future research.

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 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?

Next, 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.

Finally, we have only paid attention to explorative and exploitative interorganizational learning in line with the literature. However, Lane and Lubatkin (1998) show that the strategy and organization of partnering firms explains their capability to absorb knowledge from the partnering firm. Homqvist (2003) proposes that exploitation and exploration occur both within and between organizations and that they are deeply interlaced through intra- and interorganizational learning processes. In this study, we did not pay attention to intra-organizational learning processes. Future studies should combine the two processes of intra- and
interorganizational learning to get a better understanding of how firms have to be organized internally to improve their exploitative and explorative learning from alliance partners.
REFERENCES


Muthusamy, S.K. and M.A. White, 2005; Learning and knowledge transfer in strategic alliances: A social exchange view, Organization Studies, 26(3): 415–441


### TABLE 1

Definitions of dependent and independent variables

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

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

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

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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

![Figure 1](image1)

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

![Figure 2](image2)

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