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Eindhoven Centre for Innovation Studies

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# Explorative and exploitative learning strategies in technology-based alliance networks

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## **Abstract**

This paper aims to improve our understanding of how exploitative and explorative learning of firms is enhanced through their social capital. Both types of learning differ considerably from each other and we argue that the distinction between them may be an important contingency factor in explaining the value of direct, indirect and (non-)redundant technology-based alliances. In particular we argue that, since companies have to find a balance between explorative and exploitative learning (March, 1991), redundant and non-redundant links play a complementary role in inter-organizational learning processes: redundant information improves exploitative learning, non-redundant information enhances a firm's explorative learning. The empirical results support the predictions about the contingency of the value of redundant information for both types of learning. Direct and indirect ties improve both types of learning but the impact on explorative learning is much larger. We find that direct ties have a moderating effect on indirect ties only in the case of exploitative learning. Firm size and technological distance between a firm's partners also have a differential effect on exploitative and exploitative learning.

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## INTRODUCTION

As competition becomes increasingly knowledge-based and companies get involved in accelerating technology races reducing time to market, they face considerable problems to develop the required knowledge and capabilities internally (Gomes-Casseres, 1996; Mowery, 1988; Mytelka, 1991; Teece, 1992; Hagedoorn and Duysters, 2002). Chesbrough (2003) coined the term “open innovation” to indicate that companies – even the largest and technologically leading ones – must complement their in-house R&D with external technologies on the one hand, and open up their own technological knowledge to outsiders on the other hand. In large companies, management is replacing the traditional inward focus of its technological competence building by a more outward-looking approach that draws heavily on technologies from networks of universities, startups, suppliers, and competitors.

Technology based alliances between companies are one way to tap into these networks. During the last two decades technology based strategic alliances have started to play a major role as means of quasi-external knowledge acquisition modes (Hagedoorn, 1996; Hagedoorn and Duysters, 2002; Powell *et al.*, 1996). A growing number of firms is realizing that alliances can be employed as effective learning mechanisms. Companies are increasingly pushed to enter ‘learning alliances’ through which they can speed up their capability development and reduce technological uncertainty by acquiring and exploiting knowledge that is developed by their alliance partners (Grant and Baden-Fuller, 1995). 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. Both types of learning are complements reinforcing each other’s productivity (Cohen and Levinthal, 1990).

However, considering inter-organizational networks of technology-based alliances as a set of ‘learning alliances’ is clearly a simplification. In this study we focus on March’s (1991) distinction between exploitative and explorative learning: ‘exploitation’ is the refinement and extension of existing technologies, whereas ‘exploration’ is experimentation with new alternatives. March argues that each company needs to balance both types of learning to stay competitive in the short *and* the long run. There are considerable differences between both types of learning (March, 1991; Chesbrough, 2003), which, in turn, have important

implications in the way a company can tap into the technological capabilities of its alliance partners. 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), only few of them pay particular attention to the exploitative or explorative nature of the inter-organizational learning in alliance networks (e.g. Ahuja and Lampert, 2001; Hagedoorn and Duysters, 2002; Rowley et al., 2000)<sup>1</sup>.

The main aim of this paper is to improve our current understanding of how exploitative and explorative learning of firms is enhanced (or hampered) through technology-based alliances and the social structure of the alliance network. Ahuja (2000a) argues that three aspects of a firm's alliance network structure have an impact on the technological performance of companies: "(1) the number of direct ties maintained by the firm, (2) the number of indirect ties maintained by the firm (the firm can reach in the network through its partners and their partners), and (3) the degree to which a firm's partners are linked to each other (i.e., whether there are structural holes in the firm's ego network)" (Ahuja, 2000a: p. 428). Similarly, we argue that these three aspects of a company's network structure have an effect – albeit a different one – on its explorative and exploitative learning.

We argue that the value of a firm's alliance network is contingent on the type of learning<sup>2</sup>. Since exploitative and explorative learning are quite different in nature, alliances (both direct and indirect ones) are expected to have a different impact on both types of learning. Explorative learning implies that the firm departs from its existing technology base and the knowledge involved is both tacit and novel to the firm (Levinthal and March, 1993; March, 1991). In contrast, exploitative learning is likely not be tacit and entails less uncertainty because the company is experienced and has much of the required knowledge in-house (Hansen et al., 2001). We argue that this contingency allows us to detect significant differences in the value of direct and indirect ties.

Moreover, we will also focus on the presence of redundant ties in the alliance networks. In the literature on social networks there are two opposing views on the benefits of redundant ties.

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<sup>1</sup> Hansen et al. (2001) also enter this topic within the context of intra-organizational knowledge

<sup>2</sup> This approach is in line with recent studies that recognize that the value of social networks is contingent on particular circumstances (see Burt, 1997, 2000; Gabbay and Zuckerman, 1998; Hansen, 1999; Hansen et al. 2001; Podolny and Baron, 1997; Uzzi, 1997; Walker *et al.*, 1997)

On the one hand, there is the structural hole theory of Burt (1992a) where firms can reap rents because of the absence of ties among its contacts. As a result, companies benefit from non-redundant ties in their networks. This view is at odds with the social capital theory of Coleman (1988, 1990) where firms benefit from cohesive (redundant) ties with their alliance partners. However, a number of scholars (Ahuja 2000a; Burt 1998, 2000; Hansen *et al.*, 2001) suggest that the two forms of social capital are not necessarily contradictory, but they rather play different roles in different settings or have different purposes. In other words, the value of redundant and non-redundant ties might be contingent on particular conditions. We argue that the distinction between explorative and exploitative learning may be an important contingency factor in explaining the value of (non-)redundant ties. In particular we argue that, since companies have to find a balance between explorative and exploitative learning, redundant and non-redundant contacts play a complementary role in inter-organizational learning processes. Companies have to make choices between bridging structural holes between the dense areas of an alliance network on the one hand and creating cohesive ties to benefit from its social capital in the network on the other hand. In other words, firms should make decisions about how and when to make use of redundant and non-redundant ties in their external acquisition of technology.

In the next part, we will derive some basic hypotheses on the effect of firms' alliance network structure on their innovative performance. In the empirical part of the study we will test these hypotheses using strategic technology alliance data and patent data of companies in three different industries over a time-span of 12 years.

## **THEORETICAL BACKGROUND AND HYPOTHESES**

### **Balancing two different types of learning**

One of the major challenges in organizational learning is to find an appropriate balance between exploitative and explorative learning (March, 1991). Both types of learning serve different goals. Exploitative learning intends to refine and extend existing technologies or competencies. It is characterized as routinized learning, which adds to the existing knowledge and competencies of a firm without changing the nature of its activities (Hagedoorn and Duysters, 2002). Explorative learning involves searching and experimenting with new

technologies or entrepreneurial opportunities. This non-routinized learning involves changes in company routines and experimentation with new alternatives (see, e.g. Dodgson, 1993; March, 1991), which, if successful, does change the nature of competencies of companies and it increases their innovative performance. Diversity and experimentation are central to successful entrepreneurial activity (Burgelman, 1983; Lant and Mezias, 1990; McGrath and MacMillan, 2000; Mezias and Glynn, 1993). Consequently, exploitative and explorative learning are very different from each other. In comparison with exploitation, exploration is more experimental in nature, long-term oriented, and highly uncertain. While exploitation can be planned and controlled, explorative learning can only be managed through an option generating strategy, characterized by goal autonomy and ambiguous structures (McGrath, 2001). Because of the high level of uncertainty in explorative learning, planning is not an effective approach. Instead, companies should probe the future through a variety of low-cost probes and shape their next strategic moves accordingly (Brown and Eisenhardt, 1998; Lynn *et al.* 1996). As a result, in many companies explorative learning is organized differently than exploitation which is much more related to the day-to-day activities (Vanhaverbeke *et al.*, 2003).

As learning not only occurs within companies, but also between companies, one should take into account that exploitative as well as explorative learning take place in inter-organizational technology-based alliances (Rowley *et al.*, 2000). Some alliances are established to deepen the existing technological capabilities of a company (i.e., exploitative learning), other alliances should make a firm familiar with novel or emerging technologies (i.e. explorative learning). In a dynamic environment, with changes in both industry players and dominant technologies, exploratory learning becomes increasingly important, not only in terms of the endogenous capabilities of companies, but also in terms of learning in a dynamic environment in which the relevance of the knowledge of partners is not clear in advance. Hence, dense patterns of interaction and ‘gregariousness’, with repeated contacts and continuous flows of information, have emerged (see Hagedoorn and Duysters, 2002). These types of patterns are typical for exploratory networks.

In this knowledge acquisition process the strategy for learning should however, not be either exploration *or* exploitation as a stand-alone strategy. As argued by March (1991), firms that engage exclusively in exploration often suffer from high experimentation costs, without exploiting its benefits. It leads to undeveloped ideas and competencies. Firms that engage

exclusively in exploitation, however, often suffer from technological inertia. In other words, firms should maintain a balance between exploration and exploitation. Both types of learning compete for limited resources and there will always be a trade-off between investing in deepening and upgrading the existing technologies to safeguard profits today and exploring new technologies to secure future returns (Rowley et al., 2000; Levinthal and March, 1981).

### **Strategic alliances and their role in exploitative and explorative learning**

As internal technology development is no longer sufficient to deal with the rapidly changing technological environment, a growing number of firms seems to recognize that external acquisition through alliances allows them to explore new and promising technological areas and enables them to strengthen or upgrade their existing technological capabilities at the same time (Duysters and de Man, 2003). Studies indicate that interfirm linkages indeed help firms to develop and absorb technology (Ahuja, 2000b; Harianto and Pennings, 1990; Powell *et al.*, 1996). The growing importance of external knowledge acquisition poses a number of important challenges to companies. One of the most prominent questions relates to the degree in which firms are able to absorb their newly acquired knowledge, i.e. the degree of their absorptive capacity<sup>3</sup>. Lane and Lubatkin (1998) and Cockburn and Henderson (1998) argue that external networks enhance an organization's absorptive capacity. In fact, experience in transferring knowledge through technology-based alliances might increase the absorptive capacity of the firms involved in two ways. First, by increasing the knowledge base communication between partners becomes easier. Second, experience with alliances results in the development of specific routines that support knowledge transfer (Simonin, 1999).

In the case of exploitative learning, companies team up with partners to share R&D costs and risks, to obtain existing, complementary know-how avoiding in that way duplication of efforts (Teece, 1986), or to speed up the R&D-process in industries where time-to market is crucial. If a company establishes alliances with partners to strengthen its existing technology base (i.e. exploitative learning), it already owns much of the required expertise and know-how. The in-house technological capabilities guarantee that the problem the alliance partners wish to focus on is clearly defined, possible solutions are known and that the partners have a fairly good understanding of the “causal mechanisms among the parameters involved in the task”

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<sup>3</sup> Cohen and Levinthal (1990) define the absorptive capacity of a firm as its ability to *value, assimilate and commercialize* (or *apply*) new external knowledge.



(Hansen et al., 2001, p. xxx). Acquaintance with the technology implies that the knowledge involved is to a large extent explicit and codified (Nonaka, 1994). The inter-organizational learning process can be planned and controlled to a large extent and targets can be set at the start.

Explorative learning is different. This type of learning is not about improving the efficiency of the current businesses, but it is a search for new, technology based business opportunities. The lack of in-house knowledge on certain technological areas forces companies to team up with companies that are more knowledgeable on these technologies. Explorative learning creates diversity and variety, and as such opens options for entrepreneurial activities in established companies. Exploring new technology entails problems that are novel to the company and because of that knowledge is usually contested, tacit and hard to articulate. In explorative learning the outcome cannot be predicted at the start, but it is an entrepreneurial search process for business opportunities in technological areas that are relatively new to the company. The inter-organizational learning process itself is hard to plan: because of its explorative nature the focal firm cannot predict how frequently it has to interact with its partners and about what issues. Besides, the tacit and contested knowledge involved in the process also implies that the contact between the partners will be iterative and informal (discussing ideas, exchanging views, reformulation of the strategy when unforeseen problems emerge, etc.).

So far, we argued that an organization has to find a balance between explorative and exploitative learning, that these two learning types are different in nature, returns and organizational requirements, and that technology-based alliances are increasingly important to absorb external technological knowledge. Because there are marked differences between exploitative and explorative learning, we assume that the role of alliances and the structure of the alliance network is *contingent* on the type of learning. In line with Ahuja's (2000a) study, we suggest that three aspects of a company's technology-based alliance network should be analyzed in detail. We will argue that (1) the number of *direct ties* and (2) *indirect ties* maintained by the firm and (3) the *degree of redundancy* among the firm's partners have a differential impact on explorative and exploitative learning.

### Direct ties

By means of strategic technology alliances, firms are able to generate scale and scope advantages by internal development of core technologies, while increasing their strategic flexibility by means of learning through alliances. Strategic flexibility, in this case, refers to the ability of firms “to reposition themselves in a market, change their game plans, or dismantle their current strategies when the customer they serve are no longer as attractive as they once were” (Harrigan, 1985).

Because risk associated with unfamiliar technologies is significantly higher than the risk associated with a company’s core technologies, firms increasingly use strategic technology alliances to learn from partners with a different technology base. Because of the low investments involved (compared to internal development) these alliances can be easily terminated when a certain technology turns out to be less interesting than expected. Therefore we expect that the number of direct ties is likely to be positively related to the innovative output of the firm, both the exploitation of its core technologies and the exploration of non-core technologies.

Next, external knowledge acquisition might be even more important in the case of developing technological capabilities that are new to the company – i.e. explorative learning. Different arguments point in that direction. First, organization theorists (Levinthal and March, 1993; Cohen and Levinthal, 1990) have argued that there is a positive feedback loop between experience and competence. Experience in a particular knowledge domain leads to increased absorptive capacity and enhanced competencies in this specific domain. A higher level of competence, in its turn, will lead to increased usage of the specific knowledge and therefore increases the level of experience. In spite of the positive effect of this cycle on the specific technological competences of companies, firms may fall into the so-called familiarity trap (Ahuja and Lampert, 2001): this cycle favors specialization and inhibits experimentation with unfamiliar technologies. Hence, strong technological capabilities tend to facilitate cognitive inertia, path dependency and low levels of experimentation (Stuart and Podolny, 1996). Firms with a relatively strong and successful technology base are often even more resistant to change than other firms. This so-called ‘success breeds failure syndrome’ (Starbuck et al., 1978) is often observed in the case of established industry leaders. In this way, local search and organizational routines may eventually lead firms to miss out on new windows of opportunities related to experimenting with technologies beyond their core technologies.

Teaming up with competent partners might then prove the only way to go beyond the current knowledge base.

Second, exploitative knowledge creation can be based primarily on internal technology competencies. Companies involved in exploitative knowledge creation have much of the required knowledge in-house and teaming up with partners is only one (although maybe an important) of many alternative ways of strengthening their technological capabilities.

Third, companies are often found to be very careful in sharing core technologies because of the dangers of partners 'stealing' the specific know-how in which a company has a competitive advantage. This problem is expected to be important in exploitative learning because in that case partners are likely to have similar technology profiles. This problem is furthermore aggravated because the cooperating companies are frequently (potential) competitors. Therefore, we expect that in teaming up with companies in non-core technologies sharing of technology will pose fewer problems than in the case of core technologies. Next, knowledge resulting from exploitative and explorative learning is different in nature. Exploring realms of knowledge that a company has not yet explored generates new, breakthrough innovations. These innovations generate valuable knowledge to patent compared to the incremental innovations resulting from exploitative learning. Finally, the nature of explorative learning implies that partnering companies usually get involved in a long-lasting and informal relationship. Exploration involves tacit knowledge, high uncertainty, and problems that are novel to the focal firm; this implies that successfully broadening the technology base of a company depends on the 'quality' of the relationship with its alliance partners (much more than in the case of exploitative learning). Over time and through prior experience with alliances firms develop capabilities or routines to manage alliances. As a result, companies that established many alliances in the past develop routines and alliance management skills which in turn lead to higher innovative output for the partnering company. We expect that these skills have a stronger impact on explorative learning because of its tacit and experimental nature.

However, once firms are involved in an excessive number of technology alliances firms can start to suffer from information overload and diseconomies of scale. This occurs in particular when a firm tries to deal with too many unfamiliar streams of knowledge (Ahuja and Lampert, 2001). Management attention and integration costs also seem to grow exponentially once a certain optimal level of alliances has been established (Duysters and de Man, 2003).

An alliance portfolio with too many alliances may lead to saturation and overembeddedness (Kogut *et al.*, 1992; Uzzi, 1997). Therefore, at high levels of embeddedness marginal benefits of forming new linkages will be low and marginal costs of additional links will be relatively high (Ahuja, 2000a). As a result, we expect an inverted-U shape relationship between the social capital of companies and their exploitative and explorative learning.

Therefore we hypothesize:

***Hypothesis 1a:*** *The past involvement of a firm in technology-based alliances (its social capital) has a stronger positive impact on the broadening of its knowledge base than on the strengthening of its core technologies.*

***Hypothesis 1b:*** *The past involvement of a firm in technology-based alliances (its social capital) is related in a curvilinear way (inverted-U shape) to both the strengthening of its core technologies and the broadening of its knowledge base. The effect on the latter is significantly stronger and overembeddedness starts at lower technological capability levels.*

#### *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 many 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 contact might still differ in 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, a company may have a limited number of alliance partners, linking the focal company to a wide range a companies that have themselves alliances to other companies, and so forth. As a result, the social capital of a company is not only determined by its direct ties but also by the number of companies it can reach in the network through indirect ties.

Indirect ties are important for both exploitative and explorative learning, but the impact on the latter is expected to be larger. First, if a company can reach many other companies through indirect ties it can often receive information about the findings of a broad set of research projects in the network (Ahuja, 2000a). Their indirect ties may also serve as a “radar” function for companies in the sense that relevant technological developments are brought to

the attention of the focal firm. Next, the tacit and experimental nature of explorative learning implies that companies in search for opportunities beyond their existing technology base will have a difficult time recognizing and valuing the technology of potential partners as long as they are not connected through a common alliance partner. As a result, since indirect ties seem to play an essential role in the process of explorative learning, we hypothesize:

***Hypothesis 2:*** *The larger the number of indirect ties of a firm in the technology-based alliances network the greater the effect on both the strengthening and the broadening of its knowledge base. The impact of the number of indirect ties on the latter will be significantly larger.*

As argued by Ahuja (2000a), firms that are involved in many direct ties are likely to benefit less from their indirect ties than firms characterized by a more limited number of direct ties. His argumentation is twofold: First, firms that have many direct ties are likely to gain less new or additional information from their indirect ties. For firms establishing many direct ties, the information that can be obtained from indirect ties may be very similar to the knowledge already obtained by its direct contacts and is therefore more likely to be redundant. Second, firms with many direct ties may be more constrained in their ability to profit from new information through their indirect ties. When a company has many direct connections, the information that reaches the company through the network also reaches the partners of the focal firm's allies, who may be potential competitors.

We argue that the impact of direct ties on indirect ones is likely to depend on the context of exploitative or explorative learning. The contingency may result from the different mix of targets a company wants to reach through its alliance network. When a company intends to broaden its technology base, it is primarily interested in finding and getting access to new information and technologies. If a company explores new technologies through its alliance network, problems are novel to the firm and technological benefits might not be straightforward (Hansen *et al.*, 2001). There is a high degree of exploration as the company departs from its existing knowledge base, and much of the knowledge involved in exploratory tasks is tacit, hard to articulate and can only be acquired through experience (Hansen, 1999; Hansen *et al.*, 2001; Nelson and Winter, 1982; Von Hippel, 1994). A company will typically have many contacts with its alliance partners before an idea evolves into a valuable innovation. This, in turn, implies that having many direct contacts does not necessarily

constrain the information stemming from indirect contacts. On the contrary, several direct ties provide different ways of exploring tacit and uncertain technological knowledge. Moreover, when a company explores new technological areas, it establishes in many cases alliances with companies that are not (potential) competitors: it is unlikely that potential competitors will capture the knowledge involved. Moreover, the sticky nature of the knowledge prevents an easy diffusion among partners.

In contrast, when a company deepens its existing technology base much of the knowledge involved is likely not to be tacit, "...because the focal actor has much of the expertise required and hence is likely to understand the problem, possible solutions, and the causal mechanisms among the parameters involved in the task" (Hansen *et al.*, 2001, p. xxx) . In this case, the information gained from many direct ties will substitute for information from indirect ties. Moreover, as the knowledge is explicit in nature it is also easily diffused among partners. Finally, the competitive threat is real since the focal company is partnering with companies that are likely to have a similar technology profile. This leads to Hypothesis 3:

***Hypothesis 3:*** *The impact of the indirect ties of a firm in the technology-based alliance network is weakened by the number of direct ties. The effect of this moderating variable is more important for the strengthening of the firm's knowledge base than for the broadening.*

#### Network structure of social capital

There is an ongoing debate in the academic literature about the impact of redundant and non-redundant network ties<sup>4</sup>. Burt (1992a,b, 2000) argues that a tie will provide access to new information and entrepreneurial opportunities to the extent that it offers non-redundant sources of information. In other words, Burt suggests that firms benefit from their alliances when they are connected to companies that are themselves not connected to the same network, i.e. that the alliance spans a structural hole. Structural holes guarantee that the partnering companies on both sides of the hole have access to different flows of information (Hargadon and Sutton, 1997). The information that comes from the mutually unconnected allies is non-redundant. Burt (1992a) considers this type of network as efficient and information-rich

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<sup>4</sup> The same debate is echoed in the discussion about the impact of strong and weak ties on firms' performance (Granovetter, 1973; Powell, 1990; Rowley et al, 2000). Tie strength is generally defined as being based on a "combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie" (Granovetter, 1973: p. 348).

because the information a company gets from its alliance partners is non-redundant. As a result, from the perspective of the structural hole theory ego-networks in which partners are not tied to each other are preferred to those where a company and its partners are members of a cohesive, clique like structure. On the contrary, Coleman (1988, 1990) and Bourdieu and Wacquant (1992) argue that companies can benefit from establishing alliances with companies that are densely tied to each other. The advantage related to this so-called network closure stems from the fact that these cohesive ties enable partnering firms to combine their skills, share their knowledge, and reap economies of scale in R&D. Moreover, cohesive ties are effective in sanctioning opportunistic behavior by one of the partners. Effective coordination in clique-like structures not only requires the reduction of opportunism but also demands trust and shared norms of behavior.

The structural hole theory of Burt (1992a, 2000) where firms can reap ‘entrepreneurial’ rents because of the absence of ties among its contacts is apparently at odds with the network closure theory of Coleman (1988, 1990) where firms benefit from cohesive (redundant) ties with their partners. However, a number of scholars (Ahuja, 2000a; Burt 1998, 2000; Hansen, 1999; Hansen *et al.*, 2001) suggest that the two theories about the network structure of social capital are not necessarily contradictory, but they rather play different roles that may be valuable in different settings or for different purposes.

In a similar vein, we argue that the distinction between explorative and exploitative learning may be one of these contingency factors determining the value of the network structure of a firm’s alliance portfolio. In particular we argue that the value of redundant and non-redundant ties is contingent on the type of inter-organizational learning in which the company is interested. In other words, firms should make decisions about how and when to make use of redundant and non-redundant ties in their external technology acquisition, depending on the type of learning.

Non-redundant ties are expected to be powerful in technology networks because they can lead efficiently to novel information and technological innovations in emerging technological realms.

In exploration, companies try to get a first, quick understanding on many different alternatives. “Information is relatively broad and general in nature, because the emphasis is on

identifying alternatives rather than fully understanding how to develop any one innovation. ... This task does not have a well-defined solution space so firms perform broad searches of their environments in order to identify a variety of future options.” (Rowley *et al.*, 2000: pp. 373-374). Since explorers want to cover a relatively broad range of technologies, it can be argued that non-redundant ties are advantageous in explorative learning. First, following the arguments advanced by Granovetter (1973) and Burt (1992a, 2000), companies in search for new knowledge - explorative learning - will benefit more from non-redundant ties spanning structural holes than from dense network ties because the latter are less likely to provide new, non-redundant information or knowledge. Second, when firms are only exploring technological realms and do not need a full understanding of the technology, they may tolerate some information noise and do not need redundant sources of information to evaluate the information (Rowley *et al.*, 2000). Network inertia is a third reason why ties bridging structural holes may be advantageous in explorative learning: benefits of explorative learning will be larger the more the focal learning firm can search for knowledge outside its existing network relations<sup>5</sup>. Risk hedging might be considered a last reason why firms engage in non-redundant relationships: by employing several technology alliances at the same time firms hedge the risks associated with missing out on important new technological developments (Nicholls-Nixon and Woo, 2003).

In contrast, we argue that redundant ties offer considerable advantages when a company is primarily interested in the refinement and the extension of its existing technologies and competencies. Exploitative learning implies that companies refine and strengthen their existing technology base and for that purpose they need specific and fine-grained information that will provide a deeper knowledge of this particular technology. In contrast with explorative learning, exploitative learning “...requires a deeper understanding of specific information rather than a wider grasp of general information” (Rowley *et al.*, 2000, p. 374). Dense, clique-like structures of the ego-network provide the best network structure to meet the information requirements for exploitative learning. Exploitative learning is about strengthening and refining the firm’s *core technology*; this implies both high-quality, fine-grained information and trust-based governance (Uzzi, 1997; Larson, 1992). Information theorists argue that information noise is reduced and high-quality information is obtained when firms have access to multiple and redundant information sources (Shannon, 1957).

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<sup>5</sup> Both arguments have also been developed by Hansen (1999) within the context of inter-unit knowledge sharing.



When a firm's partners are mutually connected to each other, they provide redundant information. Thus, dense ego-networks help a company to evaluate the obtained information and to get a deep understanding of a specific technology. Moreover, these dense networks serve as an alternative social control mechanism alleviating the risks associated with opportunistic behavior (Williamson, 1985); trust is crucial in exploitative learning because a firm's core technologies are one of the major sources of its current competitiveness and profits. Partners have to be trusted before they can touch the 'heart' of the company.

March (1991) argues there should be balance between exploitative and explorative learning in order to stay competitive both in the short and the long term. Therefore, both types of learning are required simultaneously but for different purposes. Since we expect that non-redundant ties are valuable in explorative learning and redundant ties in exploitative learning, we would, therefore, argue that firms should develop a well-balanced portfolio of both types of ties with their alliance partners. Rowley *et al.* (2000) have argued that the proportion of resources allocated to exploitation and exploration differs across environments and is determined by environmental conditions: the larger the environmental uncertainty and instability the more a company will invest in explorative learning. However, different companies facing the same changes in their environment seem to choose for different portfolios of non-redundant and redundant ties depending on their overall corporate strategy; the choice for redundant or non-redundant ties is in our view not determined by the industry setting but rather by corporate actions to build and maintain competitive advantage. Therefore, we hypothesize:

***Hypothesis 4:*** *If a company intends to strengthen its existing technology base (core technologies) the replication of existing ties (creating redundancy) is most effective as put forward by the network closure theory of social capital.*

***Hypothesis 5:*** *If a company intends to broaden its technology base the use of non-redundant ties will be more effective as put forward by the structural hole theory of social capital.*

## **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. These

focal firms were observed over a 12-year period, from 1986 until 1997. The panel is, however, 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<sup>6</sup>). 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 leading companies in an industry (Ahuja, 2000a; Gulati, 1995b; Gulati and Garguilo, 1999).

All social capital measures were calculated based on the alliance matrices that were constructed from the MERIT-CATI database. For each of the three sectors an alliance matrix was constructed for each year, containing the technology-based alliances that were established by the focal firms prior to a given year. In constructing measures of social capital based on past alliances, a number of choices have been made. First, we do not consider different types of alliances separately. Second, we did not weigh each type of SA according to the ‘strength’ of their relationship as some authors did (see Contractor and Lorange, 1988; Gulati 1995b; Nohria and Garcia-Pont, 1991). The third 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. We chose 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). The lifespan of alliances is assumed to be usually no more than five years (Kogut 1988, 1989).

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, 2000 a; p. 434)<sup>7</sup>. 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.

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<sup>6</sup> The MERIT-CATI database contains information on nearly 15 thousands cooperative technology agreements and their ‘parent’ companies, covering the period 1970-1996. The alliances in the database are primarily related to technology cooperation. See Hagedoorn and Duysters (2002) for a further description.

<sup>7</sup> See also Basberg (1987) and Griliches (1990).

For companies in the three sectors the financial data came from Worldscope, COMPUSTAT and data published on the companies' websites.

## **Variables**

### *Dependent variables*

The different hypotheses test in one way or another the effect that direct ties, indirect ties and the network structure have on the deepening and broadening of the technology base of different companies in the chemical, automotive and pharmaceutical industry. Yearly patent counts were used to derive the two dependent variables. Technological profiles of all focal companies were computed to find out whether a patent in a particular year has to be categorized as 'exploitative' or 'explorative'. These technological profiles were created by adding up the patents that a firm received in each patent class during the five years prior to a given year<sup>8</sup>. A moving window of 5 years is the appropriate time frame for assessing the technological impact (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. As a result, a 5-year period is appropriate to assess the technological profile of a company. The classes were determined at two-digit level, which resulted in approximately 400 classes.

These technology profiles allow us to make a distinction between exploitative and explorative technology classes. Classes in which a company had not received a patent in the previous five years and did receive a patent in the year of observation were considered 'explorative' patent classes. 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 has been realized when the company files for a patent rather than when it is granted. Explorative patents kept this 'status' for 3 consecutive years<sup>9</sup>. 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.

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<sup>8</sup> Calculating technology profiles for larger companies poses its own problems especially when a 'mother'-company has several 'daughters'. Therefore, the focal firms were first aggregated to the mother level and the list of these firms was used to derive the technological profiles.

<sup>9</sup> This is similar to the 'novel technologies'-concept developed by Ahuja and Morris Lampert (2001). We also calculated explorative learning for a period of 5 instead of 3 years.

The dependent variable ‘broadening of technology base’ was then made up by adding up all the patents applied for in the year of observation in the explorative patent classes. The same was done for the dependent variable ‘deepening of technology base’, adding up the patents in the exploitative classes.

### Independent variables

The impact of social capital on 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 deepening or strengthening of the existing technology base and the exploration of new technological fields. We have argued that the former should benefit from a dense ego-network, while the latter is will be spurred by the presence of the structural holes. 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.

#### *Direct ties*

The first dimension of social capital is ‘direct ties’. *Direct ties* can be measured by the *degree centrality* (number of alliances between the focal firm and its allies) in the alliance network or by the number of allies that the focal firm is directly connected to (i.e., the *size* of the ego-network). Since the valued data in the adjacency matrices of the alliance networks are based on the number of alliances between firm i and j, we prefer to use the number of allies that the focal firm is directly connected to as a measure for direct ties. We also introduce the squared term of this variable since hypothesis 1b suggests an inverted U-shaped relationship between innovative performance and the number of direct ties.

#### *Indirect ties*

A second dimension of the social capital of a company consists of firms it can reach indirectly in the alliance network through its alliance partners and their partners. Two companies whose ego-networks have the same size might still differ in 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, a company may have a limited number of alliance partners, who again link the focal company to a wide range of firms that have themselves alliances to other companies, and so forth. As a result, the social capital of a company is not only determined by its direct ties but also by the number of companies it can reach in the network through indirect ties.

There are different possibilities to operationalize the breadth of coverage of indirect ties. Closeness centrality, betweenness centrality, Bonacich centrality and reach centrality are various actor centrality measures that are good proxies for this variable. However, these centrality measures do “..not account for the weakening or decay in tie strength between firms that are connected by increasingly large path distances. Yet ..it is probable that as the shortest paths connecting two firms grow longer, the likelihood of information transmission between them decreases.” (Ahuja, 2000a: p. 438). Therefore, we introduce a variable that measures the impact of indirect ties while taking into account the decline in tie strength across more distant ties<sup>10</sup>. The measure, which we call “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 nodes 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 adding up all alliances at several distances weighted by their path distances (Ahuja, 2000a).

#### *Social capital: network closure versus structural holes*

The literature offers several possibilities to operationalize the (non-)redundancy of alliances. We expect that *non-redundant ties* may be beneficial for *explorative learning* and that *redundant ties* may be helpful in *exploitative learning*. For that purpose, we constructed some (non)-redundancy variables. Most – if not all – researchers that have been involved in empirical studies on inter-organizational networking and social capital have chosen for a

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<sup>10</sup> We report only the findings for the distance-weighted centrality (see tables 3a and 3b). We tested the robustness of the findings with the before mentioned centrality measures and obtained similar results.

single measure of social capital (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 social capital. We refer to Borgatti *et al.* (1998) for an extensive analysis of network measures that can be used to formalize the notion of social capital.

Burt (1992a,b) 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 have the same alliance connections to every other company in the network. Therefore, they have the same sources of information and provide redundant information to the focal firm. 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.

The first one, *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 (not counting ties involving the focal company) divided by the number of pairs where ‘pairs’ are potential ties<sup>11</sup>. The values for this variable range from 0 to 1, where 1 indicates that all allies are directly linked to each other<sup>12</sup>.

Another variable to measure social capital in terms of structural holes is the “effective size” of a firm’s network (Burt, 1992a: chap. 2). This variable measures the number of non-redundant ties in a firm’s ego-network<sup>13</sup>. More specifically, it is the number of partners the focal firm is

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<sup>11</sup> Pairs and ties are calculated with the ego-networks procedure in UCINET VI (Borgatti *et al.*, 2002). The inclusion of the proportion density variable reduces the degrees of freedom because it is undefined for pairwise isolates.

<sup>12</sup> McEvily and Zaheer (1999) introduced the concept of ‘bridging ties’. Bridging ties link a focal firm to other companies that are not otherwise accessible to this firm (they connect a focal firm to sources of information and opportunities that are not available from other network contacts). Bridging ties measure the proportion of *non-redundant ties* and are in this way measuring the same as ‘proportion density’ but in an opposite way. For ‘bridging ties’ low (high) values indicate low (high) non-redundancy – exactly the opposite of ‘proportion density’. Hence, the significance of the coefficient for the ‘proportion density’ in tables 3a and 3b is the same for the ‘bridging ties’-variable but the sign should be reversed.

<sup>13</sup> Burt’s (1992a, chapter 2) measure for “effective size” is:

connected to, minus the redundancy in the network, i.e. it reduces to the non-redundant ties of the network. When “effective size” is divided by the number of partners in the firm’s ego - network it measures the “*network efficiency*” of that 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). We assumed in hypothesis 5 that structural holes in the alliance networks will enhance the broadening of the technology base of innovating companies. As a result we expect a positive relationship between explorative learning and network efficiency. The coefficient is expected to change sign when focusing on its effect on the deepening of the existing technology base of a company.

“*Clique overlap centrality*” is a variable that measures the information available to firms from their position in the network (Everett and Borgatti, 1998; Gulati, 1999). It measures the extent to which the actor is a member of overlapping cliques in the network. The idea is that a firm that belongs to many cliques is one that is located in the midst of dense clusters of firms that have ties with each other. Thus, clique overlap centrality indicates embeddedness in dense regions of a network. In this sense “clique centrality overlap” measures redundancy – network closure argument). Hence, firms with a high value for clique centrality overlap have access to redundant information and, therefore, we expect positive (negative) relationship with exploitative (explorative) learning<sup>14 15</sup>.

Apart from redundancy based on cohesion, redundancy can also be based on *structural equivalence* as argued by Burt (1992a,b). Two firms are structurally equivalent to the extent

$$\sum_j \left[ 1 - \sum_q p_{iq} m_{jq} \right]$$

Where  $j$  indexes all of the partners that the focal firm  $i$  has contact with, and  $q$  is every third partner other than  $i$  or  $j$ .

The quantity  $(p_{iq}m_{jq})$  is the level of redundancy between the focal firm and a particular alliance partner,  $j$ .

<sup>14</sup> “Clique overlap centrality” is calculated using UCINET VI identifying the Luce and Pe rry (1949) cliques. Those cliques identify groups of firms that are linked to each other by alliances. The minimum clique size we specified was three. The scores for the clique centrality of each firm were expressed as a ratio to the score of the most central firm in the network.

<sup>15</sup> Clique overlap centrality resembles other centrality measures that we introduced earlier, but there are significant differences: “In networks where there is just one region (as in a core/periphery structure), clique overlap centrality correlates highly with other centrality measures (as they do with each other). But when the network consists of multiple clumps separated by structural holes, clique overlap centrality can be quite different from the other measures” (Everett and Borgatti, 1998: p. 59).

that they have alliances with the same other firms 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. In this way, they are redundant contacts to the focal company; they are redundant by structural equivalence. We provide two redundancy measures based on structural equivalence.

The first variable that captures redundancy by structural equivalence is provided by Hansen (1999). Applied to an inter-organizational setting, we can calculate the Euclidian distance for all 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. Therefore, the calculation was performed on matrices excluding the row and column for the focal firm (Hansen, 1999). The Euclidean distance between two alliance partners of the focal firm,  $i$  and  $j$ , is given by Wasserman and Faust (1994: p. 367)<sup>16</sup>. This measure will equal 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. Thus we expect a positive sign when a company explores new technological fields and a negative sign when it depends on its existing technological capabilities.

Structural equivalence can also be calculated based on the correlation coefficient of every pair of profiles. Redundancy is calculated in the same way as before but with correlation instead of Euclidian distance. The advantage of using correlation to measure structural equivalence among a company's partners is that the values are independent of the overall network size. The values for this variable range from +1 (high redundancy) to -1 (non-redundancy). Consequently, opposite signs should be expected when the redundancy measure is based on correlations instead of Euclidean distances.

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<sup>16</sup> Hansen (1999, p. 96) and Wasserman and Faust (1994, p. 367):

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



Walker *et al.* (1997) have developed a variable that also measures social capital based on *structural equivalence* albeit in a complete different way. Their structural equivalence measure refers to the *pattern of partner sharing*: structural equivalent firms have relationships with the same other firms in the network. “Therefore, measuring structural equivalence in practice almost always depends on the assessment of relative partner overlap” (Walker *et al.*, 1997: p. 115). To measure in how far firms in a group share partners requires one can examine the dispersion of inter-group densities ( $G_i$ ) around the network average. An equation that calculates density dispersion is:

$$G_i = n_i \sum_j m_j (d_{ij} - d^*)^2 \quad \text{where } i \neq j \quad (1)$$

“In this equation,  $G_i$  is the measure of the dispersion of intergroup densities for the  $i$ th group in the network,  $n_i$  is the number of firms in the  $i$ th group,  $m_j$  is the number of partners in the  $j$ th partner group,  $d_{ij}$  is the density of the intersection of the  $i$ th and the  $j$ th groups, and  $d^*$  is the overall density of the network” (Walker *et al.*, 1997: p. 115). Summing  $G_i$  over all groups produces a measure of network structure:

$$G = \sum_i \sum_j n_i m_j (d_{ij} - d^*)^2 \quad (2)$$

Dividing equation (1) by equation (2) produces a measure of each group’s percentage contribution to network structure. This variable varies between 0 and 1, and represents the dispersion of group densities normalized by the way in which a network is structured in a particular industry and year (Walker *et al.*, 1997: p.116).

For our purpose, this variable represents the dispersion of alliances across different structurally equivalent (SE) groups of partners. All else equal, the more the SE group of the focal firm has alliances to all different SE groups of partners, the lower the value for this variable. High densities that are concentrated into one or a few partner groups (i.e., high values for this variable) mean that the focal firm (and its structurally equivalent group of partners) has established many alliances with selected structurally equivalent groups of partners.

We have to be cautious with this variable however, for several reasons. First, it does not measure social capital of an individual (focal) firm but it indicates how the relations of the SE group to which it belongs are distributed among partner groups. Second, this variable “..penalizes small groups of firms with small partner groups” (Walker *et al.*, 1997: p. 115). This variable tends to zero for SE groups that only establish alliances among themselves because we excluded diagonal values in the density matrix. The value for this variable increases (to a maximum of one) the larger the size of the focal group of SE and the more it has dense ties with a single but large group of SE firms.

We expect that there will be a positive relation between both exploitative and explorative learning and ‘pattern of partner sharing’. SE firms are expected to be similar to each other because they have the same relations to the other firms in the network. A large group of SE firms that has dense ties with another single, large set of SE partners (and not with other SE partner groups), represents a kind of ‘learning highway’ between two groups of firms with different technological capabilities. Moreover, since the firms of both ends of the ‘highway’ are SE, they can easily learn from each other through spillover effects. These spillover effects are small or even non-existent when a company belongs to a small SE group or when an SE group has dense ties with too many other SE partner groups (i.e., when learning is not focused). In this way, we expect a *positive* coefficient for ‘the pattern of partner sharing’ variable for both types of learning. However, the impact on explorative learning might be significantly larger than for exploitative learning because of the high uncertainty involved and the fact that it is unclear which technologies are worthwhile to explore. In this situation it might be comfortable for explorers to get feedback from other companies in their SE group about their experiences with exploring a particular technology.

#### *Control variables*

While the primary focus of this study is to analyze the effect of social capital and its network structure on exploitative and explorative learning, there may also be other factors that could affect these two types of learning. We included three types of dummy variables. A first dummy variable indicates in which economic block 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. Firms from a different economic block 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 included two organizational variables. First, the natural logarithm of 'corporate sales' - 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, 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 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 (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). The technological distance between companies can be calculated as follows:

$$\begin{aligned}
 &= \frac{1}{2 * P_{it}} * \left[ \sum_{j=1}^{P_{it}} \sum_{k=1}^{P_{it}} (DISTANCE_{jkt}) \right] \\
 &= \frac{1}{2 * P_{it}} * \left[ \sum_{j=1}^{P_{it}} \sum_{k=1}^{P_{it}} \left( \sqrt{\frac{1}{C_t} \sum_{c=1}^{C_t} \left( \frac{N_{jct}}{\sum_{c=1}^{C_t} N_{jct}} - \frac{N_{kct}}{\sum_{c=1}^{C_t} N_{kct}} \right)^2} \right) \right] \quad (4)
 \end{aligned}$$

Where j and k represent the j<sup>th</sup> and k<sup>th</sup> partner (j ≠ k) of the focal firm i. P<sub>it</sub> is the number of partners the focal firm year t. C<sub>t</sub> is number of patent classes issued to the set of all sample firms in year t. N<sub>jct</sub> and N<sub>kct</sub> represent the number of patents in the c<sup>th</sup> patent class filed for respectively by the j<sup>th</sup> and k<sup>th</sup> partner in year t.

### 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 estimator with a robust variance estimator.

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

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

where the parameter  $\lambda_{it}$  represents the mean and the variance of the event count and  $y_{it}$  the observed count variable. It is furthermore assumed that:

$$\lambda_{it} = \alpha'x_{it} \quad (2)$$

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<sup>17</sup>. Therefore, a random effects Poisson estimator with robust variance estimator is 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:

$$\lambda_{it} = \alpha'x_{it} + u_i \quad (3)$$

where  $u_i$  is a random effect for the  $i^{\text{th}}$  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. Including the sum of alliances that a firm entered in the last four years (moving window approach) as an additional variable is a common method of controlling for unobserved heterogeneity (Heckman and Borjas, 1980).

Differences in patenting behavior between companies or between different years are captured by including dummy variables in the model. First, the propensity to patent may be partly

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<sup>17</sup> The presence of overdispersion does not bias the regression coefficients. Rather the computed standard errors in the Poisson regression are understated, so that the statistical significance is overestimated.

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 all 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 ‘distance weighted indirect ties’ are not highly correlated with the number of direct ties but, among the structural hole variables, clique overlap centrality correlates strongly with the number of direct ties.

Table 3a en 3b represent the results of the regression analysis using random-effects Poisson estimations respectively for the deepening of the technology base and the broadening of it. The basic model is presented in model 1. It is worthwhile mentioning some differences between the basic models in the two tables. First, there are no statistically significant differences between the three industries (chemical industry, car manufacturing and pharmaceutical industry) concerning the innovation rate in deepening their technology base. However, pharmaceutical companies are slightly more inclined to file for patents in new patents classes than companies in the other two industries. The difference between the pharmaceutical companies and car manufacturers is weakly significant; this reflects the continuous search of pharmaceutical companies to tap into the vast new business opportunities that are embedded in emerging technologies such as biotechnology.

The country of origin of the different companies does not play a role in explaining both types of innovation. European, Asian and US-based companies have more or less the same propensity to deepen and broaden their technology base.

Increasing R&D expenditures have a positive effect on the innovation rate of companies. The estimated coefficient of the R&D-expenditures variable is, in both regressions, less than unity. As this regressor variable is in the log form, its coefficients in the Poisson specification

represent elasticities of the regressor variable with respect to the dependent variable; positive elasticities smaller than 1 indicate that the likelihood of patenting, both in existing and new patent classes, increases as more money for research is invested but there are diminishing returns on scale. This result is in line with past research (Mansfield, 1981).

Firm size is strongly and positively linked to the deepening of the technology base of companies in these three industries. This coefficient can also be interpreted as an elasticity of the firm size with respect to the innovation rate. The coefficient is much smaller than unity indicating that 'exploitative' patenting is less than proportionately growing with firm size. This is in line with previous research (Acs and Audretsch, 1991). On the contrary, the size of a company is not related to the patenting frequency in new patent classes (see table 3b). This finding is in line with the organizational learning literature: 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 Morris Lampert, 2001). According to our results, small and large companies have the same 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.

A last control variable is the technological distance between partners. Its effect on deepening the technology base of companies is negative and significant, suggesting that absorptive capacity is likely to play an important role in external technology acquisition within technological areas in which the company already has some expertise. However, the same regressor has no impact at all on the broadening of companies' technology base. As a result, it is advantageous to carefully select alliance partners who have a similar technology profile when a company intends to deepen its technology base. This is no longer true for companies that intend to experiment with technological areas beyond their technology base: allying with partners with quite different or similar technology profiles will not influence the success of the company's technological diversification strategy<sup>18</sup>.

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<sup>18</sup> This is not to say that the technological distance between the focal firm and its partners is not important. Nootboom (1999, 2000) argues that there exists an inverted U-shaped relationship between inter-organizational learning and cognitive distance: inter-organizational learning is most successful when partners have a moderately different technology profile. Wuyts et al. (2003) found empirical evidence for this hypothesis.

The estimated alpha coefficient is positive and significant for both exploitative and explorative learning. This suggests that there are important firm-level unobserved effects in the data that were captured by this parameter.

Model 2 introduces the social capital as a regressor, 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 this variable are significant in both tables: More ties help companies to both deepen and broaden their technology base up to a certain point, beyond which the effect of overembeddedness dominates. The maximums are reached at relatively high levels of social capital – 64 alliances for exploitative learning and 80 for explorative learning – indicating that overembeddedness only plays a major role at high levels of social capital. However, the impact of social capital on both types of learning differs considerably: according to model 2 companies can at best increase the patenting rate with 13.7% in case they intend to deepen their knowledge base. In contrast, companies can drastically broaden their technology base through a network of technology alliances – with a maximum increase in the (explorative) patenting rate of 142%. Similarly, the impact of a one-standard-deviation increase in social capital at the mean level (=14.16 alliances (see table 2)) is much larger for explorative learning than for exploitative learning, i.e. respectively 24.3% [ $13.42 \cdot (3.9779 - 2 \cdot 0.0309 \cdot 14.16)$ ] versus 4.2% [ $13.42 \cdot (22.0241 - 2 \cdot 0.1374 \cdot 14.16)$ ].

These results support hypothesis 1b, which predicted a stronger effect of social capital on explorative learning compared to exploitative learning. The difference happens to be quite large, 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 the strengthening of their existing technological capabilities.

Model 3 adds indirect ties as an explanatory variable. Hypothesis 2 is empirically supported: The coefficients are positive and significant in both tables and the impact is significantly larger on explorative than on exploitative learning. As a result, social capital of a company is not only determined by its direct ties but also by the number of firms it can reach in the alliance network. Moreover, the impact of indirect ties is significantly larger in case a company is involved in explorative learning. The uncertainty involved in explorative research and its tacit nature pushes the focal firm to search for solutions among the partners of its



partners. Hence, partners of a focal firm are not only valuable because of their technological know-how but also because of their social capital. The social capital of partners becomes even more important in the case of explorative learning.

Model 4 brings in the interaction term between direct and indirect ties and is an empirical test for hypothesis 3. We have argued – following Ahuja (2000a) – that the impact of indirect ties will be moderated by the number of direct ties, at least in the case of exploitative learning. This is supported by model 4 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. The coefficient of this interaction term in table 3b is positive but not significant (it becomes weakly significant in some of the following models). This is in line with our expectations of hypothesis 3. In the case of explorative learning, implying tacit knowledge and high levels of uncertainty, it might be valuable to have more direct contacts to explore and understand the possibilities related to the knowledge base of indirect contacts. In other words, because of the cognitive distance in explorative learning partners may be helpful in accessing and exploring the knowledge base of their partners. However, the coefficient of the interaction term is not (or only weakly) significant.

Models 5 to 9 allow us to test hypotheses 4 and 5. We have five variables that measure the network structure of social capital in different ways; three of them are based on cohesion and two on structural equivalence. ‘Proportion density’ gives an idea of the density of ties among a focal firm’s alliance partners. From hypothesis 4, we expect a positive and significant relation between a dense network of ties among a focal firm’s partners and its ability to deepen its existing technology base. This is what we find in model 5 in table 3a. The opposite should be true when a company intends to broaden its technology base. We find a negative and significant coefficient in model 5 in table 3b. As a result, hypothesis 5 is corroborated: when a firm’s partners are connected to each other a company becomes less successful in its explorative learning.

‘Network efficiency’ is another variable measuring the non-redundancy within a firm’s ego-network. High values for this variable indicate that a firm’s direct contacts provide non-redundant information. We expect a negative and significant coefficient in table 3a. The sign

is correct but the coefficient is not significant. The coefficient in table 3b indicates that non-redundancy among a firm's partners improves explorative learning.

A high value for the variable 'clique overlap centrality' indicates that a company is in the midst of dense clusters of ties and is confronted with a lot of redundant information. Consequently, we expect a positive and significant relation between high clique overlap centrality and exploitative learning. This is corroborated by the result in table 3a. As expected, we find that this variable has a negative effect on a firm's explorative learning. However, this coefficient is not-statistically significant.

Model 8 measures the effect of the first of two variables that captures redundancy based on structural equivalence. 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. The coefficient for exploitative learning is positive and significant as expected. For explorative learning the coefficient is negative but not statistically significant.

The last model shows the effect of 'the pattern of partner sharing' on exploitative and explorative learning. This variable is different from the other network structure variables because it does not measure social capital of an individual (focal) firm but how relations of the structurally equivalent group to which it belongs are distributed among different partner groups. We have argued that high values of this variable indicate to the presence of a 'learning highway' between two important groups of firms with different technological capabilities. Since firms of both ends of the 'highway' are structurally equivalent, they can easily learn from each other through spillover effects. We have mentioned before that this is an advantageous situation for learning – and especially for explorative learning. The coefficients in tables 3a and 3b affirm that being part of the 'learning highway' fosters both types of learning and that the impact on explorative learning is significantly larger.

## **CONCLUSION**

This paper focuses on the impact of firms' social capital on their exploitative and explorative learning. March (1991) argues that each company needs to balance both types of learning to

stay competitive in the short *and* the long run. There are considerable differences between both types of learning (March, 1991; Chesbrough, 2003), which, in turn, have important implications for the way in which a company has to get access to and profit from the technological capabilities of its alliance partners. We argued that the value of a firm's alliance network is contingent on the type of learning. Since exploitative and explorative learning are quite different in nature, we assume that the role of alliances and the structure of the alliance network are *contingent* on the type of learning: redundant information coming from alliance partners that are mutually linked to each other in dense networks improves exploitative learning. Non-redundant information enhances a firm's explorative learning and requires that the firm's ego-network spans structural holes.

We formulated several hypotheses about the impact of direct ties, indirect ties, and the alliance network structure on the success of firms' explorative and exploitative learning. We found empirical evidence that direct ties spur both types of learning although there is an optimal level of social capital beyond which the effect of overembeddedness dominates. Furthermore, there is strong evidence that social capital has a much larger impact on explorative learning than on exploitative learning. We can conclude that external acquisition of technological know-how through alliances is more important when companies are experimenting in new technological areas than when they intend to strengthen their existing technological capabilities.

Indirect ties also have a beneficial effect on both types of learning but the impact on the latter (explorative learning) is again much larger. Interestingly, the empirical results show that direct ties have a moderating effect on the impact of indirect ties on exploitative learning (which resembles the results of Ahuja (2000a)), but this is no longer the case for explorative learning. Several direct ties provide different ways to explore the tacit and highly-uncertain technological knowledge in explorative learning.

Finally, there is some empirical evidence that a firm profits from redundant ties when it is primarily interested in the refinement of its existing technology base and competencies, while non-redundant ties are advantageous in explorative learning. Consequently, we can conclude that the value of the network closure (Coleman, 1988, 1990) and the structural hole theory of social capital (Burt, 1992a, 2000) is contingent on the type of organizational learning.

In contrast with most studies we calculated several variables that measure (non)-redundancy in alliance networks in different ways. The results for the network structure variables are consistent in the sense that all coefficients had the expected sign. However, there is some variability in the statistical significance of these coefficients across the models. We draw two conclusions from this: First, these variables measure redundancy in different ways, and it is not a priori clear that these different ‘dimensions’ of redundancy should have the same effect on exploitative or explorative learning. Redundancy by cohesion or by structural equivalence represents one of these differences that are worth probing further. Second, the empirical results in prior studies may be influenced by the choice of the variable.

That ‘redundancy’ is a multi-dimensional concept is illustrated by the viable ‘pattern of partner sharing’. Walker *et al.* (1997) use this concept to detect partner overlap. The concept does not measure social capital of an individual (focal) firm but it indicates how the relations of the structural equivalent group to which the firm belongs are distributed among partner groups. Applied to inter-organizational learning, we argue that this variable measures a particular network structure that is quite different from the other redundancy measures. High values for this variable represent a type of ‘learning highway’ between two groups of firms with different technological capabilities. Firms not only learn from their direct and indirect partners, but they can also take advantage from the knowledge spillovers from structurally equivalent partners who have dense contacts with other structurally equivalent partner groups. We expected that this variable has a stronger effect on explorative learning because of the high uncertainty involved. In this situation it might be comfortable for explorers to get feedback from other companies in their structurally equivalent group about their alliance based learning. The empirical evidence shows that high values for the ‘pattern of partner sharing’-variable stimulate the two types of learning but the impact is significantly larger on explorative learning.

This study has of course its limitations. First, we focused only the redundancy of the information in a firm’s alliance network. We did not pay attention to the strength of the ties: there is empirical evidence that the value of strong and weak ties depends on the type of learning (Rowley *et al.*, 2000). Next, we have paid no attention to the cognitive distance between a company and its partners although it is beyond doubt that, compared to exploitative learning, partners should have a different technology profile than the focal-firm in explorative learning. This raises the question what the optimal ‘cognitive distance’ should be between

alliance partners, when they or involved in exploitative or explorative learning (Nootboom 1999, 2000).

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Table 1: Definitions of dependent and independent variables

Variable name	Variable description	
Exploitative learning	Count of the 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	dependent variable
Explorative learning	Count of the 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	dependent variable
Cumulative patents (Cumulative patents) <sup>2</sup>	Count of the number patents that a firm filed for during the previous five years (t-5 to t-1) Squared term of previous variable	
Indirect ties	'Distance weighted centrality': Count 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	
Network efficiency	'Effective size' divided by the number of partners in the focal-firm's ego-network (Burt, 1992, p. 53)	
Clique overlap centrality	The number of cliques to which a firm belongs, normalized to the industry maximum (Gulati, 1999)	
Structural equival. (corr.)	Average correlation of every pair of profiles of the direct partners of the focal firm (Hansen, 1999)	
Pattern partner sharing	Dispersion of densities between different structurally equivalent groups normalized by the network structure (Walker <i>et al.</i> , 1997)	
Age	The number of years since a company is founded	
Firm size (ln revenues)	Natural logarithm of the total sales of the firm in t-1 (x 1000 Euro)	
R&D expenditures (ln)	Natural logarithm of the total R&D expenditures in t-1 (x 1000 Euro)	
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	15
1 # of exploitative patents	102.23	156.81	0	1136															
2 # of exploitative 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	-0.12	0.03	-0.17												
5 Proportion density	0.146	0.231	0	1	-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 Clique overlap centrality	2.85	4.49	0	28	0.43	0.20	0.87	-0.25	-0.01	-0.04									
8 Structural equival. (corr.)	0.152	0.193	-0.012	1	-0.12	-0.06	0.05	-0.22	0.92	-0.92	0.15								
9 Pattern partner sharing	0.314	0.143	0.003	0.5	0.07	0.08	0.18	0.30	-0.04	0.00	0.17	-0.05							
10 Age	79.75	45.82	0	236	0.13	-0.06	0.12	0.01	0.02	-0.03	0.09	0.05	0.04						
11 Firm size (log sales)	8.659	1.804	0.29	11.91	0.39	0.23	0.43	-0.20	-0.08	0.05	0.39	0.03	0.03	0.38					
12 R&D expenditures(ln)	5.623	1.703	-1.83	8.94	0.42	0.23	0.40	-0.07	-0.13	0.11	0.40	-0.03	0.08	0.27	0.73				
13 Techn. distance partners	0.022	0.009	0	0.063	0.02	0.04	-0.11	0.27	-0.13	0.18	-0.20	-0.21	-0.06	0.05	-0.11	0.07			
14 Chemical company	0.376	0.485	0	1	0.03	-0.02	-0.05	-0.11	0.07	-0.07	-0.04	0.08	-0.10	0.16	0.10	-0.07	-0.17		
15 Car manufacturer	0.270	0.444	0	1	0.05	0.03	0.25	-0.33	0.13	-0.20	0.36	0.20	0.07	0.04	0.33	0.26	-0.15	-0.47	
16 Firm is European	0.233	0.423	0	1	-0.26	-0.02	0.01	-0.11	0.13	-0.18	0.02	0.18	-0.05	-0.07	-0.03	-0.06	-0.14	0.11	0.13
17 Firm is US-based	0.429	0.495	0	1	0.04	0.01	-0.02	0.17	-0.18	0.20	-0.11	-0.23	0.01	-0.05	-0.14	-0.12	0.17	-0.14	-0.18
18 Year 1986	0.081	0.273	0	1	-0.03	-0.02	-0.08	-0.27	0.05	-0.04	-0.08	0.08	-0.26	-0.05	-0.06	-0.07	0.00	0.01	-0.00
19 Year 1987	0.087	0.282	0	1	-0.03	-0.02	-0.06	-0.26	0.04	-0.04	-0.03	0.06	-0.04	-0.04	-0.03	-0.05	-0.02	-0.00	0.03
20 Year 1988	0.081	0.273	0	1	0.00	0.01	-0.03	-0.09	0.07	-0.06	-0.01	0.05	0.05	-0.03	-0.05	-0.05	-0.00	-0.02	0.01
21 Year 1989	0.081	0.273	0	1	0.01	0.02	-0.00	-0.03	0.05	-0.04	0.03	0.02	0.07	-0.02	-0.05	-0.05	-0.10	-0.01	-0.00
22 Year 1990	0.087	0.282	0	1	-0.01	-0.03	0.02	-0.01	0.03	-0.02	0.09	0.03	0.01	0.01	-0.02	-0.03	-0.09	-0.00	0.01
23 Year 1991	0.087	0.282	0	1	-0.01	-0.04	0.00	-0.00	-0.05	0.05	0.04	-0.05	0.02	0.03	0.00	-0.00	0.01	-0.00	0.01
24 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	0.03	0.03	-0.02	-0.00	0.01
25 Year 1993	0.084	0.277	0	1	0.00	-0.07	0.00	0.01	-0.05	0.05	-0.00	-0.04	-0.17	0.04	0.02	0.02	0.02	-0.01	0.01
26 Year 1994	0.081	0.273	0	1	0.01	0.01	0.01	0.10	-0.05	0.05	-0.01	-0.04	-0.20	0.02	0.02	0.03	0.06	0.00	-0.00
27 Year 1995	0.082	0.275	0	1	0.05	0.15	0.02	0.09	-0.01	0.01	-0.04	-0.03	0.10	-0.00	0.04	0.05	0.04	0.01	-0.02
28 Year 1996	0.082	0.275	0	1	-0.00	0.07	0.05	0.17	-0.00	-0.00	-0.01	-0.02	0.04	-0.00	0.04	0.06	0.04	0.02	-0.02

Table 2: Descriptive statistics and correlation matrix (continued)

Variable	16	17	18	19	20	21	22	23	24	25	26	27
16 Firm is European												
17 Firm is US-based	-0.48											
18 Year 1986	0.03	-0.02										
19 Year 1987	0.01	-0.02	-0.09									
20 Year 1988	-0.02	0.01	-0.08	-0.09								
21 Year 1989	-0.01	0.00	-0.08	-0.09	-0.08							
22 Year 1990	-0.00	-0.01	-0.09	-0.10	-0.09	-0.09						
23 Year 1991	-0.02	0.01	-0.09	-0.10	-0.09	-0.09	-0.10					
24 Year 1992	-0.01	-0.00	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09				
25 Year 1993	-0.02	0.00	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09			
26 Year 1994	-0.02	0.01	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09		
27 Year 1995	0.02	-0.00	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	
28 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 – deepening the technology base, 1986-1997

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
<b>Direct ties</b>										
Cumulative alliances /1000		3.9779*** (0.6936)	3.2458*** (0.7023)	9.7154*** (1.0153)	8.9812*** (1.0203)	9.7595*** (1.0159)	5.4633*** (1.2238)	9.2376*** (1.0181)	8.4356*** (1.0493)	
(Cumulative alliances/1000) <sup>2</sup>		-0.0309*** (0.0066)	-0.0202*** (0.0068)	-0.0636*** (0.0084)	-0.0594*** (0.0084)	-0.0637*** (0.0084)	-0.0368*** (0.0087)	-0.0607*** (0.0084)	-0.0541*** (0.0086)	
<b>Indirect ties</b>										
Distance weighted centrality			0.0011*** (0.0001)	0.0024*** (0.0002)	0.0024*** (0.0002)	0.0025*** (0.0002)	0.0026*** (0.0002)	0.0027*** (0.0002)	0.0021*** (0.0002)	
((Distance weighted centrality) * (cumulative alliances)/1000				-0.0919*** (0.0105)	-0.0865*** (0.0105)	-0.0940*** (0.0106)	-0.0800*** (0.0106)	-0.0962*** (0.0105)	-0.0853*** (0.0106)	
<b>Structural holes vs. network closure</b>										
<i>Via cohesion</i>										
Proportion density					0.1777*** (0.0295)					
Network efficiency						-0.0405 (0.0307)				
Clique overlap centrality							0.0229*** (0.0019)			
<i>Via structural equivalence</i>										
Correlation (Hansen)								0.1709*** (0.0279)		
Pattern of partner sharing									0.1650*** (0.0338)	
<b>Control variables</b>										
Car manufacturer	0.2247 (0.4527)	0.0121 (0.4609)	-0.0451 (0.4686)	-0.0411 (0.4611)	0.0135 (0.4685)	-0.0618 (0.4606)	-0.0809 (0.4724)	-0.0449 (0.4615)	-0.0584 (0.4622)	



Chemical industry	-0.1162 (0.4041)	-0.0484 (0.4082)	-0.1109 (0.4114)	-0.0660 (0.4098)	-0.0564 (0.4115)	-0.0718 (0.4101)	-0.1279 (0.4136)	-0.0694 (0.4101)	-0.0752 (0.4104)
Europe	-0.6618 (0.5171)	-0.6013 (0.5263)	-0.5185 (0.5338)	-0.6175 (0.5231)	-0.7047 (0.5282)	-0.6232 (0.5228)	-0.5188 (0.5375)	-0.6149 (0.5236)	-0.6035 (0.5236)
US	0.1074 (0.3807)	0.1225 (0.3847)	0.1777 (0.3883)	0.1547 (0.3850)	0.1239 (0.3893)	0.1577 (0.3853)	0.1657 (0.3895)	0.1563 (0.3853)	0.1701 (0.3856)
Age	-0.0008 (0.0045)	-0.0008 (0.0046)	-0.0006 (0.0046)	-0.0004 (0.0046)	-0.0009 (0.0046)	-0.0004 (0.0046)	-0.0007 (0.0047)	-0.0004 (0.0046)	-0.0004 (0.0046)
Firm size (ln sales)	0.2239*** (0.0304)	0.2205*** (0.0305)	0.2072*** (0.0307)	0.1889*** (0.0307)	0.1828*** (0.0311)	0.1939*** (0.0308)	0.2114*** (0.0309)	0.1899*** (0.0308)	0.1844*** (0.0307)
ln R&D	0.3561*** (0.1999)	0.3725*** (0.2060)	0.3984*** (0.1601)	0.3934*** (0.1092)	0.3983*** (0.0211)	0.3932*** (0.0205)	0.3897*** (0.0209)	0.3941*** (0.0210)	0.3999*** (0.0210)
Techn. distance between partners	-4.480*** (0.7298)	-4.5938*** (0.7287)	-3.6800*** (0.7405)	-3.7920*** (0.7411)	-3.8140*** (0.7416)	-3.6231*** (0.7468)	-1.9475** (0.7595)	-3.7476*** (0.7472)	-3.7021*** (0.7428)
Constant	0.4430 (0.5606)	0.4428 (0.5682)	0.5462 (0.5784)	0.6171 (0.5719)	0.7256 (0.5806)	0.6742 (0.5725)	0.5198 (0.5797)	0.6054 (0.5729)	0.5699 (0.5735)
alpha	1.9223*** (0.2781)	1.9631*** (0.2835)	1.9950*** (0.2878)	1.9704*** (0.2844)	1.9662*** (0.2860)	1.9731*** (0.2847)	2.0171*** (0.2907)	1.9728*** (0.2848)	1.9760*** (0.2851)
Number of firms	74	74	74	74	73	74	74	74	74
Number of firms-years	662	662	662	662	655	622	662	662	662
Chi-squared vs. previous nested model		34.39***	42.08***	76.54***	15.67***†	1.87	144.27***	36.00***	24.43***

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 with 74 firms and 662 firm-years (units of observation).

†:In comparison with the previous model based on 655 and not 662 observations.

Table 3b: Determinants of the patent rate of firms – broadening of the technology base, 1986-1997

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
<b>Direct ties</b>									
Cumulative alliances/1000		22.0241*** (2.4417)	15.7093*** (2.5066)	11.9549*** (3.5217)	10.5291*** (3.548)	13.1300*** (3.5372)	17.6134*** (4.0743)	11.8097*** (3.5321)	8.8143** (3.5940)
(Cumulative alliances/1000) <sup>2</sup>		-0.1374*** (0.0299)	-0.0656** (0.0306)	-0.0418 (0.0344)	-0.0307 (0.0345)	-0.0721** (0.0351)	-0.0551 (0.0345)	-0.0406 (0.0406)	-0.0203 (0.0308)
<b>Indirect ties</b>									
Distance weighted centrality			0.0042*** (0.0004)	0.0037*** (0.0005)	-0.0035*** (0.0008)	0.0017*** (0.0005)	0.0038*** (0.0005)	0.0038*** (0.0005)	0.0027*** (0.0006)
((Distance weighted centrality) * (cumulative alliances))/1000				0.0454 (0.0298)	0.0579* (0.0300)	0.0499* (0.0301)	0.0385 (0.0299)	0.0451 (0.0298)	0.0559* (0.0300)
<b>Structural holes vs. Network closure</b>									
<i>Via cohesion</i>									
Proportion density					-0.1477** (0.0707)				
Network efficiency						0.5145*** (0.0647)			
Clique overlap centrality							-0.0178 (0.0065)		
<i>Via structural equivalence</i>									
Correlation (Hansen)								-0.0539 (0.0548)	
Pattern of partner sharing									0.4612*** (0.0971)
<b>Control variables</b>									
Car manufacturer	-0.5534* (0.2987)	-0.5729* (0.3032)	-0.5291* (0.3033)	-0.5320* (0.3037)	-0.5911* (0.3193)	-0.5493* (0.3042)	-0.5207* (0.3040)	-0.5344* (0.3038)	-0.5281* (0.3035)

Chemical industry	-0.2126 (0.3069)	-0.2389 (0.3114)	-0.2065 (0.3103)	-0.2067 (0.3109)	-0.2309 (0.3173)	-0.2148 (0.3106)	-0.1980 (0.3110)	-0.2085 (0.3109)	-0.2064 (0.3106)
Europe	0.0860 (0.3485)	0.1040 (0.3524)	0.0933 (0.3502)	0.0773 (0.3519)	0.1362 (0.3663)	0.0705 (0.3517)	0.0749 (0.3517)	0.0744 (0.3520)	0.0735 (0.3519)
US	0.3843 (0.2886)	0.4037 (0.2925)	0.3834 (0.2902)	0.3714 (0.2914)	0.4358 (0.3037)	0.3688 (0.2910)	0.3683 (0.2914)	0.3699 (0.2913)	0.3655 (0.2911)
Age	-0.0061** (0.0030)	-0.0061** (0.0030)	-0.0063** (0.0029)	-0.0064** (0.0029)	-0.0058* (0.0031)	-0.0064** (0.0029)	-0.0063** (0.0030)	-0.0065** (0.0029)	-0.0064** (0.0029)
Firm size (ln sales)	-0.0285 (0.0564)	-0.0243 (0.0566)	-0.0150 (0.0569)	-0.0144 (0.0570)	-0.0272 (0.0584)	-0.0087 (0.0573)	-0.0193 (0.0574)	-0.0128 (0.0574)	-0.0141 (0.0570)
ln R&D	0.4484*** (0.0464)	0.4594*** (0.0473)	0.4498*** (0.0477)	0.4480*** (0.0478)	0.4610*** (0.0500)	0.4437*** (0.0479)	0.4502*** (0.0480)	0.4471*** (0.0480)	0.4462*** (0.0479)
Tecnh. distance between partners	-1.4257 (0.7298)	-1.5034 (2.2495)	-1.892 (2.2753)	-1.8731 (2.2751)	-2.0867 (2.2768)	-1.6801 (2.2846)	-2.1178 (2.2992)	-1.8093 (2.2925)	-2.1047 (2.2978)
Constant	0.1436 (0.5377)	0.1170 (0.5340)	0.0085 (0.5443)	0.0178 (0.5450)	0.0422 (0.5633)	0.1147 (0.5540)	0.0367 (0.5462)	0.0078 (0.5467)	0.0526 (0.5472)
alpha	0.95704*** (0.1610)	0.9747*** (0.1648)	0.9614*** (0.1627)	0.9632*** (0.1629)	0.9966*** (0.1704)	0.9628*** (0.1623)	0.9636*** (0.1691)	0.9630*** (0.1628)	0.9620*** (0.1625)
Number of firms	74	74	74	74	73	74	74	74	74
Number of firms-years	662	662	662	662	655	662	662	662	662
Chi-squared vs. previous nested model		126.90***	91.80***	2.46	6.68***†	60.32***	7.84***	0.08	24.31***

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 with 116 firms and 1137 firm-years (units of observation).

†: In comparison with the previous model based on 655 and not 662 observations.



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