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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. To study this, we differentiate among a firm's direct ties, indirect ties and the redundancy among them. Analyzing their role in the pharmaceutical, chemical and automotive industry we show that the exploration-exploitation distinction forms an important factor for understanding a firm's optimal network structure, and that the differences in network optimality between both tasks is one of degree. Moreover, we find that this differential role of a firm's alliance network remains invariant across the three industries, enhancing the generalisability of the empirical results. Finally we discuss an important new insight that arises from some unexpected findings.

INTRODUCTION

After well over a decade of study, consensus has grown in the academic literature that interfirm networks form an efficient mechanism to effectuate the potential for learning and innovation (Ahuja, 2000b; Grabher, 1993; Hagedoorn, 1993; Hagedoorn and Schakenraad, 1994; Nooteboom 1999, 2004a; Powell et al. 1996; Rowley et al., 2000; Uzzi, 1997). Initially, research on strategic alliances has focused on the question of why and when alliances are formed (Duysters et al., 2001; Kogut and Zander, 1993; Powell and Brantley, 1992). From this perspective the focus has been on the so-called exogenous factors that cause alliance formation, where interdependence and resource complementarities have been addressed as the most common explanation for firms forming inter-organizational ties (Pfeffer and Nowak, 1976; Nohria and Garcia-Pont, 1991, Gulati 1998). More recently, the strategic alliance literature has made progress in advancing our understanding of *how* inter-alliance dynamics – the so-called endogenous factors - affect the intent of creating, building and sustaining collaborative advantage through alliance formation (for example Gulati, 1995a, 1998; Walker et al., 1997; Gulati and Gargiulo, 1999; Chung et al., 2000). This endogenous dynamic refers to with whom specifically alliances are formed (Gulati, 1995a; Gulati and Gargiulo, 1999). Taken together, the understanding of both exogenous and endogenous reasons of alliance formation has brought the insight to the fore that a firm's embeddedness in networks matters for its economic and innovative action, and that it positively affects corporate performance in terms of growth (Powell et al. 1996), speed of innovation (Hagedoorn, 1993), organizational learning (Hamel, 1991) and reputation (Stuart, 1998; Stuart et al., 1999). More specifically, it is not embeddedness per sé that leads to superior performance. Rather, network embeddedness brings both informational benefits and control benefits, which together form 'social capital' that a firm obtains from its network (Burt 1992a, Gulati 1995b).

Although the literature converges regarding the reasons why and how networks of technology alliances are formed, there is lack of agreement on what constitutes an optimal network structure, once it has been formed. This connects with a central debate in the network literature on how network structures facilitate the attainment of desired outcomes for its members. The key question here is whether networks should be sparse or dense, or put differently, whether ties should be redundant or non-redundant. On the one hand, there is the structural hole theory of Burt (1992a) which claims 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 at odds with the social capital theory of Coleman (1988, 1990) who claims that firms benefit 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) found evidence against redundancy in an advice network, for the acquisition of capabilities. Ahuja (2000a) found evidence against structural holes, for innovation in collaboration. Walker, Kogut and Shan (1997) found evidence in favour of cohesion, for innovation in biotechnology. In view of these apparently inconsistent findings, subsequent studies have taken a 'contingency' approach (Bae and Gargiulo, 2003), investigating environmental conditions that would favour one view over the other (Podolny and Baron 1997; Rowley, et al., 2000; Podolny 2001; Hagedoorn and Duysters, 2002).

In fact, this apparently contradictory evidence is not surprising. The opposite claims regarding the role of redundancy may well both be true as its value may vary in different settings or with different tasks or purposes (Burt 1998, Ahuja 2000b, Rowley et al., 2000). In this paper we argue that the distinction between exploration and exploitation forms an important contingency factor in explaining the differential value of redundant versus non-redundant ties. Following March (1991), exploitation is associated with the refinement and extension of existing technologies and is needed for the short run. In contrast, exploration is concerned with the experimentation with new alternatives and is needed for the long run. As these tasks are profoundly different, we anticipate that the role of a firm's alliance network will vary accordingly between both. Although there are numerous studies that have investigated the relationship between a firm's portfolio of technology alliances and its (technological) performance (Hagedoorn and Schakenraad, 1994; Shan et al., 1994; Powell et al., 1996; Mitchell and Singh 1996; Stuart, 2000; Ahuja 2000a), there are only a few that have examined contextual factors such as the nature of the industry (Rowley et al., 2000) or the stage of industry development (Walker et al., 1997). However, none of these studies pays particular attention to how the tasks of exploitation and exploration are influenced by a firm's alliance network. Therefore, the main aim of this paper is to improve our current understanding how a firm's technological performance in terms of exploration and exploration is conditioned by the structure of its network of technology-based alliances.

In this way, we contribute to the literature along the following lines. One is that we identify *in how far* the distinction between exploration and exploitation matters for understanding a firm's optimal network structure. Is has been elucidated in literature that the distinction bears relevance internal to the firm (March 1991, Levinthal and March 1993, Tushman and Anderson 1996, He and Wong 2004), but the question is in how far it also does external to the firm. If it does, a second point is in how far a firm's alliance network contributes differentially to exploration versus exploitation, in kind of effect and in magnitude of effect. Moreover, we also address if a firm can have 'too many' alliances. In other words, when does a firm's network convey social capital and when does it become a liability (Gabbay and

Zuckerman, 1998; Leenders and Gabbay, 1999). A further contribution lies in the fact that we study three different industries, namely pharmaceuticals, chemicals and automotive. These three industries are based on very different technologies (Breschi and Malerba, 1997) and reflect different industry recipes (Spender, 1989). At the same time, these industries share some important commonalities as well, such as the need to constantly invest in R&D and innovation-related activities (Breschi and Malerba, 1997; Mowery and Nelson, 1999; Coriat and Weinstein, 2003; McKelvey et al., 2004; Cesaroni et al., 2004). Given these differences and similarities, it will be interesting to see in how far the role of a firm's alliance network will vary across these three industries, for exploration and exploitation. In this way, studying these three different industries enhances possibilities for generalization, which importantly complements the literature with its focus on single-industry studies (McEvily and Zaheer 1999; Ahuja 2000a; Walker et al., 1997; Bae and Gargiulo 2003; Podolny and Baron 1997; Ahuja, 2000; Rowley et al. 2000; Podolny 2001; Hagedoorn and Duysters 2002; Gulati 1995b).

This paper is structured as follows. First we elaborate our theoretical argument and formulate a number of hypotheses. Then, 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

In this section we first discuss the difference between exploration and exploitation. Based on that we argue how a firm's network structure may enhance or hamper both tasks.

The distinction between exploration and exploitation goes back to Holland (1975) and was later further developed by March (1991). Exploitation can be characterized as a process of routinisation, which adds to the existing knowledge base and competence set of firms without changing the nature of activities (March, 1991). As a consequence, exploitation can be planned and controlled for, which is important as competition has emerged and considerations of efficiency have become crucial. In contrast to exploitation, exploration can generally be characterized by breaking with an existing dominant design and a shift away from existing rules, norms, routines, activities and so on, in view of novel combinations. Hence exploration is not about efficiency of current activities and cannot be planned for. It is an uncertain process that deals with constantly searching for new opportunities. Returns from exploitation are positive, proximate and predictable. In contrast, returns from exploration are uncertain, more remote in time and organizationally more distant from the locus of action (Levinthal and March, 1993). Exploration and exploitation are related and build on each other: exploration develops into exploitation, and exploration emerges from exploitation, in ways that go beyond the present paper (see for a further discussion Gilsing and Nooteboom, 2006).

Performing both tasks seems especially important for firms that operate in technology-intensive industries. Given the high rate of change that generally characterises these industries (Hagedoorn, 1993), exploitation enables to recoup the (large) investments made in existing technology in a speedy manner. At the same time, these fast changing conditions make that existing technology may also obsolete rapidly and this then requires the timely creation and development of new technology. Therefore, we now further analyse how exploration and exploitation are conducted in such a technology-intensive environment, and how this is affected by a firm's alliance network.

In the case of exploitation, the focus of a firm is on strengthening its existing technology base. Firms maintain their existing scope and aim for refining insights with which they are already well familiar and for which they possess much of the required expertise (March, 1991; Levinthal and March, 1993). Here the rationale for teaming up with partners is formed by possibilities to obtain complementary know-how (Teece, 1986) and/or to speed up the R&D-process in industries where time-to market is crucial. In-house technological capabilities guarantee that the objective of cooperation with alliance partners can be clearly defined, that the range of possible solutions is known and that the partners have a good understanding of the relevant issues at hand (Hansen et al., 2001). As a consequence, the cooperation process can to a large extent be planned and controlled for as targets can be set at the start. In this process, technology tends to become more explicit and codified (Nonaka, 1994; Nooteboom, 2000) which furthers its diffusion among alliance partners, enhancing the efficiency and speed of cooperation (Gilsing, 2005).

Exploration of new technologies is different. It is not about improving the performance of current technologies and business, but it is about searching for new technologies and the potential business opportunities that can be derived from it. Alliances form an important instrument in this process, both for getting access to such novel knowledge (Freeman 1991, Ahuja 2000b) and for screening and evaluating it (Leonard-Barton 1984). Moreover, an alliance network brings together a variety of skills and experience, which provides a potential for the generation of Schumpeterian novel combinations (Schumpeter 1939). As such novelty entails issues and problems that are new to the company and to its partners, the newly obtained knowledge is usually contested, making it highly tacit and hard to articulate (Utterback, 1971; von Hippel, 1994; Nooteboom, 2000). This implies that the contact between partners will often be of a more iterative and informal nature with a focus on exchanging views and evaluating new ideas, leading to a need for rapidly changing strategy when unforeseen problems emerge (Gilsing, 2005). As a consequence, the process of collaboration and its outcomes cannot be predicted at the start, but rather forms an entrepreneurial search process that generates many dead ends and unexpected turns (Levinthal and March, 1993).

For both tasks, a firm's alliance network plays an important role as the social capital derived from it complements a firm's in-house capabilities (Rowley et al., 2000). However, given the marked differences between exploration and exploitation, we anticipate that the role of a firm's alliance network will vary with both tasks. To study this in detail we suggest, in line with Ahuja (2000b), that there are three characteristics of a firm's alliance network that should be analysed in detail, namely (1) the number of direct ties, (2) the number of indirect ties and (3) the degree of redundancy among these ties. More specifically, we argue that these three characteristics of an alliance network, apart and in combination, have a differential impact on exploration and exploitation tasks.

Direct ties

Direct ties take time to build up. Once a firm has formed a technology-based alliance with a partner, both have to start building a common understanding and developing routines for coordination and joint problem-solving. Once these investments are made, direct ties may provide different kinds of social capital: access to complementary knowledge and skills, possibilities to share risks and costs in research and the potential for bilateral trust-building between the focal firms (ego) and his partners. We anticipate that these elements of social capital will be relevant for both exploitation and exploration, although apparently more for the latter task than for the former. Let us further elaborate.

In exploitation, new knowledge creation is largely based on internal competencies. Here, knowledge and complementary skills of direct ties can be beneficial to a firm when these enable to improve its existing technologies and/or speed up its innovation process. In other words, technological similarity between ego and its direct partners is important for efficient absorption and rapid knowledge exchange, in view of competitive pressure stressing reliability and speed. So, here a focal firm looks for similarities with its alliance partners, rather than differences. In this way, direct ties may to some extent substitute for one another and adding more of them will not generate additional, valuable knowledge and skills. Moreover, direct ties may play a role in sharing costs and risks of research although these are generally limited in exploitation as the search process can largely be planned and controlled for (March, 1991; Levinthal and March, 1993). Regarding the role of trust, it is known from the literature that a history of dyadic interactions provides a potential for the build up of trust between ego and each of his partners (Gulati, 1998; Hite and Hesterly, 2001; Roijakkers et al., 2005). However, the role of trust in exploitation may be limited for two reasons. One is the generally more codified nature of knowledge and the limited risk of unforeseen contingencies, which facilitate the specification of contracts as an alternative for trust (Nooteboom 2000). This potential role for contracts may become relevant given a risk of undesirable knowledge spillovers in exploitation. Here the codification of knowledge enhances its diffusion among partners, creating such a risk. This risk may be further reinforced by two mechanisms. The focal company is partnering with companies that are likely to have a similar technology profile, which facilitates the rapid absorption of such spillovers. Moreover, as competition is clearly present in exploitation, it is tempting for firms to look for such spillovers and in this way try to freeride on their partners' efforts. As a consequence, putting too much faith in one's direct partner(s) may not be sensible and contracts may form a way to compensate for this.

In exploration the key objective is to create novel combinations and achieving this requires access to a wide variety of knowledge and skills. Here a firm looks for differences across its direct ties, rather than similarities, as this provides the basis for diversity. In this way, more direct ties increase the potential for such novel combinations. Moreover, direct ties may also be attractive for performing joint research as its costs and risks are much larger in exploration (March, 1991; Levinthal and March, 1993). At the same time, the threat of leakage through spill-overs is limited as the more tacit nature of knowledge inhibits a rapid diffusion across its direct ties or throughout the wider network. This may enhance the build up of dyadic trust that again facilitates the exchange of such tacit knowledge, as its absorption requires intensive interaction over long(er) periods of time (von Hippel, 1988; Lundvall, 1992 Hansen, 1999). In sum, this leads to our first hypothesis:

Hypothesis 1a: *Past involvement in direct ties has a positive effect on exploration and exploitation, but the effect for exploration is larger than for exploitation.*

Over time, involvement in alliance activities through direct ties may lead to the build-up of a large alliance portfolio. This creates a risk of dealing with many unfamiliar streams of knowledge that are increasingly difficult to integrate (Ahuja and Lampert, 2001). As a consequence, firms can start to suffer from information overload and diseconomies of scale. Moreover, management attention and integration costs may also grow exponentially once a certain optimal level of alliances has been established (Duysters and de Man, 2003). Therefore, at high levels of direct ties, marginal benefits of forming new linkages will be low and marginal costs of additional links will be relatively high (Ahuja, 2000a). As a consequence, an alliance portfolio with too many alliances may lead to saturation and overembeddedness (Kogut et al., 1992; Uzzi, 1997). Therefore, we expect an inverted-U shape relationship between a firm's alliance network and both of its types of learning. Given the fact that a firm looks for similarities with its direct ties in view of exploitation, whereas nourishing differences in view of exploration, we expect that this risk of overembeddedness will set in earlier and also be stronger for exploitation when compared with exploration.

As firms look for similarities with their partners in view of exploitation, this risk of overembeddedness will set in at relatively limited levels of direct ties. For exploration, a focal firm needs a larger number of direct ties in view of diversity, making this risk become real at relatively higher levels of direct ties and of a weaker degree when compared with exploitation. This leads us to the following hypothesis:

Hypothesis 1b: *Past involvement in direct ties will, beyond a certain point, show diminishing returns, but this effect sets in earlier and will be stronger for exploitation than for exploration.*

Indirect ties

Not only direct ties have an impact on the technological performance of partnering companies. Indirect ties also play a role because alliances can be a channel of communication between a focal firm and its indirect contacts, i.e. the partners of its partners, and so forth (Mizruchi, 1989; Haunschild, 1993; Gulati, 1995a). The distinction between direct and indirect ties is important because two companies that have the same number of direct contacts may still differ in terms of the number of companies they can reach indirectly, depending on the size and scope of their partners' alliance networks (Gulati, 1999). A firm may have numerous alliances with partners that are not well connected to other companies. In contrast, another firm may have a limited number of alliance partners but, through them, be linked to a wide range of companies that have may alliances to others, and so forth. In other words, 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.

Given this role of indirect ties, we argue that the impact of indirect ties on exploration is larger than on exploitation, for two reasons. First, if a firm can reach many other firms through indirect ties, it can often receive information about the findings of a broad set of research projects going on throughout the network (Ahuja, 2000a). In this way, indirect ties fulfill a 'radar' function for companies in the sense of bringing relevant technological developments to the attention of the focal firm (Freeman, 1991). Second, the tacit and experimental nature of exploration implies that firms will find it difficult to recognize and value the technology of potential partners when they are not connected through a common alliance partner. In this way, indirect ties can serve as a device for screening novel information on its potential relevance for the focal firm (Leonard-Barton, 1984). So, both for the identification of sources of novelty and for their initial assessment, indirect ties play an essential role. Given the importance of diversity and novel insights in exploration we expect this effect to be larger for exploration than for exploitation. Therefore, we hypothesize:

Hypothesis 2: *Indirect ties have a positive effect on exploration and exploitation, but the effect for exploration is larger than for exploitation.*

Direct and indirect ties combined

So, when looked upon apart, we claim that direct ties and indirect ties are beneficial for both tasks. By definition, direct ties serve as the bridge between the focal firm and its indirect ties. In other words, both ties operate in combination as well and should therefore also be considered jointly in their effect on exploration and exploitation.

As argued by Ahuja (2000a), firms that have many direct ties are likely to benefit less from their indirect ties than firms characterized by a more limited number of direct ties. There are two arguments for that. First, firms that have many direct ties are less likely to gain new or additional information from their indirect ties. In this case, the information that can be obtained from indirect ties may be very similar to the knowledge already obtained from its direct contacts. 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. A second argument is that firms with many direct ties may be more constrained in their ability to profit from new information through their indirect ties. From a management perspective, one can argue that having many direct ties consumes managerial attention at the expense of attention for indirect ties. Moreover, many direct ties increase the likelihood that the information reaching the company through its alliance network also reaches the partners of its direct ties, partners who may be potential competitors.

We argue that this logic regarding the combined effect of direct and indirect ties holds for exploitation but not for exploration. In exploitation, as we analyzed, the focal actor has much of the required expertise and is likely to understand the problem, the range of possible solutions and the causality among the key parameters (Hansen et al., 2001). In this case, the information gained from many direct ties will largely substitute for information from indirect ties. Moreover, as already argued, there is a threat of undesirable spillovers and the temptation for free-riding, implying that having many direct ties can be risky.

In contrast, in exploration a firm departs from its existing technology and searches for new insights. Such novelty emerges from making new combinations of the variety of knowledge and skills that reside within a firm's alliance network. In effectuating this potential for new combinations, a firm's direct and indirect ties play a complementary role. As they generally operate at a larger technological distance, indirect ties provide information that is novel to the focal firm but comes at a price of limited understandability for him. Direct ties will operate within closer vicinity of a focal firm's knowledge and expertise. Through their intermediary role, they can complement a focal firm's absorptive capacity through interpretation and evaluation of novel knowledge obtained from indirect ties. Moreover, as already mentioned, the threat of leakage through spillovers is limited due to the more tacit nature of knowledge, inhibiting its diffusion throughout the network. In sum, we expect a differential role of direct ties in conditioning the effect of indirect ties on exploitation and exploration. Therefore we hypothesize:

Hypothesis 3: *The effect of indirect ties on exploitation is weakened by a firm's direct ties, whereas the effect of indirect ties on exploration is enhanced by a firm's direct ties.*

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 academic literature about the impact of redundant and non-redundant network ties. Burt (1992a, b, 2000) argues that social capital is derived from ties and from entrepreneurial opportunities to the extent that they offer access to non-redundant sources of information. In contrast, Coleman (1988, 1990) argues that companies can benefit from establishing alliances with companies that are densely tied to each other. Here, social capital consists of possibilities for social control, the functioning of an efficient reputation mechanism and the build up of trust and social norms. Following the central argument of this paper, we claim that the distinction between exploration and exploitation forms an important contingency factor in explaining which of the two views on social capital has (more) validity.

In exploitation, dominant designs have emerged, and technological and market uncertainty has decreased. Here, considerations of efficiency are crucial, since competition has arisen and will be (partly) based on price. Due to this increased competition on price, there is a need to utilise economies of scale, and this opportunity arises since due to decreased uncertainty on the part of customers the market has enlarged (Abernathy and Utterback, 1978; Afuah and

Utterback 1997). Often, this may result into an increase of scale, a shakeout of producers and resulting concentration (Tushman and Anderson, 1986). In this process there is a strong drive for efficiency that requires the elimination of redundant relations. In other words, there is a requirement for a non-redundant structure. Moreover, the generally codified nature of knowledge furthers its diffusion, turning it into a collective asset that is shared throughout the industry (Breschi and Malerba, 1997). This enables a non-redundant structure, since now one can identify what competencies are and will remain relevant, who has those competencies, and who is likely to survive in the industry. Therefore, our fourth hypothesis reads as follows:

Hypothesis 4: *Redundant ties have a negative effect on exploitation.*

In exploration, as already argued, firms need to create access to heterogeneous sources of knowledge. If we follow Burt's argument here, this would imply that firms should engage in relations with non-redundant contacts, beyond their existing network, in order to access novel information (Burt, 1992a; 1992b; 1998). This is based on the (implicit) assumptions that firms know what kind of information is relevant and that the network positions of their partners, acting as sources of such novel information, remains unchanged, allowing for a rapid identification and access of such sources. Moreover, it is assumed that one has the absorptive capacity to absorb the novel information and to judge its quality and reliability. However, as we will argue, these assumptions do not apply when dealing with exploration tasks. Therefore, in contrast to Burt's idea we anticipate that redundant ties play an important role in exploration. There are three reasons for that.

First is that in exploration, there is ample uncertainty regarding the content and reliability of newly emerging varieties of technology, and regarding the location and potential relevance of novel information (Levinthal and March, 1993; Argote and Ingram, 2000; Gilsing and

Nooteboom, 2005). As a consequence, one does not yet know what ties will turn out to be redundant, since it is generally very difficult to know what the future configuration of relevant elements of knowledge will be. Such problems in the identification of sources of information were recognised earlier by Argote and Ingram (2000) and Hagedoorn and Duysters (2002). To cope with such uncertainties, one has to hedge relational bets, because if one does not know what information will be relevant, one may have to develop and maintain redundant ties to sources that may turn out to be irrelevant later. Moreover, to hedge bets concerning the presence of sources, and the continuity of ties, one has to maintain linkages even if they may later turn out to be redundant, to keep options of access open.

A second argument in favor of redundant ties is that if one is not able to adequately understand novel information from a given source, one may need apparently redundant ties to complement one's absorptive capacity (Gilsing and Nooteboom, 2005). More precisely, if A remains linked to both B and C, even if there is also a link between B and C, this may help A to understand C by comparing what A understands from C with what B understands from C. In other words, even if a tie is known to be redundant for access to sources of information, it may be needed to understand and absorb knowledge accessed in another relation. This is the case particularly in exploration, where new knowledge is emerging, and generally lacks a dominant design and standards and is still largely tacit. In addition, if one does understand a given source, one may not be able to judge the reliability of information, so that, like researchers in gathering potentially biased data, one may need a third party for triangulation. In this way, firms may be able to develop a richer understanding and a better evaluation of the acquired novelty. This connects with the argument from information theory that 'noise' is reduced when accessing multiple and redundant contacts (Shannon, 1957).

A final reason is that the costs of redundancy generally play a limited role in exploration as the key focus here is on finding and absorbing novelty, making considerations of efficiency less of an issue (March, 1991; Nooteboom and Gilsing, 2005).

In sum, when engaging in exploration tasks, we go against Burt's argument in favor of non-redundant ties and follow Coleman's view by arguing that redundant ties play an important role here. Hence, our final hypothesis is as follows:

Hypothesis 5*: Redundant ties have a positive effect on exploration.*

Taken together, these hypotheses reflect our understanding of the differential effect of a firm's alliance network on exploration and on exploitation. More specifically, hypothesis 1a, 1b and 2 specify this differential role to be one of degree regarding the role of direct and indirect ties. Hypotheses 3, 4 and 5 specify this role to be one of kind, in terms of opposed effects of the interaction between direct and indirect ties and of redundancy.

DATA, VARIABLES AND METHODS

Data

The hypotheses were tested on a longitudinal dataset consisting of the alliance and patenting activities of 116 companies in the chemicals, automotive and pharmaceutical industries. The reason to choose these three industries is that they share the importance of investing in R&D and innovation, but that they also reveal profound 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 with some more reliance on exploitation (Coriat and Weinstein, 2001). Moreover, the pharmaceutical industry has a strong focus on product innovations (Powell 1990, 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 generalizibility of the results.

The focal firms that we study were observed over a 12-year period, from 1986 until 1997. The panel is unbalanced because of new start-ups and mergers and acquisitions. This sample was selected to include the largest companies in these three industries that were also establishing technology based strategic alliances. Alliance data were retrieved from the MERIT-CATI database, which contains information on nearly 15 thousands cooperative technology agreements and their 'parent' companies, covering the period 1970-1996 (see Hagedoorn and Duysters (2002) for a further description). Information on the establishment of alliances is hard to obtain for small or privately owned companies. Previous studies on inter-firm alliances also focused on the industry leaders (Ahuja, 2000a; Gulati, 1995b; Gulati and Garguilo, 1999).

In constructing variables based on past alliances, we have made two choices. First, we have not considered different types of alliances separately and as a consequence, we have not weighed 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. The lifespan of alliances is assumed to be usually no more than five years (Kogut 1988, 1989). Therefore we have chosen for a moving window approach, in which alliances were aggregated over the five years prior to a given year, unless the alliance database indicated another life-span (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 life-span 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 (of the dependent variable).

In constructing the dependent variables, all patenting data were retrieved from the US Patent Office Database for all the companies in the sample, also those based outside the US. Working with U.S. patents – the largest patent market - 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, 2000a; p. 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.

For companies in the three sectors the financial data came from a combination of Worldscope, Compustat and data published in the companies' annual reports.

Variables

Dependent variables. The different hypotheses test in one way or another the effect that direct ties, indirect ties and redundancy have on exploitation and on exploration of different companies, in the chemical, automotive and pharmaceutical industry. To derive the two dependent variables, technological profiles of all focal companies were computed to find out whether new patents in the year of observation have to be categorized as 'exploitative' or ‘explorative’. These technological 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. 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; Henderson and Cockburn, 1996; Ahuja, 2000a). 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 two-digit level, which resulted in approximately 400 classes.

From these technology profiles we can distinguish between *exploitative* and *explorative technology classes*. Classes in which a company receives a patent in the year of observation but had not received a patent in the previous five years were considered ‘explorative’ patent classes[1]. Since knowledge remains relatively new and unexplored for a firm immediately after patenting, patent classes kept their explorative ‘status’ for 3 consecutive years, parallel to Ahuja and Lampert’s (2001) concept of novel and emerging technologies[2]. All the classes in which a company had successfully applied for a patent the previous five years and successfully applied for a patent in the year of observation were considered ‘exploitative’ patent classes.

The dependent variables ‘exploration patents’ and ‘exploitation patents’ were then made up by adding up all the patents applied for in the year of observation in the explorative and exploitative patent classes respectively.

Although the use of patents as an indicator of learning and innovative output has been criticized on many different ground (for an overview see Griliches, 1990) they are generally viewed as the single most appropriate measure of innovative performance at the company

1 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.

2 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.

level (Ahuja and Katila, 2001, Hagedoorn and Duysters, 2002), in particular in a single industrial sector context (Basberg, 1987; 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).

Independent variables. The impact of a firm's alliance network on the innovative output of companies has been explored among others by Ahuja (2000a) and Ahuja and Lampert (2001). In this paper, innovative output of a company is split up into the exploration of existing technological capabilities and the exploitation of new technological fields. We have argued that the former task should benefit from redundancy in the focal firm's network, while the latter task will be enhanced by the presence of structural holes (non-redundancy). For an accurate understanding of the impact of redundant and structural hole spanning alliances on both dimensions of innovative firm behavior, the firm's ego network should be decomposed into distinct and separate elements. Following Ahuja, (2000a) we make a distinction between *direct ties, indirect ties* and the *redundancy of ties* in the technology based alliances network. These independent variables are calculated based on the alliances that were established during the 5 year period prior to the year of observation.

Direct ties: The first dimension of a firm's alliance network is 'direct ties'. 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)[3]. We also introduce the squared term of the number of alliance partners since hypothesis 1b suggests an inverted U-shaped relationship between innovative performance and the number of direct ties.

3 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: The second dimension of the alliance network of a company consists of the number of partners it can reach indirectly in the alliance network. There are different possibilities to operationalize the breadth of coverage of indirect ties. We chose for a variable that measures the impact of indirect ties while taking into account the decline in tie strength across more distant ties. We only report the findings for the distance-weighted centrality (see tables 3a and 3b). We tested the robustness of the findings with other centrality measures that "...do not account for the weakening or decay in tie strength between firms that are connected by increasingly large path distances." (Ahuja, 2000a: p. 438) and obtained similar results. "Distance weighted centrality", 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 2000a: p. 438). The result is that alliance partners receive smaller weights the longer the path distance to the focal firm. The "distance weighted centrality" can be calculated by adding up all alliances at several distances weighted by their path distances.

Redundancy: The third dimension of a firm's alliance network reflects the degree in which its ties are redundant. The literature offers several possibilities to operationalize the (non-)redundancy of alliances. Most – if not all – researchers who have been involved in empirical studies on inter-organizational networking, the role of social capital and the like have chosen for a single measure of redundancy (Burt, 1992a; McEvily and Zaheer, 1999; Gulati, 1999; Ahuja, 2000a; Baum et al., 2000). In this paper, we develop different measures to formalize the notion of redundancy. We refer to Borgatti et al. (1998) for an extensive analysis of network measures that can be used to formalize the notion of redundancy.

Burt (1992a, 1992b) argues that the two empirical conditions that indicate a structural hole (or non-redundancy) are *cohesion* and *structural equivalence.* Both conditions reveal that there are structural holes by indicating where they are absent. The cohesion criterion indicates that two partners of the focal firm "…are redundant to the extent that they are connected [to each other] by a strong relationship. A strong relationship indicates the absence of a structural hole." (Burt, 1992b: p. 66). Structurally equivalent partners of the focal firm on the other hand have the same alliance connections to every other company in the network. Even in absence of an alliance between these two firms they will provide similar information to the focal firm because they are linked (directly and indirectly) to the same other companies in the overall alliance network. Thus cohesion focuses on the direct ties between a focal firm's partners, structural equivalence concerns the indirect ties of a focal firm's partners with more distant companies in the alliance network. In other words, cohesion based measures are based on the ego-network of a focal firm, structural equivalence based measures on the contrary are based on the position of the focal firm in the overall network.

The first measure of redundancy, *proportion density* (Burt, 1983; Hansen, 1999), captures *redundancy by cohesion* indicating the presence of alliances between a focal firm's allies. Alliance partners are redundant to the focal firm when alliances have been established between them. Proportion density is calculated as the number of ties in the ego-network of the focal firm (not counting ties involving the focal company) divided by the number of pairs where 'pairs' are potential ties. The values for this variable range from 0 to 1, where 1 indicates that all allies are directly linked to each other. High values thus indicate high redundancy.

Another variable to measure redundancy in terms of cohesion is *"network efficiency*" of a firm's ego-network (Burt, 1992a: chap. 2). This 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 minimum approaching zero, indicating high contact redundancy and therefore low efficiency" (Burt, 1992a: p. 53).

An additional variable capturing ego-network redundancy that Burt (1992a) offers is *network constraint*: this variable describes the extent to which a network is concentrated in redundant contacts. More constrained networks span fewer structural holes and, thus, we expect a positive impact of the 'network constraint'-variable on exploration and a negative effect on exploitation.

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 is 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[4]. Structural equivalence can then be calculated based on Euclidean distance or correlations. We choose correlations for the calculation of structural equivalence[5]: we can calculate the similarity (pairwise correlation) of the patterns between pairs of firms in the alliance network. Thereby we exclude the alliances between the focal firm and its partners because we intend to measure the extent to which the alliance partners of the focal firm are connected to other firms in the overall network. Correlations are then converted into a redundancy measure by taking the average of the correlations between pairs of direct partners (allies) of the focal company. The values for this variable range from

4 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.

5 Faust and Romney (1985) have shown that Euclidean distance as a measure of similarity without proper attention to appropriate standardization procedures leads to biased results when the ego-network size of the focal firms differs considerably. This is not the case when structural equivalence is based on the similarity of the patterns between pairs of individuals, e.g. correlation.

+1 (high redundancy) to –1 (non-redundancy). Finally, the variable is transformed into a measure ranging from 0 (low redundancy) to 100 (high redundancy). Following hypotheses 4 and 5, we expect a positive sign when a company explores new technological fields and a negative sign when it exploits its existing technological capabilities.

Control variables. While the primary focus of this study is to analyze 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 variable 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 Asia (Ohmae, 1985). Firms that are headquartered in different countries may differ in their propensity to patent. 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 chemical firm (default is the pharmaceutical industry).

Furthermore, we intended to include three organizational variables as controls[6]. The first one is the age of the company. Generally, one would expect older firms, with their accumulated experience, to be better at exploitation, and younger firms, with lower stakes and habituation in old technologies, to be better at exploration.

Next, the natural logarithm of 'corporate revenues'- a proxy for firm size - was included as a control variable. 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,

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

1991; Ahuja and Morris 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.

The other organizational variable is the natural logarithm of R&D expenditures. 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. Also R&D investments play a role in the ability of companies to recognize, value and assimilate external knowledge. This absorptive capacity of companies is crucial to acquire and integrate external knowledge, especially when the knowledge is tacit. Firms conduct R&D to be more able to use the technology of other companies (Cohen and Levinthal, 1990; Kim, 1998; Mowery and Oxley, 1995). This absorptive capacity argument is particularly relevant in the case of explorative learning because the knowledge to transfer is tacit and the focal firm has not yet built any capabilities in these technological areas.

Technological diversity between the firm's partners in the alliance network has to be introduced as another control variable according to Ahuja (2000a). His argument is twofold. 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; Stuart, 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 4 and 5.

Yao (2003) provides an interesting way to calculate the technological distance between a focal firm's partners. "The knowledge distance among a firm's direct alliances (excluding the firm itself) is the average distance among those firms. 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. Since each pair of firms is counted twice, we also divide the value by 2 to get the final technology distance among a firm's alliance" (Yao, 2003: p. 12). We refer to Yao (2003) for the calculation of the technological distance.

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). 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 Poisson estimation[7].

The basic Poisson model for event count data can be written as follows:

$$\Pr(Y_{it} = y_{it}) = \frac{\exp(-\lambda_{it})\lambda_{it}^{y_{it}}}{y_{it}!} \qquad (1)$$

Where the parameter λ_{it} represents the mean and the variance of the event count and y_{it} the observed count variable. It is furthermore assumed that:

$$\lambda_{it} = \beta' x_{it} \qquad (2)$$

[7] Hausman tests indicate that random effects Poisson models are better than fixed effects Poisson models.

with x_{it} being a vector of independent variables.

The above specification assumes that the mean and variance of the event count are equal. However, for pooled cross-section count data the variance often exceeds the mean. This overdispersion is particularly relevant in the case of unobserved heterogeneity. The presence of overdispersion does not bias the regression coefficients but the computed standard errors in the Poisson regression are understated resulting in an overestimation of the the statistical significance of the coefficients. Therefore, a random effects Poisson estimator used: it does not assume within-firm observational independence for the purpose of computing standard errors. For the random effects Poisson estimator equation (2) is changed into:

$$\lambda_{it} = \beta' x_{it} + u_i \qquad (3)$$

where u_i is a random effect for the i^{th} firm and reflects the firm-specific heterogeneity.

Unobserved heterogeneity may be the result of differences between companies in their innovation generating capabilities, and as a consequence, also in their propensity or ability to patent. Such unobserved heterogeneity, if present and not controlled for, can lead to overdispersion in the data or serial correlation. The model accounts for unobserved firm-level heterogeneity as we included the sum of alliances that a firm entered in the last five years (moving window approach) as an additional variable to control for differences in firms' patenting behavior (Heckman and Borjas, 1980).

Differences in patenting behavior between companies or between different years are further captured by including 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 over time:

they may capture the ever-growing importance of intellectual capital or changing macroeconomic conditions.

RESULTS

Table 1 represents the description of the different variables. Table 2 provides the descriptive statistics and the correlations between the variables for the 662 observations in the sample. Although the sample represents the prominent firms in the three sectors, there is quite some variance on most of the key variables. The alliance network based measures such as indirect ties, direct ties and the different redundancy variables are not highly correlated with each other. However, there are high correlations between the size variable, R&D-expenditures (or even R&D intensity), 'cumulative patents', and the technological distance among the partners are highly correlated (not shown in Table 2). In order to avoid multicollinearity, we have looked for one (a) latent variable(s) by means of a factor analysis. The results indicate that cumulated patents, revenues and R&D expenditures form one latent variable (Cronbach's alpha = 0.78). Factor scores were used as a new variable. The correlation between age and the latent variable is 0.30. The correlation between technological distance among partners and the latent variable is –0.04.

Insert table 1 about here

Insert table 2 about here

Tables 3a en 3b represent the results of the regression analysis using random-effects Poisson estimations respectively for exploitation and exploration. The basic model with only control variables is presented in model 1. There are no statistically significant differences between the three industries (chemical industry, car manufacturing and pharmaceutical industry) regarding the innovation rate both for exploitation and for exploration. The country of origin of the different companies plays a role in explaining both types of innovation. European companies have a lower innovation rate compared to Asian and US-based companies for exploitative patents. On the contrary, we do not find any significant differences between Asian, European and US-based companies regarding exploration.

The latent variable capturing the effects of size (revenues, R&D expenditures, and patent portfolio size) is strongly and positively linked to exploitation by companies in these three industries. So, regarding the generation of exploitative patents, large companies that have built extensive patent portfolio's in the past have an advantage over firms that have not done so. In contrast, the size and technology portfolio of a company is not related to patenting in new patent classes (see table 3b). This finding is in line with the organizational learning literature: large established organizations have 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). According to our results, small and large companies have a similar probability of patenting in new technology classes. Small firms can be as successful as large ones with respect to experimenting and exploring new technological fields.

The age of companies has no impact on exploitation, but it is negatively related to exploration. In other words, older companies have more problems than younger ones to look beyond their existing technological portfolio.

A last control variable is the technological distance between partners. Its effect on exploitation activities undertaken by firms is negative and significant, suggesting that further exploitation of existing technological capabilities is enhanced when a focal firm taps into the resources of partnering firms whose patent portfolio is not (too) different. In other words, in view of exploitation it is advantageous to carefully select alliance partners who have a similar technology profile. However, the same regressor has no significant effect on exploration. This indicates that linkages to partners with either different or similar technology profiles will not influence the innovation success of a company's exploration activities.

The estimated alpha coefficient is positive and significant for both exploitative and explorative learning. This indicates that important firm-level unobserved effects are present in the data and that a panel estimator is preferred above a pooled Poisson estimator.

Insert Tables 3a and 3b about here

Model 2 introduces direct ties and indirect ties as regressors. Direct ties are measured as the number of alliances a company established in the five previous years. Besides the linear term we also inserted the quadratic term to measure the impact of overembeddedness (Kogut et al., 1992; Uzzi, 1997). The coefficients for these variables are significant in both tables. This corroborates hypotheses 1a and 1b stating that direct ties are beneficial both for exploitation and for exploration, but that beyond a certain point the negative effects begin to dominate: embeddedness turns into overembeddedness. Moreover, the results on direct ties show that the coefficient of the linear term for exploitation is smaller than for exploration whereas the coefficient of the squared term is larger. This further confirms hypothesis 1b that the risk of overembeddedness sets in at lower levels of direct ties and is also stronger for exploitation than for exploration. The coefficients for the 'indirect ties' are positive and significant in both tables. The impact is substantially larger for exploration compared to exploitation. As a result, also hypothesis 2 is corroborated. Hence, a firm not only obtains social capital from its direct ties but also from its indirect ties. Moreover, the impact of indirect ties is substantially larger for exploration. The uncertainty involved in explorative research and the need to find novel knowledge pushes the focal firm to search also for solutions among the partners of its partners, or even beyond them.

Model 2 also introduces an interaction term between direct and indirect ties and is an empirical test for hypothesis 3. We have argued – following Ahuja (2000a) – that the number of direct ties moderates the impact of indirect ties, at least in the case of exploitative learning. This is supported by model 2 in table 3a. Because a focal firm has a good understanding of what type of knowledge is required and since the information involved is fairly explicit in exploitative learning, direct ties may easily overlap the knowledge that could be acquired from indirect contacts. However, the coefficient of this interaction term for exploration (table 3b) is also negative and significant. This is in contrast with hypothesis 3. We argued that in the case of exploration, implying tacit knowledge and high levels of uncertainty, direct contacts would be beneficial to understand more distant, novel knowledge from indirect ties. Apparently, however, direct ties also moderate the need to have alliance partners with extensive networks of partners. To understand this further, we study the interaction between direct ties and indirect ties more in-depth.

The joint impact of direct and indirect ties on both types of learning also differs considerably: according to model 2 companies can at best increase the patenting rate with 18% (calculated at the average level of indirect ties) in the case of exploitative patents. In contrast, companies can improve the innovation rate with a maximum increase of 39% in the case of explorative patents. The level of indirect ties plays a crucial role here: when the 'distance weighted centrality drops to '10', companies can improve performance with 39% in case of exploitation with 61% for exploration respectively[8]. In fact, these results provide further support hypotheses 1a and 1b, which predicted a stronger effect of direct ties on explorative learning compared to exploitative learning. The difference is considerable, indicating that the impact of external acquisition of technological know-how through alliances is larger when companies are experimenting in new technological areas compared to exploitation.

Returning to the role of direct ties, the maximum innovation performance is reached at medium levels of direct ties – i.e. 15 alliances for exploitation and 28 alliances for exploration, calculated at the average level of indirect ties – indicating that overembeddedness may play a role at higher levels of direct ties, especially when a company engages in exploitation[9]. However, these maximums increase significantly if the level of indirect ties drops: if the 'distance weighted centrality drops to '10', maximums are reached at 41 and 62 alliances respectively. Hence, when companies are not situated in the dense pack of the alliance network, they need more direct ties to reach the maximal innovation rate. In other words, there are different optimal strategies possible: firms can establish few alliances with partners that have extensive alliance networks with other firms, or alternatively, firms can partner with a larger set of companies who only maintain linkages to a few others. The results are illustrated in Figures 1 and 2.

8 Since model 2 in tables 3 and 3b offers a saddle point solution, there is also a strong effect on innovation when the number of direct ties are limited and the number of indirect ties are high. Hence, allying with partners that are centrally located in the network improves the innovation rate of the focal firm both in terms of exploitation and exploration.

9 These maxima are calculated from the first order conditions from model 2 in tables 3a and 3b at the mean value of indirect ties (=68.13):
Table 3a: $x^* = (12.1445 - 0.1184*68.31)/ (2*0.1339) \approx 15$ alliances
Table 3b: $x^* = (15.5020 – 0.1350*68.31)/(2*0.1140) \approx 28$ alliances

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Insert Figures 1 and 2 about here

Models 3 to 6 allow us to test hypotheses 4 and 5. Each model introduces a variable that measures redundancy in a firm's alliance network in a different way; three of them are based on cohesion and one on structural equivalence. Following hypothesis 4, we expect a negative effect from redundant ties on exploitation. Model 3 introduces 'proportion density' that measures the density of ties among a focal firm's alliance partners and is thus a redundancy-measure. In line with hypothesis 4, our findings show such a negative effect. Model 4 introduces 'network efficiency' that measures **non**-redundancy within a firm's ego-network: high values for this variable indicate that a firm's direct contacts provide non-redundant information. Here we find a positive and significant coefficient in table 3a, which is also in line with hypothesis 4. Model 5 introduces 'network constraint' that forms a measure for redundancy again. The coefficient for this regressor is negative and significant, which again confirms hypothesis 4. Model 6 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 the correlation coefficient of every pair of profiles of the direct partners of the focal firm: high (low) values represent (non-)redundancy. In line with hypothesis 4, the impact of this variable on exploitation is negative and significant. Following these results of our four different measures of (non) redundancy, we may conclude that redundancy among a focal firm's direct and indirect ties indeed form a liability when firms engage in exploitation activities.

In comparison with exploitation, the results for exploration are less convincing. Three of our four measures have the right sign (proportion density (+), network efficiency (-) and SE-based correlation (+)), but none of them is significant. Moreover, network constraint not only lacks significance but also carries the wrong sign (negative instead of an anticipated positive sign). These results seem to indicate that, when engaging in exploration tasks, a firm benefits only from direct ties and indirect ties but that redundancy among these ties, or lack thereof, plays no role whatsoever.

The dependent variables was also calculated in a slightly different way to test for robustness; Patents in new technology classes kept the status of an 'explorative patent' for 5 years instead of 3 years. Even if exploitative and explorative patents were calculated this way, the results are very similar to those in tables 3a and 3b.

DISCUSSION AND CONCLUSIONS

The main aim of this paper is to understand how a firm's technological performance in terms of exploration and exploitation is conditioned by the structure of its network of technology-based alliances. To study this we have differentiated between a firm's direct ties, indirect ties and the redundancy among them. We found that these three characteristics of an alliance network, apart and in combination, have a differential impact on exploration and exploitation tasks.

The effect of direct ties and indirect ties is positive for both tasks, with the difference being that (for both types of ties) the effects are larger for exploration than for exploitation. Also the risk of overembeddedness could be identified for both tasks, whereby it sets in earlier and is stronger for exploitation than for exploration. Regarding the interaction between direct and indirect ties we found the expected, negative effect for exploitation but unexpected was that this interaction turned out negative for exploration as well. The anticipated positive effect of non-redundancy for exploitation was confirmed. In contrast, the predicted positive effect of redundant ties for exploration could not be confirmed, although not entirely rejected either. This leads to the following conclusions.

First, these findings confirm the key claim of this paper that the distinction between exploration and exploitation forms a relevant contingency factor for understanding a firm's optimal network structure. So, an important lesson here is that the distinction between exploration and exploitation is apparently not only relevant from a firm's internal perspective (March, 1991; Levinthal and March, 1993; Tushman and Anderson, 1996) but also from the perspective of its external alliance network. Second, the differential role of a firm's alliance network is one of degree, and not of kind. In other words, optimal alliance networks for exploitation and exploration are not completely different but 'only' differ from each other to some degree. This is finding is important as it implies that a firm's alliance network can be instrumental for both tasks and that one does not need a (completely) different type of network structure nor that investments made in building existing ties have to be made anew, for each task. Instead, one can use the same network for exploration and exploitation, if one takes the differential degree of the effect of one's alliance network on the two tasks into account. Although we have to be cautious here regarding the effect of redundancy on exploration, an issue we will come back to.

A third conclusion is that we found no significant differences for the three industries that we studied, despite some of their key differences regarding innovation. Our findings indicate that the role of a firm's alliance network for exploration and exploitation remains invariant across the three industries. This indicates that our choice to study three different types of industries has paid off as it enables us to generalize across them. Moreover, this implies that the distinction between exploration and exploitation seems to have larger explanatory potential for understanding the role of a firm's alliance network than type of industry (Rowley et al., 2000), stage of industry development (Walker et al., 1997) or type of innovation (Tidd et al., 1997).

A fourth conclusion relates to the interaction between direct and indirect ties. We did not find evidence for our claim that the combination of direct ties and indirect ties has a positive effect on exploration. However, further analysis revealed that different strategies for combining direct and indirect ties can both yield optimal innovation output as has been illustrated in figures 1 and 2. Establishing a few direct ties with partners that have extensive alliance networks with other firms throughout the network leads to an innovation performance that is comparable to a strategy of partnering with a large number of firms who themselves are connected to only a few others. This insight nuances the dominant view in the literature that especially centrally positioned firms will show superior performance (Merton, 1949; Burt, 1992b; 2000; 2004; Galaskiewicz, 1979; Krackhardt, 1990; Stuart, 1998; Gulati, 1999; Owen-Smith and Powell, 2004). In contrast, our findings convey an optimistic message for firms occupying more peripheral positions. By investing in many direct ties with very limited ties themselves (in other words, few indirect ties are reached), a focal firm can obtain an innovation performance that is largely comparable to their centrally positioned counterparts. However, the price varies significantly between both strategies as peripheral firms have to absorb higher transaction costs (each tie entails set-up and maintenance costs) and face a greater risk of overembeddedness due to this large number of direct ties (following hypothesis 1b).

A final conclusion is that our study has not completely elucidated which view on the role of redundancy has more validity under which conditions. We have found clear empirical evidence in favor of Burt's view when firms engage in exploitation tasks. His argument that shedding off redundant contacts creates efficiency in a firm's network seems to form the explanation here, as efficiency forms a prime consideration in exploitation (March, 1991; Gilsing and Nooteboom, 2005). At the same time, we claimed an important role of redundant ties in exploration, in favor of Coleman's view, which could not be confirmed. This seemingly implies that Coleman's view on redundancy does not hold for exploration, but we think there is more to this. It is striking to see that two expected effects on exploration could not be identified, i.e. a rejection of a positive interaction between direct and direct ties and a lack of confirmation of a positive effect of redundancy. Apparently, the role of a firm's alliance network in exploration cannot be entirely predicted based on arguments as advanced by the existing literature.

Implicit in most studies on the role of embeddedness is that it has been understood under conditions of relative environmental stability (Stuart, 1998; Gulati, 1995; Gulati and Garguilo, 1999; Ahuja, 2000b). It is under such 'structure-reinforcing conditions' (Madhavan et al., 1998) that the role of embeddedness is increasingly well understood, conditions that connect with March's category of exploitation (1991). This leaves open how to understand the role of network embeddedness in view of exploration. Following our findings, it seems that the difference between an 'embeddedness logic' for exploitation versus exploration is one of degree, not of kind. On the other hand, others have shown that the role of redundant contacts differs profoundly between a setting that stresses efficiency versus one that emphasizes dynamics and learning (Duysters and Hagedoorn, 2002; Nooteboom and Gilsing, 2005). At this point, we suggest leaving these issues for future research.

Other issues for future research and limitations of this study can be summarized as follows. We did not consider the effect 'tie strength' on exploitation and exploration. Different types of alliances can be weighted according to the 'strength' of the relationship as some authors did (see Contractor and Lorange, 1988; Gulati 1995b; Nohria and Garcia-Pont, 1991). This would require additional research and hypothesis building regarding which alliance type is more instrumental for exploration of new technological fields and which types for exploitation of a firm's existing set of technologies. We suspect that tie strength will influence the role of direct ties and indirect ties as well as their interaction, but here we have chosen to abstract from this role as we first want to determine whether direct and indirect ties play a role in the first place. If so, a distinction between different types of alliances is likely to improve the analysis - as has been suggested in the context of 'open innovation' (Chesbrough, 2003) - but this is beyond the scope of the current paper.

Finally, exploration and exploitation have been operationalized in different ways in the literature (Benner and Tushman, 2002; Faems et al., 2005; Katila 2005; Katila and Ahuja 2002; Rosenkopf en Nerkar, 2001; Rothaermel and Deeds, 2004; Rowley et al., 2000; Schildt et al., 2005). Our definition of exploration and exploitation comes close to that of Benner and Tushman. However, none of these measures tries to transform the dichotomy between exploitation and exploration into a continuous variable measuring the degree of explorativeness. Entering a new patent class can be more or less explorative depending on the technological distance between a company's patent portfolio and the newly entered patent class(es) (Nooteboom 1999, 2000). This qualification may enrich the analysis of the balance between exploration and exploration considerably.

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TABLE 1
Definitions of dependent and independent variables

Variable name	Variable description	
Exploitative learning	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
Explorative learning	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
Cumulative patents	Number patents that a firm filed for during the previous five years (t-5 to t-1)	
$(\text{Cumulative patents})^2$	Squared term of previous variable	
Indirect ties	'Distance weighted centrality': Number of indirect ties but weighted to account for the decline in tie strength across progressively distant ties	
Proportion density	Density of ties among a focal firm's direct partners expressed as a proportion of all possible ties between them in year t-1	
Network efficiency	'Effective size' divided by the number of partners in the focal-firm's ego-network (Burt, 1992a, p. 53)	
Network constraint	The extent to which a network is concentrated in redundant contacts (Burt 1992a)	
Network hierarchy	The extent to which the redundancy can be traced to a single contact in the network (Burt, 1992 a)	
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	
Latent variable	Factor scores based on ln sales, ln R&D expenditures and technological capital in year t-1	
Year	Dummy variable indicating a particular year (1986-1997)	
Chemical company	Dummy variable set to one if the firm is a chemical company	
Car manufacturer	Dummy variable set to one if the firm is a car manufacturer	
Europe	Dummy variable set to one if the firm is headquartered in Europe	
US	Dummy variable set to one if the firm is headquartered in the US	

Note: 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	14
1 # of exploitative patents	102.23	156.81	0	1136														
2 # of explorative patents	9.19	14.92	0	125	0.24													
3 Direct ties	14.16	13.42	2	113	0.51	0.25												
4 Indirect ties	68.31	32.01	0	177	-0.12	0.03	-0.17											
5 Proportion density	14.60	23.10	0	100	-0.16	-0.09	-0.11	-0.15										
6 Network efficiency	0.884	0.167	0.1	1	0.15	0.08	0.05	0.16	-0.96									
7 Network constraint	0.224	0.181	0	1.125	-0.33	-0.19	-0.56	-0.11	0.51	-0.34								
8 Structural equival. (corr.)	0.152	0.193	-0.012	1	-0.12	-0.06	0.05	-0.22	0.92	-0.92	0.38							
9 Pattern partner sharing	0.314	0.143	0.003	0.5	0.07	0.08	0.18	0.30	-0.04	0.00	-0.22	-0.05						
10 Age	79.75	45.82	0	236	0.13	-0.06	0.12	0.01	0.02	-0.03	-0.05	0.05	0.04					
11 Latent variable	8.659	1.804	0.29	11.91	0.66	0.26	0.49	-0.11	-0.10	0.08	-0.28	-0.02	0.04	0.30				
12 Techn. distance partners	0.022	0.009	0	0.063	0.02	0.04	-0.11	0.27	-0.13	0.18	-0.01	-0.21	-0.06	0.05	-0.04			
13 Chemical company	0.376	0.458	0	1	0.03	-0.02	-0.05	-0.11	0.07	-0.07	-0.08	0.08	-0.10	0.16	0.11	-0.17		
14 Car manufacturer	0.270	0.444	0	1	0.05	0.03	0.25	-0.33	0.13	-0.20	0.11	0.20	0.07	0.04	0.21	-0.15	-0.47	
15 Firm is European	0.233	0.423	0	1	-0.26	-0.02	0.01	-0.11	0.13	-0.18	-0.07	0.18	-0.05	-0.07	-0.16	-0.14	0.11	0.13
16 Firm is US-based	0.429	0.495	0	1	0.04	0.01	-0.02	0.17	-0.18	0.20	-0.06	-0.23	0.01	-0.05	-0.04	0.17	-0.14	-0.18
17 Year 1986	0.081	0.273	0	1	-0.03	-0.02	-0.08	-0.27	0.05	-0.04	0.10	0.08	-0.26	-0.05	-0.04	0.00	0.01	-0.00
18 Year 1987	0.087	0.282	0	1	-0.03	-0.02	-0.06	-0.26	0.04	-0.04	0.07	0.06	-0.04	-0.04	-0.03	-0.02	-0.00	0.03
19 Year 1988	0.081	0.273	0	1	0.00	0.01	-0.03	-0.09	0.07	-0.06	0.03	0.05	0.05	-0.03	-0.03	-0.00	-0.02	0.01
20 Year 1989	0.081	0.273	0	1	0.01	0.02	-0.00	-0.03	0.05	-0.04	-0.01	0.02	0.07	-0.02	-0.02	-0.10	-0.01	-0.00
21 Year 1990	0.087	0.282	0	1	-0.01	-0.03	0.02	-0.01	0.03	-0.02	0.01	0.03	0.01	0.01	-0.02	-0.09	-0.00	0.01
22 Year 1991	0.087	0.282	0	1	-0.01	-0.04	0.00	-0.00	-0.05	0.05	-0.00	-0.05	0.02	0.03	0.00	0.01	-0.00	0.01
23 Year 1992	0.082	0.275	0	1	0.01	-0.07	-0.00	0.02	-0.07	0.06	-0.02	-0.06	0.14	0.04	0.02	-0.02	-0.00	0.01
24 Year 1993	0.084	0.277	0	1	0.00	-0.07	0.00	0.01	-0.05	0.05	-0.02	-0.04	-0.17	0.04	0.02	0.02	-0.01	0.01
25 Year 1994	0.081	0.273	0	1	0.01	0.01	0.01	0.10	-0.05	0.05	-0.03	-0.04	-0.20	0.02	0.02	0.06	0.00	-0.00
26 Year 1995	0.082	0.275	0	1	0.05	0.15	0.02	0.09	-0.01	0.01	-0.03	-0.03	0.10	-0.00	0.03	0.04	0.01	-0.02
27 Year 1996	0.082	0.275	0	1	-0.00	0.07	0.05	0.17	-0.00	-0.00	-0.06	-0.02	0.04	-0.00	-0.02	0.04	0.02	-0.02

TABLE 2

Descriptive statistics and correlation matrix (continued)

Variable	15	16	17	18	19	20	21	22	23	24	25	26
15 Firm is European												
16 Firm is US-based	-0.48											
17 Year 1986	0.03	-0.02										
18 Year 1987	0.01	-0.02	-0.09									
19 Year 1988	-0.02	0.01	-0.08	-0.09								
20 Year 1989	-0.01	0.00	-0.08	-0.09	-0.08							
21 Year 1990	-0.00	-0.01	-0.09	-0.10	-0.09	-0.09						
22 Year 1991	-0.02	0.01	-0.09	-0.10	-0.09	-0.09	-0.10					
23 Year 1992	-0.01	-0.00	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09				
24 Year 1993	-0.02	0.00	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09			
25 Year 1994	-0.02	0.01	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09		
26 Year 1995	0.02	-0.00	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	
27 Year 1996	0.02	0.01	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09

TABLE 3a
Determinants of the patent rate of firms – Exploitation, 1986-1997

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Direct ties						
Cumulative alliances /1000		12.1445***	11.8128***	12.3351***	6.3301***	12.7228***
		(1.2178)	(1.2183)	(1.2209)	(1.3395)	(1.2274)
$(\text{Cumulative alliances}/1000)^2$		-0.1339***	-0.1312***	-0.1349***	-0.0954***	-0.1362***
		(0.0097)	(0.0097)	(0.0097)	(0.0103)	(0.0097)
Indirect ties						
Distance weighted centrality		0.0020***	0.0018***	0.0020***	0.0012***	0.0020***
		(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0003)
((Distance weighted centrality)		-0.1184***	-0.1131***	-0.1185***	-0.0979***	-0.1183***
* (cumulative alliances))/1000		(0.0093)	(0.0093)	(0.0093)	(0.0053)	(0.0093)
Structural holes vs. network closure						
Via cohesion						
Proportion density			-0.1175***			
			(0.0385)			
Network efficiency				0.1171**		
				(0.0558)		
Network constraint					-5.8519***	
					(0.5770)	
Via structural equivalence						
Correlation (Hansen)						-0.1585***
						(0.0412)
Control variables						
Car manufacturer	0.2240	0.1384	0.1992	0.1475	0.1348	0.1506
	(0.3931)	(0.3803)	(0.3836)	(0.3792)	(0.3747)	(0.3791)
Chemical industry	0.6108	0.5069	0.5176	0.5072	0.4871	0.5112
	(0.4088)	(0.3888)	(0.3877)	(0.3875)	(0.3829)	(0.3875)
Europe	-1.5788***	-1.4280***	-1.4661***	-1.4182***	-1.4255***	-1.4173***
	(0.4391)	(0.4173)	(0.4198)	(0.4162)	(0.4104)	(0.4161)

US	-0.0914	-0.0352	-0.0611	-0.0334	-0.0268	-0.0329
	(0.3575)	(0.3449)	(0.3462)	(0.3438)	(0.3401)	(0.3437)
Age	0.0031	0.0021	0.0016	0.0021	0.0020	0.0021
	(0.0043)	(0.0040)	(0.0040)	(0.040)	(0.0039)	(0.0040)
Factor (Firm size, # patents	0.4311***	0.6636***	0.6667***	0.6671***	0.6766***	0.6630***
R&D intensity)	(0.0206)	(0.0276)	(0.0276)	(0.0277)	(0.0275)	(0.0276)
Techn. distance	-3.8682***	-2.6439***	-2.8607***	-2.8234***	-2.0338***	-3.0092***
between partners	(0.7261)	(0.7420)	(0.7416)	(0.7465)	(0.7503)	(0.7472)
Constant	3.8368***	3.6954***	3.7768***	3.5878***	3.8983***	3.7067***
	(0.4644)	(0.4440)	(0.4486)	(0.4455)	(0.4382)	(0.4424)
alpha	1.7263***†	1.6000***	1.5785***	1.5895***	1.5539***	1.5888***
	(0.2518)	(0.2362)	(0.2353)	(0.2349)	(0.2304)	(0.2347)
Number of firms	74	74	73	74	74	74
Number of firms-years	662	662	655	662	662	662
Wald chi-squared	1343.24	1657.32	1632.59	1662.12	1762.86	1671.69

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 Poisson estimator. The sample is an unbalanced panel.
† Significance of the likelihood test of alpha = 0. High significance indicates that the panel estimator is preferred over the pooled estimator.

TABLE 3b
Determinants of the patent rate of firms – Exploration, 1986-1997

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Direct ties						
Cumulative alliances/1000		15.5020***	14.5247***	15.5406***	14.2272***	15.48569***
		(4.9709)	(5.0049)	(4.9773)	(5.4507)	(4.9736)
$(\text{Cumulative alliances}/1000)^2$		-0.1140**	-0.1047**	-0.1139**	-0.1038**	-0.1142**
		(0.0449)	(0.0451)	(0.0449)	(0.0482)	(0.0449)
Indirect ties						
Distance weighted centrality		0.0036***	0.0036***	0.0034***	0.0035***	0.0037***
		(0.0006)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
((Distance weighted centrality)		-0.1350***	-0.1284***	-0.1212***	-0.1309***	-0.1364***
* (cumulative alliances))/1000		(0.0391)	(0.0395)	(0.0385)	(0.0398)	(0.0392)
Structural holes vs. Network closure						
Via cohesion						
Proportion density			0.13792			
			(0.0994)			
Network efficiency				-0.2028		
				(0.1405)		
Network constraint					-0.0827	
					(0.1462))	
Via structural equivalence						
Correlation (Hansen)						0.0819
						(0.1102)
Control variables						
Car manufacturer	-0.1649	-0.1495	-0.1226	-0.1713	-0.1472	-0.1582
	(0.3138)	(0.3180)	(0.3306)	(0.3207)	(0.3175)	(0.3187)
Chemical industry	-0.1224	-0.0923	-0.0876	-0.1042	-0.0937	-0.0967
	(0.3228)	(0.3287)	(0.3304)	(0.3309)	(0.3280)	(0.3294)

Europe	-0.4064	-0.5221	-0.5523	-0.5267	-0.5181	-0.5282
	(0.3676)	(0.3687)	(0.3803)	(0.3713)	(0.3680)	(0.3695)
US	-0.3525	-0.4025	-0.4188	-0.4019	-0.4008	-0.4047
	(0.2865)	(0.2898)	(0.2983)	(0.2918)	(0.2894)	(0.2903)
Age	-0.0065**	-0.0078***	-0.0080***	-0.0078***	-0.0078***	-0.0078***
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
Factor (Firm size, # patents,	0.0610	0.0975	0.0921	0.0978	0.0960	0.0989
R&D intensity)	(0.0580)	(0.0671)	(0.0664)	(0.0669)	(0.0671)	(0.0672)
Techn. distance	-1.2734	-1.8148	-1.9670	-1.5180	-1.7512	-1.5882
between partners	(2.2508)	(2.2879)	(2.2897)	(2.2987)	(2.2932)	(2.3092)
Constant	2.8328***†	2.6524***	2.6720***	2.8355***	2.6833***	2.6437***
	(0.3296)	(0.3368)	(0.3482)	(0.3618)	(0.3409)	(0.3375)
alpha	1.0505***	1.0500***	1.0828***	1.1064***	1.0469***	1.0539***
	(0.1665)	(0.1681)	(0.1741)	(0.1702)	(0.1677)	(0.1687)
Number of firms	74	74	73	74	74	74
Number of firms-years	662	662	655	662	662	662
Wald chi-squared	232.76	252.50	250.26	254.43	252.92	252.94

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 Poisson estimator. The sample is an unbalanced panel.
† Significance of the likelihood test of alpha = 0. High significance indicates that the panel estimator is preferred over the pooled estimator.

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

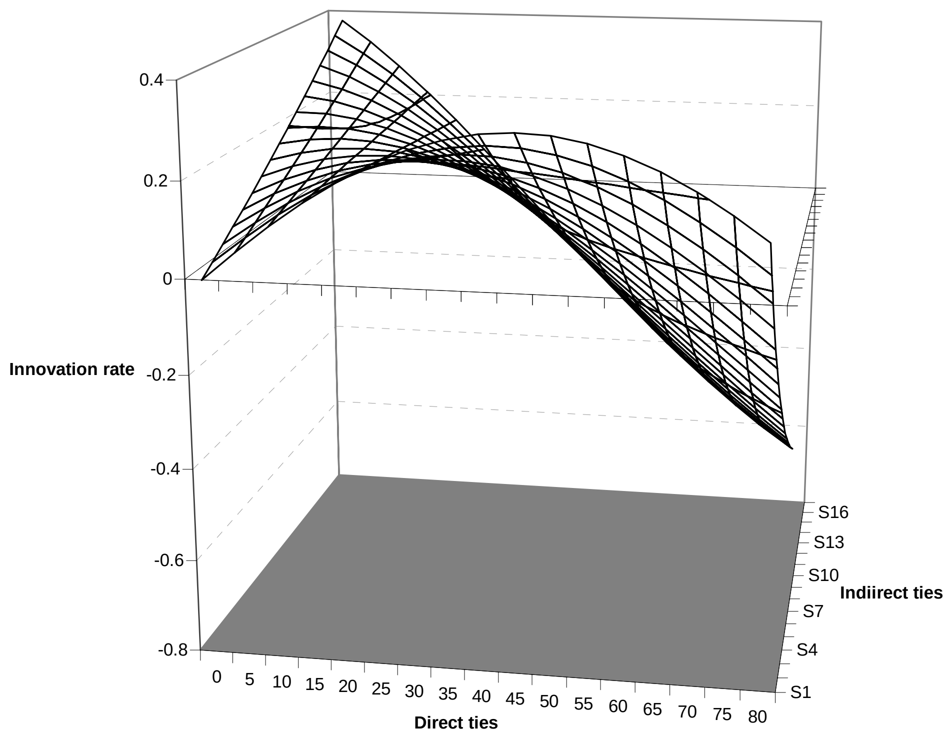
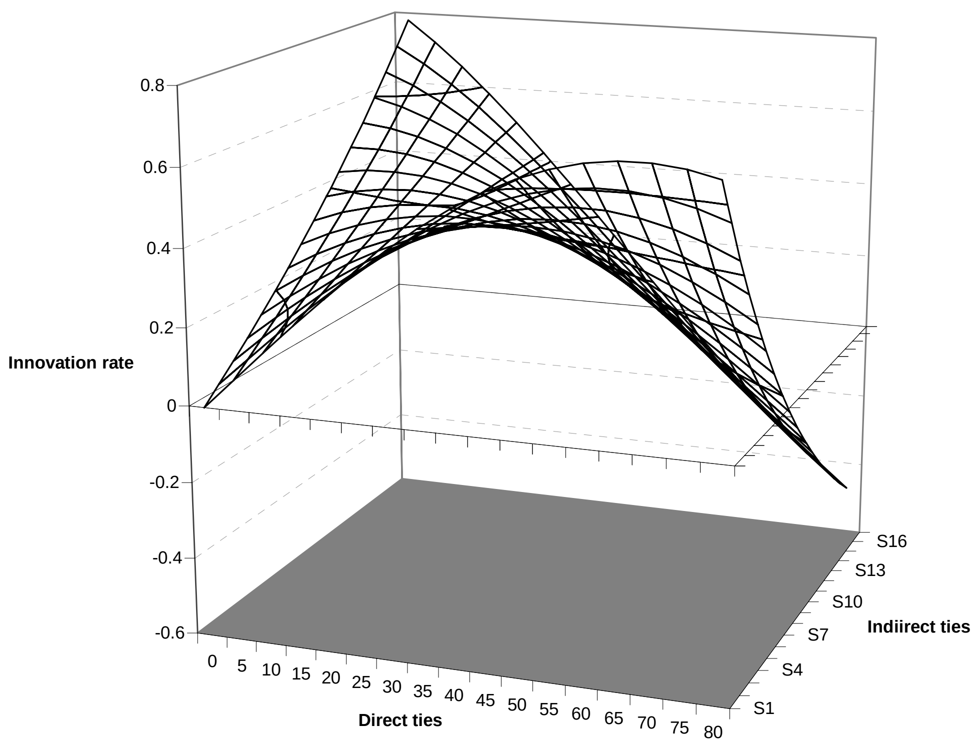


Figure 2: The innovation rate for different levels of direct and indirect ties – exploration



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