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Bonnie Beerkens

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Beerkens, Bonnie Elisabeth

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Bonnie Elisabeth Beerkens

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prof.dr. G.M. Duijsters
en
prof.dr. A.P. de Man

Copromotor:
dr. W.P.M. Vanhaverbeke

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Voor Pap en Mam

PREFACE

Five years of academic research at the Technische Universiteit Eindhoven have resulted in this PhD thesis. These years were the most challenging of my life so far, both professionally and personally. My personal struggles made my academic work difficult at moments, yet the ongoing confidence of my promotors in my abilities and qualities stimulated me to bring this thesis to an end. Therefore, first of all, I'd like to express my gratitude to Geert Duysters, my first promotor, for all his encouragement and understanding at times when I lacked both motivation and energy. The irresistible relaxing chair in my office seduced Geert into long conversations in which Geert shared with me his ongoing positive look on life. Another source of great inspiration has been Wim Vanhaverbeke, my daily supervisor. Wim, thank you for understanding and stimulating my passion for empirical work. Wim helped me regain and sustain my motivation. I have always enjoyed our discussions and Wim's detailed and precise style of working. I look forward to working on research with both Wim and Geert in the future.

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CHAPTER 1

INTRODUCTION

Technology has become extremely important in determining the competitive advantage of companies in a growing number of industries. Products are becoming increasingly complex and require more and more sophisticated technologies. Emerging technologies challenge the competitive positions of incumbents more than ever and have opened up new windows of opportunities for innovative firms. In an attempt to deal with these forces of 'creative destruction' firms are increasingly forced to combine internal technological strengths with those of other firms as R&D costs soar rapidly and technological dynamics speed up.

The ongoing increase in the number of newly established strategic technology alliances among companies has led to the emergence of dense inter-organizational networks in which companies position themselves in order to benefit from the specific know-how of competent partners. A number of recent studies have investigated the relationship between a portfolio of technology alliances and (technological) firm performance (Hagedoorn and Schakenraad, 1994; Shan *et al.*, 1994; Powell *et al.*, 1996; Mitchell and Singh, 1996; Stuart, 2000). In similar vein, many publications have argued that a centrally positioned firm may have access to a larger and wider base of knowledge than a company in the periphery of an alliance network (Duysters and de Man, 2003). Others (Stuart, 2000) find evidence that alliances with partners that are technologically well endowed have a larger positive impact on post-alliance performance of the focal firm than those with partners that are less well endowed. Companies with a large stock of technological resources are often considered to be highly attractive potential alliance partners. Similarly, we could argue that the alliances of a focal firm's partners matter, since these indirect contacts provide access to an even broader range of information. These and other arguments which will be put forward in the thesis lead us to believe that not only the dyadic level of alliances matter, but increasingly aspects of ego-networks or the entire network play a major role in determining the technological performance of a firm. Whereas most previous studies have taken on a dyadic perspective on alliances we take on a network approach to firm's innovative performance. In particular we will focus on the effect of specific networking strategies on the degree of technological performance of firms. Therefore, we derive the following research question:

> *What is the effect of particular alliance networking strategies on the degree of technological performance of firms?*

In order to come up with an answer to this research question three aspects will be studied in this thesis. First, it is important for firms to make a distinction between the internal development of technological knowledge and the external acquisition of technological know-how.

INTERNAL LEARNING / EXTERNAL LEARNING

In large companies, management is gradually 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. Hence, technological performance 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 considered to be complements reinforcing each other's productivity (Cohen and Levinthal, 1990; Duysters and Hagedoorn, 2000). However, little is known about the interaction between and the mutual reinforcing effect of internal learning and external learning. Thus, chapter two of this thesis is devoted to finding an answer to the following question:

How do internal learning and external learning mutually affect a firm's technological performance?

For firms with low degrees of technological competences and social capital – in terms of the number of alliances they have – entering new alliances can be greatly beneficial since they provide access to new and valuable technological knowledge. However, these firms may be less attractive to other firms to cooperate with, because of their low technological know-how. Firms with unique internal knowledge resources, on the other hand, are likely to be attractive to other firms that expect to benefit from getting access to these unique resources (Baum *et al.*, 2000). However, as these firms are already well endowed with technological capital, they have fewer incentives to cooperate in order to improve their own rate of innovation (Ahuja, 2000). As a result, a company that is well endowed with technological competences is likely to benefit only marginally from extending its alliance network beyond a critical threshold.

Hence, both types of firms need to find a balance between internal and external development of technological know-how, and the optimal mix will be different for both types. Although it is very unlikely that companies can develop their technological resources completely in-house, those that have unique technological resources need only a relatively small alliance network to ensure high rates of innovation. On the other hand, companies with moderate levels of technological knowledge may opt for investing in much larger alliance networks. Whether internal and external learning have mutually reinforcing effects under all circumstances is still open for debate. We believe that beyond a critical threshold both types of capital substitute each other and extending social capital may become a liability. This will be addressed in chapter two.

After discussing this first aspect of the central research question, we can further explore how companies can optimally use this externally acquired knowledge. This leads us to the second aspect that will be studied in this thesis, i.e. the optimal positioning of a company in an innovation network in order to deepen the existing knowledge base (exploitation) or to widen the existing knowledge base (exploration).

EXPLORATIVE AND EXPLOITATIVE TECHNOLOGICAL PERFORMANCE

Teaming up with competent partners allows firms to share the costs and risks involved in Research and Development and enables them to increase their speed-to-market considerably. Many of these technology based alliances are referred to as 'learning alliances' through which companies can speed up their capability development and exploit knowledge developed by others (Grant and Baden-Fuller, 1995).

However, considering inter-organizational networks of technology-based alliances as a set of 'learning alliances' is clearly a simplification. We therefore follow March (1991) in distinguishing between exploitative and explorative learning, and argue that the value of a firm's alliance network is contingent on the type of learning. Exploitation is associated with the refinement and extension of existing technologies, whereas exploration can be seen as the experimentation with new alternatives. 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. 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.

How do networking strategies affect explorative and exploitative learning?

In chapter three we suggest, in line with Ahuja's (2000a) study, that three more aspects of a company's technology-based alliance network should be analyzed in detail. We will argue that (1) the number of direct ties, (2) the indirect ties maintained by the firm, and (3) the degree of redundancy among the firm's partners all have a differential impact on explorative and exploitative learning.

We argue that the distinction between explorative and exploitative learning may be an important contingency factor in explaining the value of (non-)redundant ties. 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 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.

Network positioning is often studied from a deterministic point of view. In the existing literature we find that firms can exert little influence on the entire network. However, as opposed to the small influence firms have on the network as a whole, firms can actually play a part in their direct surroundings. Therefore the third aspect studied in this thesis is network positioning from the perspective of the ego-network. This implies that no longer the entire network with all the indirect contacts (i.e., contacts of partners, thus the partner's partners) are taken into consideration, but the effectiveness of network strategies at the level of the direct contacts (that can be influenced) are the focus of this study.

LOCAL ACTION

Inspired by seminal work of Granovetter (1985), Coleman (1988) and Burt (1992a, b) many authors have subsequently dealt with the question of which specific structural network positions enable firms to achieve the highest level of performance. The existing literature seems to take on a rather deterministic approach to network structure and positioning where firms are primarily influenced by the exogenous network structure they are part of. Most of the work in this area thus neglects the endogenous micro-level dynamics of organizational action (Bae and Gargiulo, 2003). In this thesis we argue that these endogenous micro-level dynamics prove to be instrumental in building the overall network structure. In order to fill this gap in the existing academic literature we follow Bae and Gargiulo (2003) by arguing that networks are basically the outcome of the combined local alliance actions of all individual players in the network. In order to assess the role of these micro-level dynamics on technological performance we decided to focus on the outcomes of local alliance action on the innovative performance in chapter four. The main question we seek to answer in the fourth chapter is:

> *What is the role of local alliance action on technological performance?*

In this part of the thesis we argue that the efficiency of alliance strategies is primarily dependent on two major factors, i.e. the local actions of a focal firm (ego) and the local actions of its alliance partners (alters). Local actions can be associated with the establishment (or dissolution) of direct ties (ego-alter) whereas the local actions of the alliance partners are associated with indirect ties (alter-alter). Of course, direct and indirect ties are interrelated. Some of the actions of a focal firm's alliance partners might be beneficial to the focal company and some of the actions might have a negative effect on the focal firm's network position.

Rowley *et al.* (2000) argue that local density rather than global (network wide) density influences the performance of the focal firm. Ego-network measures are consistent with this view. We therefore leave behind the network level, and descend to the level of the ego-network, which provides a micro-level analysis of local actions and their impact on the innovative performance of companies.

EMPIRICAL TESTING

The various issues as described above are empirically studied by using two main longitudinal datasets. Both these datasets contain information on the alliance activity and patent activity of the companies under study.

The first part of the research in this thesis (aspect one as mentioned above) is performed in the ASIC-industry (application-specific integrated circuits), a branch of the micro-electronics industry that develops and produces custom-made chips for customers. The data that is used consists of observations for 99 ASIC-related firms in the period 1988 until 1996. ASIC-related patents were used exclusively since we wanted to compare the effectiveness of R&D cooperation within the ASIC-field on the technological performance of firms as well as the effect of internal development on technological performance.

The second part of the empirical research (the above mentioned aspects two and three) in this thesis was performed on a dataset with 116 firms in the chemicals, automotive and pharmaceutical industries. The firms were observed over a period of twelve years, from 1986 until 1997. The patent and alliance activity data were complemented with company data such as financial data (from Worldscope, COMPUSTAT and data published on the companies' websites) and the country of origin. In this instance both patent-activity and alliance-activity were measured broader than the industries under study to be able to measure explorative technological performance.

In the final chapter, we will summarize the most interesting findings of the next three chapters. The three research questions will be put together and commented starting from a unifying framework about optimal alliance portfolios. We will explore issues like the balancing between internal and external (technological) learning, portfolio size, indirect ties, redundancy in the alliance network and the capabilities of the alliance partners. Finally, a number of avenues for future research will be explored: the current thesis has its limitations and it seems that empirical research about the effect of particular alliance networking strategies on the degree of technological learning is still in its infancy. We will provide a number of directions in which future research may evolve.

CHAPTER 2

TECHNOLOGICAL CAPABILITY BUILDING THROUGH NETWORKING STRATEGIES WITHIN HIGH-TECH INDUSTRIES [1]

Abstract

Learning through networks has been a research topic for several years now. Technological learning is more and more based on a combination of internal and external learning and firms need to develop both technological and social capital for that purpose. This chapter analyses the relationship between both types of capital and their impact on the technological performance of companies in high-tech industries. We claim and find strong empirical evidence that technological capital and social capital mutually reinforce each other's effect on the rate of innovation for companies with small patent and alliance portfolios. However, when companies have a strong patent portfolio and an extensive network of alliances then both types of capital become substitutes. We also found that there are two possible equilibria: the first one emphasizes the development of strong internal technological capabilities supported by a small alliance portfolio. The second is the mirror image of the first one: these firms focus mainly on technology acquisition through alliance partners supported by a minimum of internal technological capabilities. Both strategies can co-exist in an industry. Finally, we find empirical evidence that companies who explore novel and pioneering technologies have a higher rate of innovation in subsequent years.

[1] This chapter is based on a paper written with Wim Vanhaverbeke and Geert Duysters

INTRODUCTION

This study aims to relate technological performance of companies in high-tech industries to their degree of technological and social capital. More specifically, we focus on three main research topics. First, we consider whether a firm's technological and social capital are mutually enforcing factors that together determine the rate of innovation, or whether they can be considered as substitutes. We also address the question of whether there is an optimal mix of resources, which produces above average results. Second, following Stuart (2000) we argue that not so much the size of the alliance portfolio, but the technological performance of the partnering firms to whom a focal firm is connected determines the rate of innovation of the latter. Finally, we aim to find out whether companies that explore new technologies have higher rates of innovation than companies that are primarily engaged in exploiting and strengthening their existing technology base.

The apparent importance of knowledge, especially in high tech industries, has given rise to a stream of research focusing on knowledge as the single most important resource within an organization (Kogut and Zander, 1996; Conner and Prahalad, 1996) and has led to the emergence of the knowledge based theory of the firm (Grant, 1997). In a similar vein, a number of recent studies have investigated the relationship between a portfolio of technology alliances and (technological) firm performance (Hagedoorn and Schakenraad, 1994; Shan *et al.*, 1994; Powell *et al.*, 1996; Mitchell and Singh, 1996; Stuart, 2000). Firms are increasingly forced to combine internal technological strengths with those of other firms as R&D costs soar rapidly and technological dynamics speed up. Products require more and more sophisticated technologies and emerging technologies have the potential to undermine the competitive positions of incumbents. Many of these alliances are 'learning alliances' through which companies can speed up their capability development and exploit knowledge developed by others (Grant and Baden-Fuller, 1995). Because in today's turbulent technological environment no single firm is able to come up with all the required technological capabilities themselves, firms are increasingly induced to form these 'learning alliances'. In order to overcome the lack of specific technological capabilities they try to tap into other companies' technological assets. Market transactions are generally considered to be only a weak alternative to alliances because most valuable knowledge is cumulative and tacit in nature. This specific nature makes it hard to transfer between organizations through market transactions (Mowery, 1988; Mowery *et al.*, 1995; Osborn and Baughn, 1990).

Technological performance is more and more based on a combination of internal and external learning: internal learning by the internal development of new products and processes as a result of internal R&D, external learning from the technology acquired through technology alliances. Both types of learning are considered complements reinforcing each other's productivity (Cohen and Levinthal, 1990; Duysters and Hagedoorn, 2000). Moreover, companies can only tap into other companies' technology base successfully if they have sufficient absorptive capacity (Lane and Lubatkin, 1998). In its turn, absorptive capacity results from investments in internal technological know-how. Hence, internal technological knowledge and external technology acquisition via alliances are considered complements. But surprisingly, there are to our knowledge no large-sample empirical studies that focus on the combined effect of internal and (quasi) external knowledge acquisition on the technological innovative performance[2].

THEORETICAL BACKGROUND AND HYPOTHESES

Technological and social capital

This chapter builds on the knowledge-based view of the firm. Over time accumulated knowledge assets constitute the source of a firm's sustainable competitive advantage in the marketplace (Kogut and Zander, 1996; Spender, 1996). Firm specific knowledge assets are of strategic interest – they are distinctive competences – because they are rare, imperfectly tradable and hard to imitate and must be build within the organization internally as long as part of the technological know-how is not articulated or tacit in nature. The development of knowledge assets (or technological capital) is difficult, time consuming and expensive. Moreover, developing technological capabilities is a risky venture because R&D up-front costs may be huge and the technological and commercial outcomes may be highly uncertain (Mitchell and Singh, 1992).

[2] Ahuja (2000) focuses on the impact of technical, commercial and social capital of companies on the formation of new alliances. Commercial resources are those required to convert technical innovations to products and services. They consist of manufacturing and marketing capabilities and entail manufacturing facilities and service and distribution networks (Mitchell, 1989; Teece, 1986). In what follows we focus on the relationship between technical and social capital and neglect the linkages with commercial capital.

Because of the cumulative character of technology, the current technological position of a company is shaped by the path it has traveled (Teece *et al.*, 1997). Hence, path dependency is crucial: previous investments in and strategic choices about technology development not only explain the current position of a company, but they also constrain the future options of companies. Therefore, companies that failed to build up a technological capability in the past may find it difficult to catch up later by internal development (Shan, 1990). Furthermore, existing technological capabilities may reduce a firm's capacity to adapt to new commercial challenges or to rejuvenate its capabilities in the face of new, 'competence destroying' technologies (Abernathy and Clark, 1985).

Accumulated technological competence can therefore be seen as the result of past innovative activities of a firm (Podolny and Stuart, 1995; Stuart *et al.*, 1999). As a result, we can expect that firms with well developed technological assets will be more innovative than other firms under conditions of relative technological stability – i.e. when companies can build on their previously developed knowledge. This argument suggests the following hypothesis.

Hypothesis 1: The greater the technological capabilities of a firm at *t-1* the higher its rate of innovation at *t*.

Being centrally positioned in a network of technology alliances has been recognized as a distinctive and important form of capital – social capital – of innovative companies (Gulati, 1995, 1999). Especially in fast changing technological fields internal R&D efforts need to be complemented by external means of technology acquisition. The creation of a strategic alliance network can facilitate the access to technological resources across industries or technological field. Alliances are often used by companies as instruments to acquire technological knowledge and to develop new skills that reside within the partnering companies (Hamel, 1991; Hagedoorn and Schakenraad, 1994; Powell *et al.*, 1996). Previous research established that alliances often have a positive impact on the performance of companies (Baum and Oliver, 1991; Mitchell and Singh, 1996; Uzzi, 1996; Powell *et al.*, 1996; Hagedoorn and Schakenraad, 1994). These authors found in different research settings a positive relationship between technological alliances and rates of innovation. A notable exception is the work of Stuart (2000) who found no significant relationship between the number of alliances and the growth rate or rate of innovation of semiconductor firms.

A 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, 2000).

Nahapiet and Ghoshal (1998: 245) argue that the collective social capital resulting from dense networks can limit a firm's "openness to information and to alternative ways of doing things, producing forms of collective blindness that sometimes have disastrous effects". At the same time managerial costs increase significantly because not only individual alliances need management attention, but management also has to coordinate across linkages (Harrigan, 1985). Gomes-Casseres (1996) has shown that there is a natural limit to the number of alliances that a company can manage successfully. Therefore, we argue that there is a non-linear relationship between the social capital of a company and its rate of innovation. Highly embedded companies or firms with poorly developed social capital will have the lowest rates of innovation. In particular firms at intermediate levels of embeddedness will show the highest rates of innovation. This argument suggests the following hypothesis:

Hypothesis 2: The involvement of a company in technology-based alliances at *t-1* is related in a curvilinear way (inverted-U shaped) to its rate of innovation at *t.*

As discussed above, technological performance is increasingly based on a combination of internal and external learning. Both types of learning have been described in the literature as complements reinforcing each other's productivity (Cohen and Levinthal, 1990; Duysters and Hagedoorn, 2000).

Whether social and technological capital would have mutually reinforcing effects under all circumstances is however open for debate. Firms with low degrees of technological competences and social capital, in terms of the number of alliances they have, will benefit considerably from entering new alliances since they provide access to new and valuable technological knowledge. Firms with poorly developed technological capital have strong incentives to get access to the technological capital of other firms through interorganizational alliances (Mitchell and Singh, 1996). These companies will also profit from strengthening the internal knowledge base as this increases their absorptive capacity so that its partners' knowledge can better be valued and assimilated (Lane and Lubatkin, 1998).

Firms with unique internal knowledge resources are likely to be attractive to other firms that expect to benefit from getting access to these resources through means of alliances (Baum *et al.*, 2000). As a result, firms with unique technological resources have more opportunities to collaborate than firms with poorly developed resources. However, firms that are already well endowed with technological capital have fewer incentives to cooperate in order to improve their own rate of innovation (Ahuja, 2000). Because these companies have already developed leading edge technological competences they are likely to learn to a lesser extent from their partners than vice versa (Hamel *et al.*, 1989; Kale *et al.*, 2000; Khanna *et al.*, 1998).

As a result, a company that is well endowed with technological competences is likely to benefit only marginally from extending its alliance network beyond a critical threshold because it increases the chance that internally developed and externally acquired technology may overlap or that the marginal value of getting access to another company's knowledge base is smaller than the cost to set up and manage the alliance (Harrigan, 1985). Hence, although it is very unlikely that companies can develop their technological resources completely in-house those that have unique technological resources need only a relatively small alliance network to ensure high rates of innovation. Beyond a critical threshold both types of capital substitute each other and extending social capital may become a liability. This argument suggests the following hypothesis:

Hypothesis 3: At low levels, internal technological capabilities (technological capital) and external acquisition of technology through technological alliances (social capital) reinforce each other's effect on the rate of innovation. At high levels, they weaken each other's effect.

Combining hypotheses 2 and 3, we expect that companies can realize the highest rates of innovation by two different types of strategies that can coexist in the same industry. The first strategy is based on a considerable alliance network and small (potentially specialized) technological capital. This provides the company with ample opportunities to tap into its partners' technology resources or to co-develop innovations by combining (complementary) skills. The second strategy emphasizes the internal development of innovations in the company. The company has an extensive patent portfolio and needs only a few alliances to ensure that it has the required technology to strengthen or to continue its strong technological performance. Companies with moderate values for both types of capital, failing to stick to one of these two strategies, are 'stuck in the middle'. Thus:

Hypothesis 4: Companies with extensive (small) internal technological capabilities and a small (extensive) alliance network have the highest rates of innovation. Both profiles may successfully coexist in an industry.

Stuart (2000) argues that the technological (and economic) performance of companies is not so much determined by the size of the alliance network but rather by the characteristics of the focal company's alliance partners[3]. If companies enter alliances to get access to other firms' technology, then those with a large stock of technological resources are highly attractive as potential alliance partners. Stuart finds evidence that alliances with partners that are technologically well endowed have a larger positive impact on post-alliance performance of the focal firm. In high-tech industries the technological competencies of alliance partners determine in part the focal company's potential to learn. Teaming up with skilled innovative companies with unique technological assets offers a company the best opportunities to learn and thus to invigorate its competitive position.

Hypothesis 5: The stronger the technological capabilities of a company's alliance partners at *t-1*, the higher its rate of innovation at *t*.

EXPLORING NEW TECHNOLOGIES

We have already argued that a mutual positive feedback between experience and competence exists. This virtuous cycle enables companies to build up unique technological skills, which potentially lead to competitive advantages in the marketplace. The increased ease of learning within particular technologies facilitates the exploitation of these technologies compared to the exploration of new technologies (Levinthal and March, 1993; March, 1991).

The downside of this path dependency is that it increases the likelihood of a company falling in the so-called familiarity trap (Ahuja and Lampert, 2001). It is argued that experience and competence in a specific set of technologies lead to the emergence of a dominant and increasingly rigid technological paradigm. This, in turn, reduces the probability of a company's willingness to experiment with other problem solving approaches. This absence of experimentation reduces the chance that a company will discover new technological opportunities that are assumed to be large in high tech industries (Jaffe, 1986; Lunn and Martin, 1986; Levin *et al.*, 1985).

[3] Similarly, Baum *et al.* (2000) argue that the performance of biotechnology start-ups is positively influenced by the technological capabilities of the partnering companies.

To avoid familiarity traps companies can explore novel technologies, i.e. technologies that are new to the organization even though they may have been in existence earlier (Ahuja and Lampert, 2001). Experimenting with novel technologies allows a company to value the potential of these technologies in a more accurate way (Cohen and Levinthal, 1990). Explorative companies are better positioned to discover the technological and commercial potentials of novel technologies. They may also be better prepared to value the potential competitive threat of disruptive technologies (Bower and Christensen, 1995; Christensen and Overdorf, 2000) or competence destroying technologies early on (Abernathy and Clark, 1985; Tushman and Anderson, 1986). Exploring novel technologies challenges the dominant problem-solving paradigm in companies (Lei *et al.*, 1996). Unfamiliar technologies may force a firm to search for new cognitive maps that open up new avenues for research. Hence, we may expect that companies that experiment with novel technologies are better positioned to have a higher rate of innovation than firms that invest all their efforts in exploiting existing, familiar technologies.

Exploring novel technologies, however, is only advantageous up to a point. Investing excessively in exploration of novel technologies may lead to confusion: exploration of unfamiliar technologies and exploitation of familiar ones have to be balanced to be productive. As argued by March (1991) and Levinthal and March (1993) firms engaging in exploration exclusively, only suffer from the costs associated with experimentation without exploiting its benefits. Moreover, 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 profits (Rowley *et al.*, 2000; Levinthal and March, 1981). Finally, scattering R&D resources on many novel technologies may eventually lead to diseconomies of scale within the individual technologies (Ahuja and Lampert, 2001). Therefore, we argue that:

Hypothesis 6: A firm's rate of innovation at *t* is related in a curvilinear way (inverted-U shaped) to its exploration of novel technologies at *t-1*.

Innovative firms generally search for technological solutions within the scope of what has been invented before. They tend to build on their own technological successes and on those of others[4]. Previous solutions offer technologists or scientists an anchor to move forward. As a result, building on technological antecedents is less risky than working on a de novo innovation (Hoskisson *et al.*, 1993; Hoskisson *et al.*, 1994).

[4] An average of 18 patent citations for the 1850 patents in the sample of ASIC related patents.

Ahuja and Lampert (2001) refer to the tendency of firms to search near to old solutions as the propinquity or nearness trap. Often interesting technological fields remain unexplored when companies rely too much on old solutions. The literature however suggests that important inventions emerge, in particular, from these unexplored areas (Utterback, 1994). Experimenting with pioneering technologies – i.e. technologies that do not build on existing technologies (Ahuja and Lampert, 2001) – is one possible way to circumvent the dangers of the propinquity trap. Experimenting with pioneering technologies is an attempt to jump to different technological trajectories (Dosi, 1988; Foster, 1986; Sahal, 1985). Since pioneering technologies offer fundamentally new solutions they may generate large future profit streams for the innovative company. At the same time, they entail large risks typical for radical innovations: However, when a company increases the number of experiments it also inflates the probability that a major, successful innovation will pop up sooner or later. We expect that a company having successfully patented a 'pioneering technology'-innovation will increase its rate of innovation in the subsequent years.

Hypothesis 7: A firm's rate of innovation at *t* is positively related to its success in pioneering new technologies at *t-1*.

EMPIRICAL SETTING

Definition and characteristics

The hypotheses were tested on the population of ASIC-producers that were active in the period 1988-1996. ASICs – i.e. application-specific integrated circuits – are a special type of ICs (integrated circuits) accounting for about 12 % of worldwide IC sales in 1995. The term 'ASIC', as now in use in the industry, is a misnomer. In reality these ICs are customer-specific rather than application-specific since an ASIC is a device made for a specific customer[5].

[5] A device which is made for one particular type of system function (e.g. disk-drives, CD-players, video compressing) but is sold to more than one customer, is called an ASSP (application-specific standard product, sometimes also called ASIPs -

I.	***Semicustom IC:*** A monolithic circuit that has one or more customized mask layers, but does not have all mask layers customized, and is sold to only one customer. **Gate arrays:** A monolithic IC usually composed of columns and rows of transistors. One or more layers of metal interconnect and are used to customize the chip. **Linear array:** An array of transistors and resistors that performs the functions of several linear ICs and discrete devices.
II.	***Custom IC:*** A monolithic circuit that is customized on all mask layers and is sold to only one customer. **Standard cell IC:** A monolithic circuit that is customized on all mask layers using a cell library that embodies pre-characterized circuit structures. **Full custom IC:** A monolithic circuit that is at least partially “handcrafted”. Handcrafting refers to custom layout and connection work that is accomplished without the aid of standard cells.
III.	***Programmable Logic Device (PLD):*** A monolithic circuit with fuse, antifuse, or memory cell-based logic that may be programmed (customized), and in some cases, reprogrammed by the user. **Field Programmable Gate Array (FPGA):** A PLD that offers fully flexible interconnects, fully flexible logic arrays, and requires functional placement and routing. **Electrically Programmable Analog Circuit (EPAC):** A PLD that allows the user to program and reprogram basic analog devices.

Table 2.1 ASIC definitions

The ASIC market is a typical high-tech industry where technology is the driving force shaping competition among firms. R&D-to-sales ratios are exceptionally high. The ASIC market can be divided into different submarkets. According to the "Integrated Circuit Engineering Corporation" (ICE) the ASIC market includes the following categories of ICs: arrays, custom ICs,

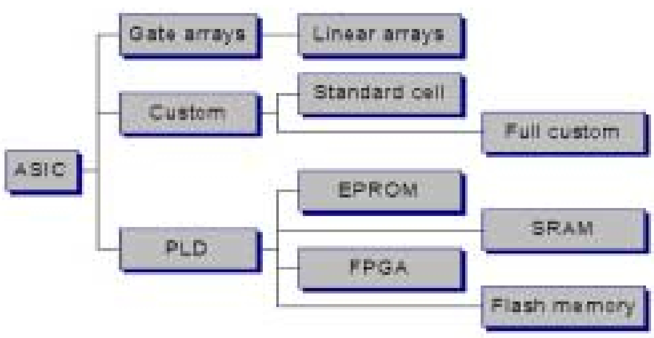

Figure 2.1 ASIC diagram

application-specific integrated processors). Although ASSPs are manufactured using ASIC technology, they are ultimately sold as standard devices to large numbers of users.

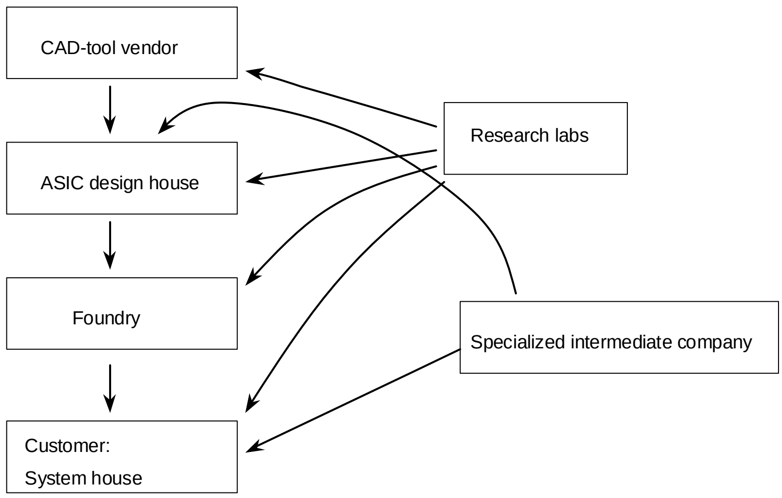

Figure 2.2 The ASIC technology field

and programmable logic devices (PLDs). Formal definitions are given in Table 2.1 and diagrammed in Figure 2.1.

The development and production of ASICs requires the interplay between different economic agents. The most important participants are the ASIC design houses, IC manufacturing facilities, electronic system houses and CAD-tool vendors. This list can be enlarged by a number of auxiliary and/or intermediate players, such as companies offering services in the microelectronics field, firms that translate customers' needs into the specifications for the design of ASICs, and university labs. The interplay between different agents is shown in Figure 2.2.

Given these characteristics of the industry, most strategic alliances in the ASIC-industry are high-tech, since firms are likely to link up with each other in order to keep up with the latest technologies (Duysters and Hagedoorn, 1996).

DATA, VARIABLES AND MODELING

Data

Three types of data are combined in this chapter. The technology alliances between the different players in the ASIC technology field cumulated over the previous five years capture social capital.

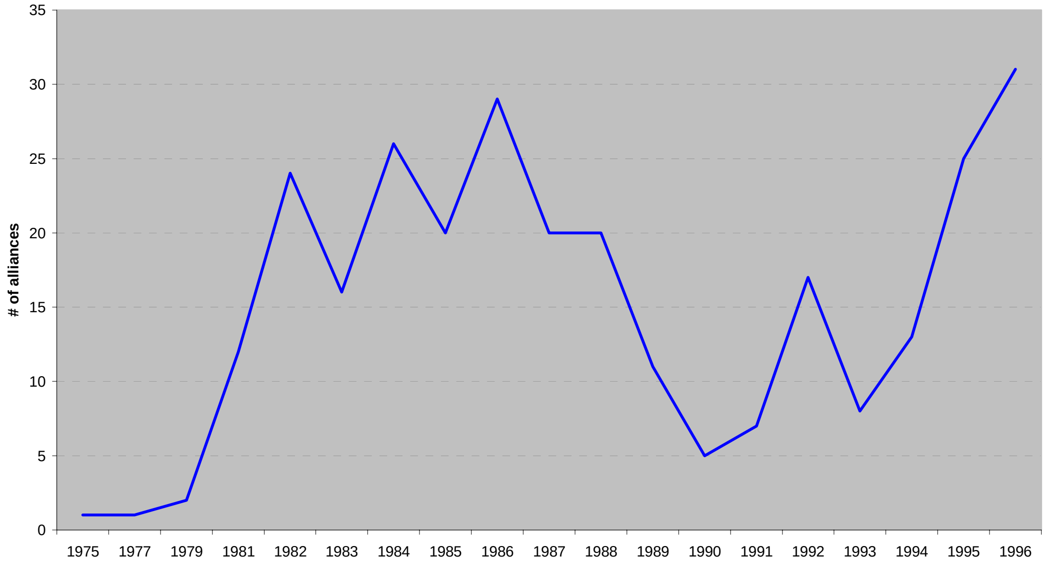

Figure 2.3 Number of technology based SAs in the ASIC industry

Technological capital is measured by means of the cumulated US patents related to ASIC technologies of each company. Finally, a set of financial data is gathered for each ASIC producer.

The data on strategic alliances were selected from the MERIT-CATI databank on strategic

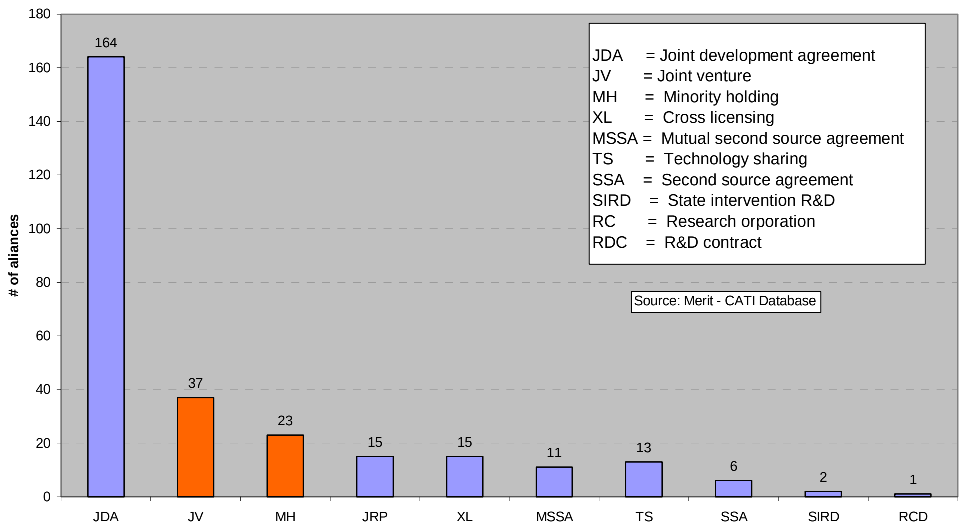

Figure 2.4 Different types of SAs in the ASIC industry

technology alliances (Duysters and Hagedoorn; 1993)[6]. The selection included strategic alliances (SAs) which major focus was on (technological developments in) the ASIC-industry. The MERIT-CATI databank covers the period between 1975 and 1996: For that period 288 ASIC related strategic technology alliances were detected. There were 130 different firms involved in these SAs.

A sharp increase in SAs occurred in the early and mid-eighties (see figure 2.3). Their popularity diminished in the late eighties and the early nineties. SAs in the ASIC industry are mainly non-equity agreements (79.2%) of which the majority is joint development agreements (56.9% of all SAs). Joint ventures, which account for 12.8% in the ASIC industry, are the most important form of equity SAs. The distribution of different types of SAs is presented in figure 2.4.

To measure technological capital, we used patent data from the U.S. Patents Database for all companies involved in the design and production of ASICs, also those based outside the US[7]. Working with U.S. patents – the largest patent market – is preferable to the use of several national patent systems. Nations differ in their application of standards, systems to grant patents and value of the protection granted (Basberg, 1987; Griliches, 1990). Especially in industries where companies operate on a global scale, such as the ASIC-industry, U.S. patents may be a good proxy for companies' worldwide innovative performance[8].

Financial data of ASIC producers have been gathered from different sources among which the annual ICE reports (McClean, 1985-1998). The data contain the ASIC-sales of these companies, their total IC-sales, the distribution of the ASIC-sales across the three segments, and total sales. We furthermore included the nationality of each company.

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[6] Strategic technology alliances include joint research projects, joint development agreements, cross licensing, (mutual) second source agreements, technology sharing, R&D consortia, minority holdings and joint ventures, but no licensing agreements or production and marketing agreements.

[7] The patents were selected by means of a query on 'ASIC' and related concepts/definitions such as 'gate array', 'linear array', 'FPGA', 'PLD', 'full custom', 'SPGA' and 'EPAC'.

[8] Patents can be categorized by means of the International Patent Classification, an internationally recognized hierarchical classification system comprising 118 broad sections and 624 subclasses nested within the classes. It is furthermore possible to subdivide the subclasses into 67.000 groups. ASIC-related patents are classified in a relatively small set of subclasses (75 in total).

Variable definitions and operationalization

To test the hypotheses we constructed a number of variables. Table 2.2 summarizes them.

Dependent variable

Explaining the technological performance capacity of different ASIC producers requires an operationalization of the change in size of a company's technological capital. Changes in technological capital are operationalized by patents granted to an innovating company. However, the patent is recorded in the database at the time the company applied for the patent (rather than the year when it was granted to the firm) because a patent application is a signal that a company has successfully developed a technological innovation. The dependent variable is a count variable measured by the number of patents that a company applied for in a particular year[9].

Independent variables

The first 5 hypotheses suggest a relationship between a firm's prior technological capital past, its social capital and the technological characteristics of its alliance partners on the one hand and its ex post technological performance on the other hand.

Cumulative technological capital is calculated as the number of ASIC-related patents that an ASIC-producer obtained in the previous 4 years. Patents granted to a company are used to measure, in an indirect way, the technological competence of a company (Narin *et al.*, 1987). A moving window of 4 to 5 years is the appropriate time frame for assessing the technological impact in high-tech industries (Podolny and Stuart, 1995; Stuart and Podolny, 1996; Henderson and Cockburn, 1996; Ahuja, 2000). Studies about R&D depreciation (Griliches, 1979, 1984) suggests that knowledge capital depreciates sharply, losing most of its economic value within 5 years. As a result, a 4 or 5-year period is appropriate to assess technological relevance. In this chapter we use the cumulated patents obtained by a firm during the last 4 years as a measure for the technological

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[9] Of course, we only keep track of patents that have been granted by the U.S. Patent Office before the end of 2000. The observation period is 1988-1996. We do not expect to have a significant bias at the end of that period, because most patents are granted within a period of 2 to 3 years (average time for all patents in the sample is 26 months). Of the 1381 patents that were filed between 1/1/1988 and 31/12/1996 only 50 (or 3.6%) were granted after 4 years.

Table 2.2 Definitions of dependent and independent variables

Variable name	Variable description	Expected effect
Number of patents	Count of the number of patents related to the ASIC-industry a firm filed for in the current year (t). Only patents that were granted to the company are taken into consideration	--------
Cumulative patents$_{t-1}$	Count of the number of ASIC-related patents that a firm filed for during the previous four years (t-4 to t-1)	Positive
Cumulative technology alliances$_{t-1}$	Count of the number of ASIC-related technology alliances a firm established in the five previous years (t-5 to t-1)	Positive
(Cumulative technology alliances$_{t-1}$)^2	Squared term of the previous variable	Negative
(Cum. technology alliances $_{t-1}$) * (cum. patents $_{t-1}$)	Interaction between the number of ASIC-related patents a firm files for during the last 4 years and the number of alliances it formed in the previous 5 years	Negative
Innovative performance of alliance partners	Sum of the patent citations received by the firm's alliance partners	Positive
Novel technologies$_{t-1}$	Number of patents filed during the last 3 years in patent classes in which the company had not patented in the previous 4 years	Positive
(Novel technologies$_{t-1}$)^2	Squared term of the previous variable	Negative
Pioneering technologies$_{t-1}$	Number of a firm's patents that cite no other patents	Positive
Log ASIC sales$_{t-1}$	Natural logarithm of the ASIC sales of the firm	Positive
Firm size (log sales)$_{t-1}$	Natural logarithm of the total sales of the firm	Positive
ASIC market growth$_{t-1}$	Annual growth rate of the ASIC market	Positive
Firm is a captive producer	Dummy variable denoting that the firm is not selling ASICs on the market	Negative
Firm is Asian	Dummy variable denoting that the firm is headquartered in Asia	
Firm is European	Dummy variable denoting that the firm is headquartered in Europe	
Firm is GA-producer	Dummy variable denoting that the firm is producing only gate arrays	
Firm is SC-producer	Dummy variable denoting that the firm is producing only standard cells	
Firm is PLD-producer	Dummy variable denoting that the firm is producing only PLDs	
Firm is GA and SC producer	Dummy variable denoting that the firm is producing gate arrays and standard cells	
Firm is GA and PLD producer	Dummy variable denoting that the firm is producing gate arrays and PLDs	

competence of an ASIC producer. Variables using a 3 and 5-year time window were also calculated to check for the sensitivity of this variable to the length of the time period. These variables are highly correlated with the 4-year time window (r = 0.94 for the 3 year window and 0.96 for the 5 year window), suggesting that the measurement of technological capital is not sensitive to the choice of a particular time window.

Following Gulati (1995), we computed social capital from matrices including all alliance activities of the ASIC-producers 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[10]. Second, some authors weigh each type of SA according to the 'strength' of their relationship (see Contractor and Lorange, 1988; Nohria and Garcia-Pont, 1991; Gulati 1995). As some technology alliances are more important than others in creating and transferring technological know-how we followed this weighting procedure to construct the social capital variable[11]. 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. All past alliances can be included into the calculation of social capital assuming that all prior ties, no matter how long ago they were established, have an impact on current firm behavior. However, we chose for a moving window approach, assuming that only 'ongoing' alliances have an impact on the technological performance of the focal firm. For the alliance activities of the ASIC producers we have an indication about the termination of 62 (21.5%) alliances in the observation period 1988-1996. We assumed they have an impact on the rate of innovation as long as they were not terminated. For the other alliances we assume that the lifespan of alliances is usually no more than five years (Kogut, 1988, 1989).

The innovative performance of a company's partners can be modeled in different ways. Basically, we follow the method developed by Stuart (2000). The innovative performance of a firm i at time t is denoted as d_{it}. For each year in the observation period 1988-1996, an $Nx1$ vector $\boldsymbol{d_t}$

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[10] Figure 5 gives an overview of the different alliance types: alliances vary from equity joint-ventures and minority holdings with a strong organizational commitment and interdependence between allies to non-equity alliances which imply only moderate levels of organizational commitment (although stronger than arms' length licensing agreements).

[11]

Type	*Weight*	*Type*	*Weight*
Cross licensing	1	R&D contract	4
Technology sharing	2	Joint development agreement	4
(Mutual) second source agreement	3	Minority holding	5
State intervention R&D	3	Joint venture	6
Research corporation	3		

represents the innovation scores of the *N* firms in the sample. Combining these innovation scores with alliance activity in the ASIC-industry allows the construction of compact, time-varying innovation measures of the alliance partners of each company. These measures are computed by creating first a *NxN* (firm-by-firm) time changing symmetrical alliance matrices, labeled $\mathbf{W_t}=[w_{ijt}]$.

The innovative performance of the alliance partners of each ASIC-producer at time *t* ($\boldsymbol{p_t}$) is the product of the alliance matrix with the corresponding vector of innovative performance scores. As a result $\boldsymbol{p_t}$ is a time-changing vector containing the summed innovative performance scores for the allies of each ASIC producer.

The innovative performance of the partners can be measured in different ways. One possible way is to count the patents received by each of the companies during the previous 4 or 5 years (Stuart and Podolny, 1996; Ahuja, 2000; Baum *et al.*, 2000). An alternative is to weight these patents by the number of times they have been cited by more recent patents. Patent citation counts are important indicators of the technological importance of an innovation (Narin *et al.*, 1987; Albert *et al.*, 1991). A small inconvenience of patent citations is that the patents applied for in the last years of the observation period 1988-1996 have a shorter 'citation-period' than those that have been filed for in the beginning of that period. The majority of citations appear in the first five years after the patent was granted: as a result, although we cannot exclude a potential bias we expect that this will not have a major impact on the results.

Novel technologies measure the degree to which a company experiments with technologies that were not used previously (Ahuja and Lampert, 2001). To construct this variable we used the International Patent Classification (IPC), which is an internationally recognized hierarchical classification system. We computed this variable using the subclass level of the IPC. Novel technologies were calculated as the number of new technology 'subclasses' that were entered in the previous 3 years and a company was assumed "…to have entered a new subclass when it first applies for a patent in a subclass in which it had not patented in the previous 4 years" (Ahuja and Lampert, 2001: 533). This four-year time window results from the fact that technological knowledge depreciates rapidly: not being active in a technology subclass for a considerable period of time will significantly shrink a company's viable knowledge in that technological field. A time window of 4 to 5 years is considered an appropriate time span over which the technology is valuable for a company in high-tech industries (Stuart and Podolny, 1996; Ahuja, 2000).

Ahuja and Lampert (2001) define pioneering technologies as technologies that do not build on prior technologies. Patent regulations require companies to indicate how much they are indebted to the technological heritage by citing the patents they build on. Companies that apply for a patent that cite no other patents are exploring technological fields that have been left untouched so far. Therefore this variable is computed as the number of a company's patents that cite no other patents.

Control variables

We included four types of dummy variables. A first variable indicates in which economic region 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 North America. Firms from a different home country may differ in their propensity to patent. Next to that, Asian and European firms may be less inclined to patent in the USA even when the semiconductor industry is widely recognized as a global industry.

Annual dummy variables were included to capture changes over time in the propensity of companies to patent their innovations. The number of ASIC-technology related patents increased from 50 patents in 1988 up to 342 in 1995. In 1996 the number dropped again to 289 patents. Part of this growth is the result of the growing importance of ASIC-products and the accelerating changes in this technological field. Moreover, firms are increasingly aware of the earnings they can reap from by improving intellectual property management (Grindley and Teece, 1997; Teece, 1998; Rivette and Kline, 2000).

Next, dummy variables were used to indicate which type of ASIC-producer a company is. Firms can be involved exclusively in the production of gate arrays, standard cells or PLDs, or they can be involved in more segments at the same time. Segments are important in the sense that firms in each segment face different technologies, different competitors and different competitive or technological dynamics. Therefore, firms can vary in their propensity to patent simply because they are active in other segments.

A last dummy variable is included to control for possible biases due to the fact that some large companies produce ASICs only for their internal needs (captive market), i.e. for internal supply as parts in their electronic systems. These captive producers are a small minority of ASIC-producing companies but are nonetheless important in terms of technological capabilities (e.g. IBM and DEC). They establish technological alliances for the same reasons as ASIC-vendors.

We furthermore included two organizational variables. First, the natural logarithm of 'corporate sales' was included as a control variable. Large companies have the possibility to invest large amounts of money in R&D. Assuming that there exists a positive correlation between technological input and output (Pakes and Griliches, 1984) large firms will have a higher rate of innovation than small firms[12]. The second control variable is the natural logarithm of the ASIC-sales of a company. Firms with a considerable stake in the ASIC-market can defend or improve their market position by rejuvenating or reinforcing their technological capital. This, in turn, requires a high rate of innovation.

Finally, we introduced the annual growth rate of the ASIC market. High growth rates offer companies new economic opportunities stimulating them to invest more in R&D, which in turn should lead to more patents granted to the firm. As a result, we expect a positive coefficient for this variable.

Model specification and econometric issues

The dependent variable is a count variable and takes only nonnegative integer values – i.e. the number of patents a firm filed for in a particular year. 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:

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

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

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

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

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[12] No R&D figures were available for the few privately owned companies in the sample. However, corporate sales are a good proxy for R&D expenditures: for the companies of whom figures where available the correlation between sales en R&D expenditure was 0.91.

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[13]. 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:

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

where u_i is a random effect for the i[th] firm.

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).

Part of the differences between companies or between different years can be captured by including dummy variables in the model. First, the propensity to patent may be partly determined by the nationality of ASIC-producing companies. It is for instance reasonable to assume that Asian or European companies are less inclined to file for patent in the USA. Similarly, we introduced annual dummy variables to account for changes over time: they may capture the ever growing importance of intellectual capital forcing companies to file more patents over the years, or macroeconomic conditions that may affect the ASIC industry as a whole.

RESULTS

Table 2.3 presents a correlation matrix and descriptive statistics for the different variables. Table 2.4 shows the results from the random effects Poisson regressions testing the different hypotheses.

[13] The presence of overdispersion does not bias the regression coefficients but the computed standard errors in the Poisson regression are understated, so that the statistical significance is overestimated.

Model 1 in table 2.4 functions as a baseline model and includes the three types of dummy variables (annual dummy variables are not reported), control variables such as corporate sales, ASIC-sales, annual market growth rate, and the technological capital (cumulative patent count) as an unobserved heterogeneity control variable. In this model, the existing technological capital of a company has a positive and highly significant effect on its innovative performance. This supports the first hypothesis: companies that have an extensive technological capital get relatively more patents than other companies[14].

Firm size (corporate sales) also has a positive and significant impact on the rate of innovation: although this suggests that large companies are technologically and financially better equipped to innovate in the ASIC technology field, this is not entirely true. Since we did not control for R&D expenditures, firm size will take the effect of R&D expenditures along. This implies that the positive coefficient also accounts for increasing investments in R&D to positively influence technological performance. Annual dummy variables have no significant impact. The same holds for captive producers and the ASIC market growth. The significant coefficients of some industry segment indicate that the patenting rate is not homogenous for the whole ASIC market: however, the impact is no longer significant when additional independent variables are included in other models. Asian firms have a similar patent rate as their American counterparts, but European firms patent significantly less. Finally, overdispersion is a feature of our data: the dispersion parameter α is significantly different from zero indicating that the assumptions of a simple Poisson model do not hold and that we have to allow for overdispersion. A random effects Poisson estimator is an appropriate way to do so.

Model 2 includes the technology alliances formed by each company during the last five years. We also included the squared term because the 2nd hypothesis suggests an inverted-U shaped relationship between the patent rate and the technological capital of a company. The findings strongly support this hypothesis: firms at intermediate levels of embeddedness have the highest rate of innovation. Firms with poorly developed alliance networks as well as overembedded firms have lower rates of innovation.

Model 3 adds the interaction term between ‘social capital’ and ‘technological capital’ in order to understand how they jointly affect the rate of innovation of companies. The negative and highly significant coefficient corroborates hypothesis 3 and 4. Before we explain their joint effect on the rate of innovation we first have a look at their partial effects.

[14] Poisson regressions assume a multiplicative relationship between the dependent variable and the regressors, so that the partial effect of a variable can be understood as a multiplier rate.

Table 2.3 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	16
1	Number of patents	1.22	3.40	0	42																
2	Cumulative technology alliances$_{t-1}$	4.05	6.90	0	38	0.25															
3	Cumulative patents$_{t-1}$	3.93	8.15	0	72	0.67	0.33														
4	Log ASIC sales$_{t-1}$	2.95	2.03	-0.65	7.43	0.38	0.43	0.49													
5	ASIC market growth$_{t-1}$	0.14	0.03	0.10	0.21	-0.16	0.09	-0.02	-0.06												
6	Firm size (log sales)$_{t-1}$	6.20	3.30	-0.65	12.60	0.19	0.40	0.37	0.52	-0.02											
7	Novel technologies$_{t-1}$	0.86	1.31	0	11	0.48	0.39	0.61	0.41	-0.05	0.36										
8	Pioneering technologies$_{t-1}$	0.08	0.10	0	2	0.12	0.01	0.11	0.11	0.12	0.12	0.12									
9	Firm is a captive producer	0.12	0.32	0	1	-0.01	-0.01	0.01	-0.31	-0.01	0.21	-0.00	0.01								
10	Innovative performance of alliance partners	46.91	129.48	0	1251	0.26	0.48	0.36	0.28	0.01	0.26	0.37	0.01	-0.01							
11	Firm is Asian	0.22	0.42	0	1	0.02	0.00	0.17	0.14	0.00	0.40	0.10	0.12	-0.04	-0.01						
12	Firm is European	0.17	0.38	0	1	-0.11	0.15	-0.12	-0.01	0.01	0.10	-0.12	-0.04	0.10	0.04	-0.25					
13	Firm is GA-producer	0.12	0.32	0	1	-0.10	-0.16	-0.14	-0.07	0.00	-0.13	-0.13	0.01	-0.03	-0.12	-0.12	-0.14				
14	Firm is SC-producer	0.18	0.39	0	1	-0.13	-0.15	-0.16	-0.12	-0.03	-0.20	-0.19	-0.04	-0.01	-0.12	-0.21	0.14	-0.17			
15	Firm is PLD-producer	0.07	0.25	0	1	0.31	-0.01	0.17	0.16	-0.02	-0.13	0.13	-0.02	-0.10	0.09	-0.14	-0.12	-0.10	-0.13		
16	Firm is GA and SC producer	0.30	0.46	0	1	0.06	0.07	0.17	0.44	-0.00	0.38	0.24	0.10	-0.13	0.09	0.35	-0.04	-0.23	-0.31	-0.17	
17	Firm is GA and PLD producer	0.08	0.09	0	1	0.04	0.09	0.00	0.07	0.04	0.00	0.03	-0.01	-0.03	0.02	-0.05	-0.04	-0.03	-0.04	-0.02	-0.06

N = 830 observations

All correlations with magnitude > |0.077| are significant at the 0.05 level

To demonstrate the impact of both types of capital we first focus on their partial effects on the rate of innovation (i.e. multiplier of the patent rate)[15]. Technological capital moderates the relationship between social capital and the rate of innovation of the firm. This basically has two consequences. First, a larger technological capital decreases the positive impact of social capital on the rate of innovation. In other words, companies with small internal technological capabilities – e.g. start-ups, technological laggards or incumbents that want to get access to a new technology developed by other companies – profit most from their network of technological alliances. Second, higher technological capital requires lower social capital to 'maximize' the rate of innovation.

Similarly, social capital moderates the impact of prior technological capital on the rate of innovation of a company. The relationship is positive for companies that did not establish a network of alliances. It gradually drops the stronger the company is embedded in its alliances network. The relationship becomes negative for companies that are highly embedded – according to model 3 the relationship becomes negative when the company has more than 16 'weighted' technology alliances. Companies that are moderately embedded in an alliance network can tap from the internal technological resources as well as from the knowledge of their partners: their social capital weakens the relation between prior technological capital and the current rate of innovation.

The total impact of both types of capital on the rate of innovation is visualized in figure 2.5. The graph compares the patenting rate of companies with no technological and social capital – the benchmark – to patenting rates of companies that have invested previously in one or both types of capital. A positive (negative) patenting rate indicates that the rate of innovation of a company is higher (lower) than that of the benchmark.

The figure shows a number of interesting points. First, there is a 'curve of optimal solutions' maximizing the rate of innovation for each ratio of technological and social capital: left (right) of that curve companies can improve their rate of innovation by increasing (decreasing) their technological or/and social capital. Moreover, the 'optimal' size of the alliance network decreases with an increase of technological capital. If a company has no patents the optimal number of 'weighted' alliances is 29. This number is reduced to 6 alliances when the company has a technological capital of 50 patents. Companies can improve their rate of innovation by investing in social or/and technological capital when the size of their existing internal technological capabilities and social network is small. Hence, technological capital and social capital have mutually reinforcing effects on the rate of innovation. On the contrary, when a company has strong internal

[15] The partial effect of the prior technical capital (TC) in Table 4, Model 3 is exp[TC(0.0262-0.0016SC)], where SC is the social capital. The partial effect of social capital is exp[SC(0.0994-0.0017SC-0.0016TC)].

Table 2.4 Determinants of the patent rate of ASIC producers, 1988-1996

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Cumulative patents$_{t-1}$	0.0162***	0.0153***	0.0262***	0.0292***	0.0309***
	(0.0048)	(0.0052)	(0.0053)	(0.0054)	(0.0073)
Cumulative technology alliances$_{t-1}$		0.0786***	0.0994***	0.0965***	0.0872***
		(0.0172)	(0.0201)	(0.0246)	(0.0302)
(Cumulative technology alliances$_{t-1}$)^2		-0.0018***	-0.0017**	-0.0017**	-0.0012*
		(0.0006)	(0.0007)	(0.0008)	(0.0007)
(Cum. technology alliances $_{t-1}$) * (cum. patents $_{t-1}$)			-0.0016***	-0.0019***	-0.0020***
			(0.0003)	(0.0003)	(0.0003)
Innovative performance of alliance partners				0.00061*	
				(0.00033)	
Novel technologies$_{t-1}$					0.2229**
					(0.0888)
(Novel technologies$_{t-1}$)^2					-0.0230*
					(0.0135)
Pioneering technologies$_{t-1}$					1.3429**
					(0.5546)
Log ASIC sales$_{t-1}$	0.1269**	0.1087***	0.1212**	0.1319**	0.1281*
	(0.0541)	(0.0575)	(0.5874)	(0.0584)	(0.0658)
Firm size (log sales)$_{t-1}$	0.2936***	0.2381***	0.1935***	0.1841***	0.1554***
	(0.0569)	(0.0535)	(0.0553)	(0.0552)	(0.0568)
ASIC market growth$_{t-1}$	8.3684	6.9522	5.294	7.3250	3.6514
	(60.7947)	(66.9714)	(76.8344)	(63.1954)	(93.0791)
Firm is a captive producer	-0.5178	-0.3482	-0.1770	-0.1305	-0.0460
	(1.0519)	(0.9906)	(0.3082)	(0.9108)	(0.8288)
Firm is Asian	0.9609	-0.6905	-0.4957	-0.4454	-0.3269
	(0.8214)	(0.7896)	(0.8021)	(0.7879)	(0.6925)
Firm is European	-1.7333***	-1.6781***	-1.6275**	-1.6088**	-1.4219**
	(0.6326)	(0.6643)	(0.7011)	(0.6874)	(0.6314)
Firm is GA-producer	0.5137*	0.5375*	0.4132	0.3429	0.0813
	(0.2772)	(0.2990)	(0.3447)	(0.3438)	(0.3250)
Firm is SC-producer	-0.5131**	-0.4198*	-0.4573*	-0.4677**	-0.3706
	(0.2343)	(0.2248)	(0.2425)	(0.2341)	(0.2976)
Firm is PLD-producer	0.8335	0.8496*	0.7167	0.6707	0.6608
	(0.5972)	(0.4697)	(0.4776)	(0.4778)	(0.4762)
Firm is GA and SC producer	-0.1456	-0.0250	-0.1116	-0.1777	-0.2186
	(0.1541)	(0.1544)	(0.1608)	(0.1697)	(0.1915)
Firm is GA and PLD producer	0.8286	0.3909	0.3623	0.3272	0.4156
	(1.4550)	(2.4542)	(2.7874)	(2.7063)	(2.8703)
Constant	-4.3035	-4.1684	-3.8625	-4.1907	-3.5583
	(11.5597)	(12.7302)	(14.6083)	(12.0047)	(17.6953)
α	1.7460***	1.4786***	1.3206***	1.2837***	0.9574***
	(0.3759)	(0.3376)	(0.3082)	(0.3025)	(0.2508)
Number of firms	99	99	99	99	99
Number of firms-years	830	830	830	830	830
Log-likelihood	370.87	382.50	392.20	394.51	410.38
Chi-squared	741.74	765.00	784.40	789.02	820.75

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$
'Year dummy variable'-coefficients are not statistically significant. They are not reported in the table.
The models use a random effects Poisson estimator. The sample is an unbalanced panel with 99 ASIC producers and 830 firm-years (units of observation).

technological resources and an extensive alliance portfolio it can only improve its rate of innovation by reducing its alliance network. In that case the two types of capital are substitutes as they overlap in the technology they provide to the focal company. These findings corroborate hypothesis 3.

Second, the plane in figure 2.5 has a typical saddle shape. The rate of innovation reaches its highest values for two types of strategies: the first strategy is based on relatively high levels of social capital combined with low levels of technological capital. The other strategy in contrast combines strong internal technological capabilities with a minimum of social capital. Hence, these two strategies may successfully coexist in an industry and strategies that are based on equal emphasis of both types of capital are clearly less successful in terms of technological performance. These results provide strong support to hypothesis 4.

Third, firms may over-invest in social capital as has been argued in the literature (Kogut *et al.*, 1992; Harrigan, 1985): there exists an area in figure 2.5 where the effect of social capital is negative. For companies with no patents this area starts at high levels of embeddedness (59 'weighted' alliances) but this threshold decreases with the increase of technological capital of a

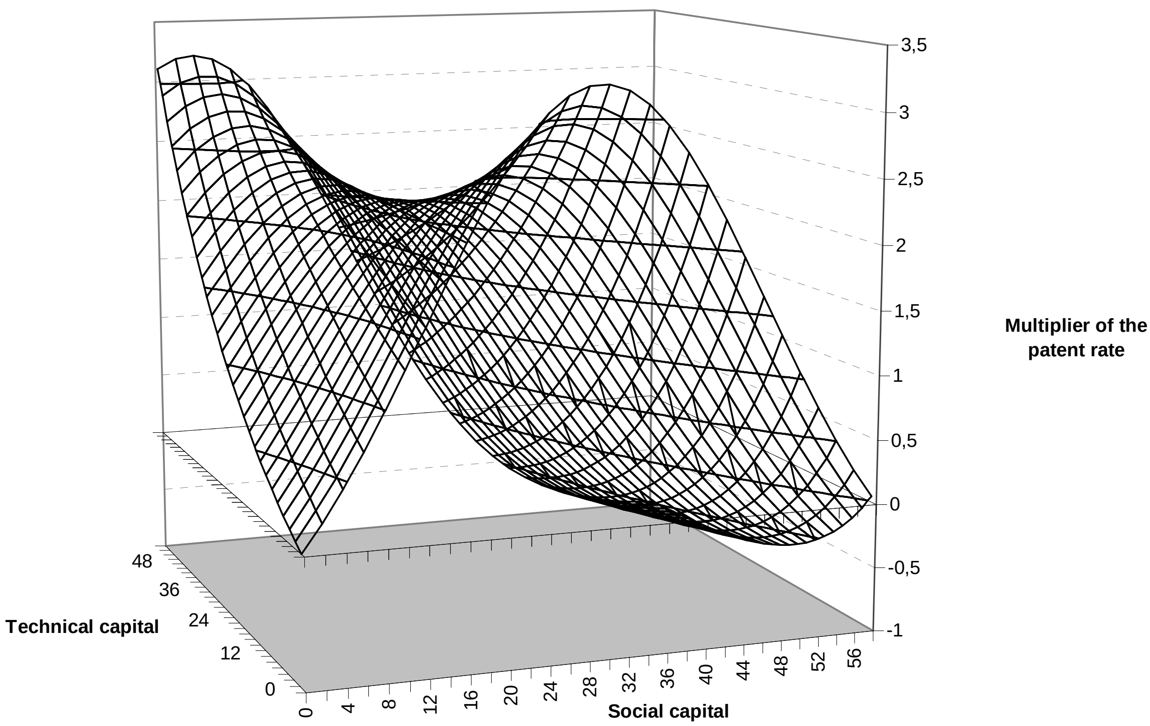

Figure 2.5 Impact of social and technical capital on the patent rate

company.

Model 4 introduces the innovative performance of the alliance partners. The positive but only weakly significant coefficient indicates that we have some support – although not very convincing – that a company benefits from the technological strengths of its alliance partners. Other variables held constant a one-standard deviation increase in the innovative performance of a firm's alliance partners results in an 8.2 percent increase in the rate of innovation (= exp(0.00061*129.48) = 1.08219).

As a result we could state that companies connected to technologically advanced partners seem to innovate at a higher rate than those connected to less prominent companies. However, we need to be cautious about these outcomes. There is a high bi-variate correlation between the total number of alliances a company established during the previous five years and the accumulated innovative performance scores of its partners over that same period. Therefore we executed the same two additional steps as Stuart (2000) to test whether or not this result is driven by collinearity. First, we omitted the variables based on the cumulative technological alliances (social capital). In that case, the coefficient of the 'innovative performance of the partners'- variable remains positive but is no longer significant (not reported). Second, we replaced the variable 'innovative performance-of-partners' in Model 4 with the 'average innovative performance score computed over the set of partners in each firm's alliance portfolio' (Stuart, 2000: 803). The advantage of this variable is that even though it is not correlated with the total count of alliances (r = 0.02), it still gives a flavor of the innovative performance of the alliance partners. Again, the coefficient is positive but not significant. As a result, it is not safe to claim any support for hypothesis 5.

Model 5 tests the two final hypotheses. We have argued that firms experimenting with novel technologies are more likely to have a higher rate of innovation. These firms are able to value the potential of novel technologies in a more accurate way. They perceive the potential threats of disruptive technologies more easily, and they are more open to new avenues for research. However, too much experimentation with unfamiliar technologies is counterproductive: it should be in balance with the exploitation of familiar technologies. In line with this argument we expect a positive sign for the coefficient of the 'novel technologies'-variable and a negative sign for the squared term. Model 5 indicates strong support for hypothesis 6. Moreover, the magnitude of the effect is substantial: other variables held constant, one-standard deviation increase above the mean in the experimentation with novel technologies results in a 26.5 percent increase in a company's rate of innovation[16].

Finally, hypothesis 7 suggests that experimenting with pioneering technologies increases the rate of innovation of a company. The results in Model 5 support this hypothesis. A one-standard deviation increase in the experimentation of pioneering technologies leads to a 14.4 percent (=exp[1.3429*0.10]) increase in the rate of innovation. Hence, companies that successfully patented a 'pioneering technology'-innovation increase their rate of innovation in the subsequent years.

DISCUSSION AND CONCLUSIONS

The increasing requirements of the organizational environment have forced companies in high tech industries to establish networks of technology alliances. The internal development of technological resources is interwoven with the external acquisition of technologies through alliances. Both technological and social capital determine the rate of innovation of companies. In the literature, both types of capital have been conceived as complements: they are mutually reinforcing each other's effect on the rate of innovation of a company (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998; Duysters and Hagedoorn, 2000).

In this chapter we claim that the effect of an increase in the internal technology capabilities of a company or an extension of the alliance portfolio on its rate of innovation depends on the size of its existing technological and social capital. For low degrees of internal technological capabilities and/or small alliance portfolios increases in either one of both types of capital will increase a company's rate of innovation. Technological and social capital are found to mutually reinforce each other's impact on the technological performance of a company. However, we also found strong empirical support for the change in interaction between both types of capital in the

[16] The partial effect of the novel technologies (NT) in Table 4, Model 5 is exp[NT(0.2229 -0.023.NT)]. For an average company this implies a rate of innovation increase of 19.1 percent (exp[0.86(0.2229-0.0230*0.86)]). For a company that is highly involved in experimenting with novel technologies (one-standard deviation above the mean) this increase is 45,6 percent (exp[2.17(0.2229-0.0230*2.17]). The highest possible value for the partial effect (71.6 percent) is reached for companies having experimented with 4.85 novel technologies.

case technological capabilities and the alliance network of a company increase. At high levels, technological and social capital are substitutes: the company with strong technological resources does not need an extensive portfolio of alliances to come up with a strong technological performance. Similarly, companies that learned how to acquire technology from their allies can curtail their internal research and development efforts compared to companies with a small alliance network.

We also found strong support for the possibility of local equilibria. Two main strategies are found to provide an optimal rate of innovation. The first emphasizes the development of strong internal technological resources in combination with a small alliance portfolio. The other emphasizes the establishment of an extensive alliance network supported by a minimal amount of technological capital.

Stuart (2000) argued that the technological performance of a company is not so much determined by the size of the alliance network but rather by the characteristics of the focal firm's alliance partners. Contrary to his findings we find no credible support for this claim. It is possible that in the specific context of the ASIC industry the technological prominence of the partners are less important because of the continuous stream of 'competence destroying' innovations by new entrants. Another possibility is that slightly different variables will confirm the importance of technological characteristics of the partners. One possible alternative is to calculate differences between the technological capital of the focal firm and that of its partners.

Finally, companies that experiment with novel and pioneering technologies are found to have a higher rate of innovation in subsequent years. This is an interesting finding because it indicates that companies, which almost exclusively focus on the exploitation of their existing technologies, are likely to get trapped in their own technological competences. This supports the idea of Leonard-Barton (1992) that core competencies can turn into core rigidities if companies are not rejuvenating their existing capabilities by exploring new technological fields.

This chapter clearly contains a number of limitations. One important limitation is that we did not model the 'interorganizational absorptive capacity' of companies explicitly. We assumed (and found empirical evidence) that the technological capital in a company has a moderating effect on the relationship between its social capital and its rate of innovation. Modeling explicitly the industry and organizational factors that have an impact on the absorptive capacity of a company could improve our understanding of the interaction between technological capital and alliance portfolios.

Future research on the dyadic level (dyad-year as unit of observation) could also complement the firm level analysis about the relationship between technological resources and alliance networks. An analysis on the dyadic level allows us to focus on the question how the probability of the formation of new alliances is affected by (the difference between) the existing technological capital of the allying companies.

CHAPTER 3

EXPLORATIVE AND EXPLOITATIVE LEARNING STRATEGIES IN TECHNOLOGY-BASED ALLIANCE NETWORKS [17]

Abstract

This chapter 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 higher. We find that direct ties have a moderating effect on indirect ties only in the case of exploitative learning. However, the empirical results indicate that the relationship between (non)-redundancy and explorative and exploitative learning are more complicated than a simple one-to-one relationship. Redundancy in alliance networks is a multi-dimensional concept: network density negatively affects exploitative learning and dependence on one or few alliance partners reduces both exploitative and explorative learning.

[17] This chapter is based on a paper written with Wim Vanhaverbeke and Geert Duysters

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 all the required knowledge and capabilities internally (Mowery, 1988; Mytelka, 1991; Teece, 1992; Gomes-Casseres, 1996; Hagedoorn and Duysters, 2002). Chesbrough (2003) coined the term "open innovation" to indicate that companies – even the largest and most technologically advanced ones – must complement their in-house R&D with technologies that are developed externally. In large companies, management is gradually 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. 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).

Technology based alliances between companies are one way to tap into these networks. A growing number of firms are realizing that alliances can be employed as effective learning mechanisms (Hagedoorn, 1996; Powell *et al.*, 1996; Hagedoorn and Duysters, 2002). 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 associated with the refinement and extension of existing technologies, whereas exploration is concerned with the experimentation with new alternatives. 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; Mitchell and Singh, 1996; Powell *et al.*, 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. Rowley *et al.*, 2000; Ahuja and Lampert, 2001; Hagedoorn and Duysters, 2002).

The main aim of this chapter is to improve our current understanding of how exploitative and explorative learning of firms is enhanced (or hampered) by the use of technology-based alliances and the social structure of the alliance network. In this chapter we argue that the value of a firm's alliance network is contingent on the type of learning (Burt, 1997, 2000; Gabbay and Zuckerman, 1998; Hansen *et al.*, 2001). 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.

Moreover, we will also focus on the effect of redundant ties in alliance networks. In the literature on social networks there are two opposing views on the benefits of redundant ties. 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 (Burt 1998, 2000; Ahuja 2000a; 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. We argue that the distinction between explorative and exploitative learning may be an important contingency factor in explaining the value of (non-)redundant ties. 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.

Strategic alliances and their role in exploitative and explorative learning

Several studies indicate that interfirm linkages are efficient means to develop and absorb new technological capabilities (Harianto and Pennings, 1990; Powell *et al.*, 1996; Ahuja, 2000b). 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 (Cohen and Levinthal, 1990). 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 can 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 (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 tasks at hand (Hansen *et al.*, 2001). 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. Exploring new technology entails problems that are novel to the company and because of that particular characteristic 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. Besides, the tacit and contested knowledge involved in the process also implies that the contact between the partners will often 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. 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). 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 often generates new, breakthrough innovations. 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.
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.

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.

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 the strengthening of its knowledge base.

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 contacts 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 2a: The larger the number of indirect ties of a firm the higher their effect on the strengthening of its knowledge base.

Hypothesis 2b: The larger the number of indirect ties of a firm the higher their effect on the broadening of its knowledge base.

Hypothesis 2c: The number of indirect ties is more positively related to the broadening of a firm's knowledge base than to the strengthening of its knowledge base.

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. The 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 (Nelson and Winter, 1982; Von Hippel, 1994; Hansen, 1999; Hansen *et al.*, 2001). 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 competitors: it is therefore unlikely that 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: 26) . 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 3a: The impact of the number of indirect ties of a firm on strengthening a firm's knowledge base is weakened by the number of direct ties.

Hypothesis 3b: The impact of the number of indirect ties of a firm on broadening a firm's knowledge base is not weakened by the number of direct ties.

Network structure of social capital

There is an ongoing debate in the academic literature about the impact of redundant and non-redundant network ties. Burt (1992a, 1992b, 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. 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 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 (Burt 1998, 2000; Hansen, 1999; Ahuja, 2000a;

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.

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: 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 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. 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: 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). 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. Therefore, we hypothesize:

Hypothesis 4: If a company intends to strengthen its existing technology base the replication of existing ties (creating redundancy) is more effective than the use of non-redundant ties.

Hypothesis 5: If a company intends to broaden its technology base the use of non-redundant ties is more effective than the replication of existing ties.

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

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 all the technology-based alliances of the focal firms in year t-1, i.e. the year previous to the year of observation. 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 since this would require additional research and hypothesis building on the issue of which alliance type is more instrumental in exploring new technological fields and which types are effective modes for deepening firms' existing set of technologies. Making a distinction between different types of alliances is likely to improve the analysis – as has been suggested in the context of 'open innovation' (Chesbrough, 2003) – but this is beyond the scope of our chapter. Given the constraints of this contribution this is put forward as future research. 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; Nohria and Garcia-Pont, 1991; Gulati 1995b): Combining the strength of the alliances and the redundancy in the alliance network opens up new research avenues that go beyond the scope of this contribution. 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. The lifespan of alliances is assumed to be usually no more than five years (Kogut 1988, 1989). Therefore 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).

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

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

The dependent variables were calculated for year *t*, the year of observation. All the independent variables as well as the control variables were calculated for the year previous to the year of observation to allow for the effect to take place. The social capital measures were based on the alliance matrix of year *t-1*, which contains alliances that were established in year *t-5* to *t-1*, since we assume a life-span of 5 years, unless indicated differently in the MERIT-CATI database.

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 new patent in the year of observation 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 the year of observation. 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. The classes were determined at three-digit level, which resulted in 358 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 patent classes kept this 'status' for 3 consecutive years. Since knowledge remains relatively new and unexplored for a firm immediately after patenting, patent classes kept their explorative 'status' for 3 consecutive years, parallel to Ahuja and Lampert's (2001) concept of novel and emerging technologies. All the classes in which a company had successfully applied for a patent the previous five years and successfully applied for a patent in the year of observation were considered ‘exploitative’ patent classes.

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

Although the use of patent as an indicator of learning and innovative output has been criticized on many different ground (for an overview see Griliches, 1990) they are generally viewed as the single most appropriate measure of innovative performance at the company level (Ahuja and Katila, 2001; Hagedoorn and Duysters, 2002) in particular in a single industrial sector context (Basberg, 1987; Cohen and Levin, 1989; Ahuja and Katila, 2001). We must acknowledge that although patents are increasingly used as a proxy for learning it does not equate learning. In our view it is a proxy for the output of learning (knowledge stock increase).

Independent variables

The impact of social capital on innovative output of companies has been explored among others by Ahuja (2000a) and Ahuja and Lampert (2001). In this chapter, 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. All measures are calculated on the alliance matrices of year *t-1*.

Direct ties

The first dimension of social capital is ‘direct ties’. We prefer to use the number of allies that the focal firm is directly connected to (i.e., the size of the ego-network) as a measure for direct ties, above the use of the degree centrality (number of alliances between the focal firm and its allies). We also introduce the squared term of the number of allies 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. There are different possibilities to operationalize the breadth of coverage of indirect ties. We chose for a variable that measures the impact of indirect ties while taking into account the decline in tie strength across more distant ties. We only report the findings for the distance-weighted centrality (see tables 3a and 3b). We tested the robustness of the findings with other centrality measures that do "…not account for the weakening or decay in tie strength between firms that are connected by increasingly large path distances." (Ahuja, 2000a: 438) and obtained similar results. 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: 438). The result is that alliance partners receive smaller weights the longer the path distance to the focal firm. The "distance weighted centrality" can be calculated by adding up all alliances at several distances weighted by their path distances (Ahuja, 2000a).

Social capital: network closure versus structural holes

The literature offers several possibilities to operationalize the (non-)redundancy of alliances. Most – if not all – researchers that have been involved in empirical studies on inter-organizational networking and social capital have chosen for a single measure of social capital (Burt, 1992a; McEvily and Zaheer, 1999; Gulati, 1999; Ahuja, 2000a; Baum *et al.*, 2000). In this chapter, we develop different (non-)redundancy 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, 1992b) argues that the two empirical conditions that indicate a structural hole (or non-redundancy) are cohesion and structural equivalence. Both conditions reveal that there are structural holes by indicating where they are absent. The cohesion criterion indicates that two partners of the focal firm "…are redundant to the extent that they are connected [to each other] by a strong relationship. A strong relationship indicates the absence of a structural hole." (Burt, 1992b: 66). Structurally equivalent partners of the focal firm on the other hand have the same alliance connections to every other company in the network. Even in absence of an alliance between these two firms they will provide similar information to the focal firm because they are linked (directly and indirectly) to the same other companies in the overall alliance network. Thus cohesion focuses on the direct ties between a focal firm's partners, structural equivalence concerns the indirect ties of a focal firm's partners with more distant companies in the alliance network.

The first measure of social capital, 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. The values for this variable range from 0 to 1, where 1 indicates that all allies are directly linked to each other.

Another variable to measure social capital in terms of cohesion is "network efficiency" of a firm's network (Burt, 1992a). This is calculated by dividing the "effective size" (a variable measuring the number of non-redundant ties in a firm's ego-network by subtracting the redundancy in the network from the number of partners the focal firm is connected to) by the number of partners in the firm's ego-network. This efficiency ratio ranges "…from a maximum of one, indicating that every contact in the network is non-redundant, down to a minimum approaching zero, indicating high contact redundancy and therefore low efficiency" (Burt, 1992a: 53).

Burt (1992a) offers two variables that capture different aspects from redundancy. The first one is network constraint: this variable describes the extent to which a network is concentrated in redundant contacts. More constrained networks span fewer structural holes and, thus, we expect a positive impact of the 'network constraint'-variable on the strengthening of a technology base and a negative effect on the broadening of technology base. The other variable is 'network hierarchy'. It measures the extent to which the redundancy can be traced to a single contact in the network: high values indicate that redundancy is concentrated around one or a few alliance partners. We expect that network hierarchy should be positively related to the strengthening of a technology portfolio (hypothesis 4) and negatively to its broadening (hypothesis).

Another variable measuring redundancy by cohesion, "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 overlap centrality" measures redundancy – network closure argument. Hence, firms with a high value for clique centrality overlap have access to redundant information and, therefore, we expect a positive (negative) relationship with exploitative (explorative) learning. "Clique overlap centrality" is calculated using UCINET VI identifying the Luce and Perry (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.

Apart from redundancy based on cohesion, redundancy can also be based on structural equivalence as argued by Burt (1992a, 1992b). 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 correlations 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. Correlations can be converted into a redundancy measure by taking the average of the correlations between pairs of direct partners (allies) of the focal company. The values for this variable range from +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. Thus we expect a negative sign when a company explores new technological fields and a positive sign when it depends on its existing technological capabilities.

Walker *et al.* (1997) have developed a variable that also measures social capital based on structural equivalence albeit in a completely 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: 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:

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

“In this equation, G_i is the measure of the dispersion of intergroup densities for the ith group in the network, n_i is the number of firms in the ith group, m_j is the number of partners in the jth partner group , d_{ij} is the density of the intersection of the ith and the jth 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: 116). For further explanation of this measure we refer to Walker *et al.* (1997).

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: 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.

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 region 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 region 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 a number of correlating organizational variables in one factor. First, the natural logarithm of 'corporate revenues' – a proxy for firm size - was included in the factor. 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 (March, 1991; Levinthal and March, 1993; Ahuja and Lampert, 2001). As a result we expect that large firms have an advantage over small ones in exploiting technological dynamics with a cumulative nature, but they may be at a disadvantage with respect to experimenting and exploring new technological fields.

The second organizational variable included in the factor is the natural logarithm of R&D expenditures of year *t-1*. 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. Therefore we also included previous technical capital, i.e. the number of patents received in the previous five years, as an indicator of absorptive capacity.

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: 12). The technological distance between companies can be calculated as follows:

$$= \frac{1}{2 * P_{it}} * \left[\sum_{j=1}^{P_{it}} \sum_{k=1}^{P_{it}} \left(DISTANCE_{jkt} \right) \right]$$

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

Where j and k represent the j[th] and k[th] partner (j γ k) of the focal firm i. P_{it} is the number of partners the focal firm year t. C_t is number of patent classes issued to the set of all sample firms in year t. N_{jct} and N_{kct} represent the number of patents in the c[th] patent class filed for respectively by the j[th] and k[th] 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:

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

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

$$\lambda_{it} = \beta' x_{it} \tag{2}$$

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. 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. 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:

$$\lambda_{it} = \beta' x_{it} + u_i \tag{3}$$

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

Unobserved heterogeneity may be the result of differences between companies in their innovation generating capabilities, and as a consequence, also in their propensity or ability to patent. Such unobserved heterogeneity, if present and not controlled for, can lead to overdispersion in the data or serial correlation. Including the sum of alliances that a firm entered in the last five 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 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.

Table 3.1 represents the description of the different variables. Table 3.2 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 3.2 shows high correlations between several regressors. These inter-correlations might affect the empirical results. In particular the variables 'revenues', 'R&D-expenditures' (or even R&D intensity), 'cumulative patents', and the technological distance among the partners are highly correlated. In order to avoid multicollinearity, we were looking for (a) latent variable(s) by means of a factor analysis. The results indicate that cumulated patents, revenues and R&D expenditures form one latent variable (Cronbach's alpha = 0.78). Factor scores were used as a new variable. The correlation between age and the latent variable is 0.25. The correlation between technological distance among partners and the latent variable is –0.03.

Tables 3.3a en 3.3b 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 with only control variables is presented in model 1. There are no statistically significant differences between the three industries (chemical industry, car manufacturing and pharmaceutical industry) concerning the innovation rate both in deepening and broadening their technology base. However, the sign of the intercept dummy variables indicates that pharmaceutical companies (the default) slightly more inclined to file for patents in new patents classes than companies in the other two industries. The differences between the pharmaceutical industry and the two other industries are not significant, but they reflect the continuous search of pharmaceutical companies to tap into the new business opportunities that are embedded in emerging technologies such as biotechnology.

The country of origin of the different companies plays a role in explaining both types of innovation. European companies have a lower innovation rate compared to Asian companies for exploitative patents. Asian companies are also a bit more active than European and US-based companies in broadening their technology base. However, these differences are not statistically significant.

Table 3.1 **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	Count of the number patents that a firm filed for during the previous five years (t-5 to t-1)	
$(\text{Cumulative patents})^2$	Squared term of previous variable	
Indirect ties	'Distance weighted centrality': 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, 1992a, p. 53)	
Network constraint	The extent to which a network is concentrated in redundant contacts (Burt 1992a)	
Network hierarchy	The extent to which the redundancy can be traced to a single contact in the network (Burt, 1992 a)	
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 *et al.*, 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

The latent variable capturing the effects of size (revenues, R&D expenditures, and patent portfolio) 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

Table 3.2 Descriptive statistics and correlation matrix

	Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	# of exploitative patents	102.23	156.81	0	1136													
2	# of explorative patents	9.19	14.92	0	125	0.24												
3	Direct ties	14.16	13.42	2	113	0.51	0.25											
4	Indirect ties	68.31	32.01	0	177	-0.12	0.03	-0.17										
5	Proportion density	14.60	23.10	0	100	-0.16	-0.09	-0.11	-0.15									
6	Network efficiency	0.884	0.167	0.1	1	0.15	0.08	0.05	0.16	-0.96								
7	Network constraint	0.224	0.181	0	1.125	-0.33	-0.19	-0.56	-0.11	0.51	-0.34							
8	Network hierarchy	0.022	0.057	0	1	0.14	0.06	0.38	-0.08	0.27	-0.27	-0.08						
9	Clique overlap centrality	2.85	4.49	0	28	0.43	0.20	0.87	-0.25	-0.01	-0.04	-040	0.19					
10	Structural equival. (corr.)	0.152	0.193	-0.012	1	-0.12	-0.06	0.05	-0.22	0.92	-0.92	0.38	0.26	0.15				
11	Pattern partner sharing	0.314	0.143	0.003	0.5	0.07	0.08	0.18	0.30	-0.04	0.00	-0.22	-0.09	0.17	-0.05			
12	Age	79.75	45.82	0	236	0.13	-0.06	0.12	0.01	0.02	-0.03	-0.05	-0.02	0.09	0.05	0.04		
13	Factor (Firm size, # patents, R&D int)	-7.32e-10	1	-10.077	3.317	0.66	0.26	0.50	-0.21	-0.10	0.08	-0.28	0.23	0.40	-0.02	0.04	0.31	
14	Techn. distance partners	0.022	0.009	0	0.063	0.02	0.04	-0.11	0.27	-0.13	0.18	-0.01	-0.01	-0.20	-0.21	-0.06	0.05	-0.11
15	Chemical company	0.376	0.458	0	1	0.03	-0.02	-0.05	-0.11	0.07	-0.07	-0.08	-0.31	0.04	0.08	-0.10	0.16	0.10
16	Car manufacturer	0.270	0.444	0	1	0.05	0.03	0.25	-0.33	0.13	-0.20	0.11	0.27	0.36	0.20	0.07	0.04	0.33
17	Firm is European	0.233	0.423	0	1	-0.26	-0.02	0.01	-0.11	0.13	-0.18	-0.07	0.10	0.02	0.18	-0.05	-0.07	-0.03
18	Firm is US-based	0.429	0.495	0	1	0.04	0.01	-0.02	0.17	-0.18	0.20	-0.06	-0.12	-0.11	-0.23	0.01	-0.05	-0.14
19	Year 1986	0.081	0.273	0	1	-0.03	-0.02	-0.08	-0.27	0.05	-0.04	0.10	0.32	-0.08	0.08	-0.26	-0.05	-0.06
20	Year 1987	0.087	0.282	0	1	-0.03	-0.02	-0.06	-0.26	0.04	-0.04	0.07	0.29	-0.03	0.06	-0.04	-0.04	-0.03
21	Year 1988	0.081	0.273	0	1	0.00	0.01	-0.03	-0.09	0.07	-0.06	0.03	0.17	-0.01	0.05	0.05	-0.03	-0.05
22	Year 1989	0.081	0.273	0	1	0.01	0.02	-0.00	-0.03	0.05	-0.04	-0.01	0.09	0.03	0.02	0.07	-0.02	-0.05
23	Year 1990	0.087	0.282	0	1	-0.01	-0.03	0.02	-0.01	0.03	-0.02	0.01	0.03	0.09	0.03	0.01	0.01	-0.02
24	Year 1991	0.087	0.282	0	1	-0.01	-0.04	0.00	-0.00	-0.05	0.05	-0.00	-0.01	0.04	-0.05	0.02	0.03	0.00
25	Year 1992	0.082	0.275	0	1	0.01	-0.07	-0.00	0.02	-0.07	0.06	-0.02	-0.07	-0.02	-0.06	0.14	0.04	0.03
26	Year 1993	0.084	0.277	0	1	0.00	-0.07	0.00	0.01	-0.05	0.05	-0.02	-0.11	-0.00	-0.04	-0.17	0.04	0.02
27	Year 1994	0.081	0.273	0	1	0.01	0.01	0.01	0.10	-0.05	0.05	-0.03	-0.13	-0.01	-0.04	-0.20	0.02	0.02
28	Year 1995	0.082	0.275	0	1	0.05	0.15	0.02	0.09	-0.01	0.01	-0.03	-0.06	-0.04	-0.03	0.10	-0.00	0.04
29	Year 1996	0.082	0.275	0	1	-0.00	0.07	0.05	0.17	-0.00	-0.00	-0.06	-0.23	-0.01	-0.02	0.04	-0.00	0.04

Table 3.2 **Descriptive statistics and correlation matrix (continued)**

Variable		14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
15	Chemical company	-0.17														
16	Car manufacturer	-0.15	-0.47													
17	Firm is European	-0.14	0.11	0.13												
18	Firm is US-based	0.17	-0.14	-0.18	-0.48											
19	Year 1986	0.00	0.01	-0.00	0.03	-0.02										
20	Year 1987	-0.02	-0.00	0.03	0.01	-0.02	-0.09									
21	Year 1988	-0.00	-0.02	0.01	-0.02	0.01	-0.08	-0.09								
22	Year 1989	-0.10	-0.01	-0.00	-0.01	0.00	-0.08	-0.09	-0.08							
23	Year 1990	-0.09	-0.00	0.01	-0.00	-0.01	-0.09	-0.10	-0.09	-0.09						
24	Year 1991	0.01	-0.00	0.01	-0.02	0.01	-0.09	-0.10	-0.09	-0.09	-0.10					
25	Year 1992	-0.02	-0.00	0.01	-0.01	-0.00	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09				
26	Year 1993	0.02	-0.01	0.01	-0.02	0.00	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09			
27	Year 1994	0.06	0.00	-0.00	-0.02	0.01	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09		
28	Year 1995	0.04	0.01	-0.02	0.02	-0.00	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	
29	Year 1996	0.04	0.02	-0.02	0.02	0.01	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09

‘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 3.3b). 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 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.

The age of companies has no impact on deepening the technology base, but it is negatively related to the broadening of the technology base. Hence, older companies have more problems than younger ones to look beyond the existing technological portfolio. 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.

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

Model 2 introduces direct ties (the social capital of a company) and indirect ties as regressors. Social capital is measured as the number of alliances a company established in the five previous years. Besides the linear term we also inserted the quadratic term to measure the impact of overembeddedness (Kogut *et al.*, 1992; Uzzi, 1997). The coefficients for these variables are significant in both tables: 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 coefficients for the ‘indirect ties’ as an explanatory variable are positive and significant in both tables. Hypotheses 2a and 2b are empirically supported: The impact is significantly larger on the broadening compared to the strengthening of the technology base. As a result, also hypothesis 2c is corroborated. Hence, 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 exploring new technological fields. 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 especially when the focal company is exploring new technologies.

Model 2 also introduces an interaction term between direct and indirect ties and is an empirical test for hypothesis 3. We have argued – following Ahuja (2000a) – that the number of direct ties moderates the impact of indirect ties, at least in the case of exploitative learning (hypothesis 3a). This is supported by model 4 in table 3.3a. Because a focal firm has a good understanding of what type of knowledge is required and since the information involved is fairly explicit in exploitative learning, direct ties may easily overlap the knowledge that could be acquired from indirect contacts. However, the coefficient of this interaction term in table 3.3b is also negative and significant. This is not in line with our expectations of hypothesis 3b. In the case of broadening the technology base, implying tacit knowledge and high levels of uncertainty, direct contacts are also moderating the need to have alliance partners with extensive networks of partners. In other words, there are different possible strategies for companies: they can choose to establish few alliances with partners that have extensive alliance networks with other companies, or they may establish more alliances with partners whom themselves are only connected to few other companies. This is the case for both the strengthening of the existing technology base as for the broadening of it.

Returning to the direct ties, the maximums are reached at medium levels of social capital – i.e. 15 alliances for strengthening and 27 alliances for broadening the technology portfolio, calculated at the average level of indirect ties – indicating that overembeddedness may play a role at higher levels of social capital, especially when the company intends to strengthen its existing technology base. However, these maximums increase significantly if the level of indirect ties drops: if the 'distance weighted centrality drops to '10', maximums are reached at 41 and 62 alliances respectively. Hence, when companies are not situated in the dense pack of the alliance network, they need more direct ties to reach the maximal innovation rate.

The impact of social capital (only direct ties) on both types of learning differs considerably: according to model 2 companies can at best increase the patenting rate with 3.1% (calculated at the average level of indirect ties) in case they intend to strengthen their knowledge base. In contrast, companies can broaden their technology base through a network of technology alliances – with a maximum increase of 9.0%. The level of indirect ties plays a crucial role here: when the 'distance

Table 3.3a Determinants of the patent rate of firms – strengthening the technology base, 1986-1997

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Direct ties									
Cumulative alliances /1000		12.1445***	11.8128***	12.3351***		12.3503***		12.7228***	11.2050***
		(1.2178)	(1.2183)	(1.2209)		(1.2186)		(1.2274)	(1.2422)
(Cumulative alliances/1000)^2		-0.1339***	-0.1312***	-0.1349***		-0.1339***		-0.1362***	-0.1263***
		(0.0097)	(0.0097)	(0.0097)		(0.0097)		(0.0097)	(0.0099)
Indirect ties									
Distance weighted centrality		0.0020***	0.0018***	0.0020***		0.0020***		0.0020***	0.0018***
		(0.0003)	(0.0003)	(0.0003)		(0.0003)		(0.0003)	(0.0003)
((Distance weighted centrality) * (cumulative alliances))/1000		-0.1184***	-0.1131***	-0.1185***		-0.1153***		-0.1183***	-0.1156***
		(0.0093)	(0.0093)	(0.0093)		(0.0093)		(0.0093)	(0.0093)
Redundancy									
Via cohesion									
Proportion density			-0.1175***						
			(0.0385)						
Network efficiency				0.1171**					
				(0.0558)					
Network constraint					-0.5524***				
					(0.0506)				
Network hierarchy						-0.5635***			
						(0.1313)			
Clique overlap centrality							-0.0028*		
							(0.0015)		
Via structural equivalence									
Correlation (Hansen)								-0.1585***	
								(0.0412)	
Pattern of partner sharing									0.1457***
									(0.0371)

Control variables									
Car manufacturer	0.2240	0.1384	0.1992	0.1475	0.2132	0.1466	0.2275	0.1506	0.1347
	(0.3931)	(0.3803)	(0.3836)	(0.3792)	(0.3849)	(0.3801)	(0.3923)	(0.3791)	(0.3802)
Chemical industry	0.6108	0.5069	0.5176	0.5072	0.6015	0.5127	0.6041	0.5112	0.5093
	(0.4088)	(0.3888)	(0.3877)	(0.3875)	(0.4005)	(0.3890)	(0.4072)	(0.3875)	(0.3888)
Europe	-1.5788***	-1.4280***	-1.4661***	-1.4182***	-1.5887***	-1.4327***	-1.5602***	-1.4173***	-1.4261***
	(0.4391)	(0.4173)	(0.4198)	(0.4162)	(0.4289)	(0.4173)	(0.4374)	(0.4161)	(0.4171)
US	-0.0914	-0.0352	-0.0611	-0.0334	-0.0773	-0.0376	-0.0847	-0.0329	-0.0321
	(0.3575)	(0.3449)	(0.3462)	(0.3438)	(0.3511)	(0.3448)	(0.3567)	(0.3437)	(0.3449)
Age	0.0031	0.0021	0.0016	0.0021	0.0029	0.0021	0.0030	0.0021	0.0021
	(0.0043)	(0.0040)	(0.0040)	(0.040)	(0.0042)	(0.0040)	(0.0043)	(0.0040)	(0.0040)
Factor (Firm size, # patents R&D intensity)	0.4311***	0.6636***	0.6667***	0.6671***	0.4370***	0.6580***	0.4546***	0.6630***	0.6632***
	(0.0206)	(0.0276)	(0.0276)	(0.0277)	(0.0206)	(0.0276)	(0.0240)	(0.0276)	(0.0276)
Techn. distance between partners	-3.8682***	-2.6439***	-2.8607***	-2.8234***	-3.4006***	-2.9729***	-4.0680***	-3.0092***	-2.5805***
	(0.7261)	(0.7420)	(0.7416)	(0.7465)	(0.7350)	(0.7438)	(0.7335)	(0.7472)	(0.7433)
Constant	3.8368***	3.6954***	3.7768***	3.5878***	3.9142***	3.7072***	3.3837***	3.7067***	3.6529***
	(0.4644)	(0.4440)	(0.4486)	(0.4455)	(0.4568)	(0.4437)	(0.4631)	(0.4424)	(0.4439)
alpha	1.7263***†	1.6000***	1.5785***	1.5895***	1.6610***	1.5987***	1.7172***	1.5888***	1.5994***
	(0.2518)	(0.2362)	(0.2353)	(0.2349)	(0.2437)	(0.2327)	(0.2507)	(0.2347)	(0.2361)
Number of firms	74	74	73	74	74	74	74	74	74
Number of firms-years	662	662	655	662	662	622	662	662	662
Wald chi-squared	1343.24	1657.32	1632.59	1662.12	1463.19	1669.63	1350.22	1671.69	1674.98

Notes: Standard error between brackets
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$
'Year dummy variable'-coefficients are not reported in the table.
The models use a random effects Poisson estimator. The sample is an unbalanced panel.
† Significance of the likelihood test of alpha = 0. High significance indicates that the panel estimator is preferred over the pooled estimator.

weighted centrality drops to ‘10’, companies can improve performance with 25% (55%) when they intend to strengthen (broaden) their technology base. Because of the interaction term between direct and indirect terms, it is important to consider their joint effect: at an average level of indirect ties, this total effect of ‘social capital’ (indirect ties included) amounts to 25.1% for the strengthening and 39.4% for the broadening of the technology base.

These results support hypothesis 1a, which predicted a stronger effect of social capital on explorative learning compared to exploitative learning. The difference is considerable indicating that the impact of external acquisition of technological know-how through alliances is larger when companies are experimenting in new technological areas compared to the strengthening of their existing technological capabilities.

Models 3 to 9 allow us to test hypotheses 4 and 5. We have seven variables that measure the network structure of social capital in different ways; five 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 strengthen its existing technology base. The opposite should be true when a company intends to broaden its technology base. We find a negative and significant coefficient in model 3 in table 3.3a. The coefficient in model 3 of table 3.3b has a positive sign but is not statistically significant. Hence, the results of model 3 in both tables are not corroborating hypotheses 4 and 5. The opposite seems to be true: when a firm’s partners are connected to each other a company becomes less successful in strengthening but not in broadening its technology base. Connections between partners even seem to foster the process of broadening the technology base, but the relationship is weak and hence, no hard conclusions, can be drawn.

‘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 3.3a according to hypothesis 4. Again, the empirical results are not supporting the hypothesis: the coefficient is positive and significant. The coefficient in table 3.3b is expected to be positive: also here we find the opposite sign although the coefficient is not significant. Hence, both regressors – proportion density and network efficiency – indicate (contrary to the hypotheses) that non-redundancy among a firm’s partners improves the strengthening of a firm’s technology base. Broadening the technology base is not enhanced by non-redundancy – as was expected by hypothesis 5. Rather the opposite seems to be true but the evidence is not conclusive.

The direct and indirect ties are eliminated in Model 5 because of the strong correlation between 'network constraint' and these variables. The coefficients for 'network constraint' are in both tables negative and significant and the absolute value of the coefficient in table 3.3a is (significantly) larger than the one in the other table. The negative sign is expected for the broadening of the technology portfolio, but not for the strengthening of it. Moreover, based on hypotheses 4 and 5 we expect that the negative impact should be stronger in the case of the broadening of the technology base. Before we try to explain these results we move to the results of model 6.

The results for 'network hierarchy' (model 6) are closely related to those of the 'network constraint'-variable. The coefficients have a negative sign and are significant. The absolute values of both coefficients are not significantly different from each other. These results indicate that innovation performance always suffers from a strong dependence on one or a few alliance partners. Hence, companies should try to avoid to become too dependent on one alliance partner: redundancy seems to be fine in a number of 'explorative strategies' as long as the focal firm can avoid dependence on one or a few dominant partners.

Now we can come back to the explanation of the results for the 'network constraint variable'. Network constraint varies with three qualities of the alliance network: size, density and hierarchy. Size is captured by the direct ties and density is related to proportion density and network efficiency. Hence, the negative sign for network constraint in table 3.3a is in line with the negative impact of both density and hierarchy on the strengthening of the alliance portfolio. In table 3.3b density and hierarchy have an opposite impact on the broadening of the technology portfolio; the negative sign of the 'network constraint'-variable indicates that the hierarchy effect is dominant.

The direct and indirect ties are eliminated in model 7 because of the strong correlation between clique overlap centrality and these variables. 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, according to hypothesis 4 we expect a positive and significant relation between high clique overlap centrality and the strengthening of the technology portfolio. Again, this is not corroborated by the result in table 3.3a. We also find a negative effect on the broadening of a firm's technology portfolio, as expected by hypothesis 5. 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

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
Direct ties									
Cumulative alliances/1000		15.5020***	14.5247***	15.5406***		15.2677***		15.48569***	16.7151***
		(4.9709)	(5.0049)	(4.9773)		(4.9660)		(4.9736)	(5.0427)
$(\text{Cumulative alliances}/1000)^2$		-0.1140**	-0.1047**	-0.1139**		-0.1103**		-0.1142**	-0.1233***
		(0.0449)	(0.0451)	(0.0449)		(0.0448)		(0.0449)	(0.0454)
Indirect ties									
Distance weighted centrality		0.0036***	0.0036***	0.0034***		0.0036***		0.0037***	0.0039***
		(0.0006)	(0.0009)	(0.0009)		(0.0009)		(0.0009)	(0.0009)
((Distance weighted centrality) * (cumulative alliances))/1000		-0.1350***	-0.1284***	-0.1212***		-0.1311***		-0.1364***	-0.1384***
		(0.0391)	(0.0395)	(0.0385)		(0.0391)		(0.0392)	(0.0392)
Redundancy									
Via cohesion									
Proportion density			0.13792						
			(0.0994)						
Network efficiency				-0.2028					
				(0.1405)					
Network constraint					-0.2499*				
					(0.1285)				
Network hierarchy						-0.4675*			
						(0.2565)			
Clique overlap centrality							-0.0016		
							(0.0049)		
Via structural equivalence									
Correlation (Hansen)								0.0819	
								(0.1102)	
Pattern of partner sharing									-0.1787
									(0.1264)

Control variables									
Car manufacturer	-0.1649	-0.1495	-0.1226	-0.1713	-0.1622	-0.1308	-0.1616	-0.1582	-0.1497
	(0.3138)	(0.3180)	(0.3306)	(0.3207)	(0.3103)	(0.3182)	(0.3143)	(0.3187)	(0.3185)
Chemical industry	-0.1224	-0.0923	-0.0876	-0.1042	-0.1267	-0.0846	-0.1225	-0.0967	-0.0976
	(0.3228)	(0.3287)	(0.3304)	(0.3309)	(0.3187)	(0.3291)	(0.3231)	(0.3294)	(0.3293
Europe	-0.4064	-0.5221	-0.5523	-0.5267	-0.3991	-0.5238	-0.4066	-0.5282	-0.5260
	(0.3676)	(0.3687)	(0.3803)	(0.3713)	(0.3628)	(0.3692)	(0.3677)	(0.3695)	(0.3695)
US	-0.3525	-0.4025	-0.4188	-0.4019	-0.34333	-0.4033	-0.3543	-0.4047	-0.4065
	(0.2865)	(0.2898)	(0.2983)	(0.2918)	(0.2834)	(0.2901)	(0.2868)	(0.2903)	(0.32903)
Age	-0.0065**	-0.0078***	-0.0080***	-0.0078***	-0.0065**	-0.0078***	-0.0666**	-0.0078***	-0.0078***
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
Factor (Firm size, # patents,	0.0610	0.0975	0.0921	0.0978	0.0555	0.0920	0.0665	0.0989	0.0947
R&D intensity)	(0.0580)	(0.0671)	(0.0664)	(0.0669)	(0.0574)	(0.0664)	(0.0612)	(0.0672)	(0.0668)
Techn. distance	-1.2734	-1.8148	-1.9670	-1.5180	-1.0451	-2.2889	-1.3556	-1.5882	-2.2838
between partners	(2.2508)	(2.2879)	(2.2897)	(2.2987)	(2.2641)	(2.2950)	(2.2646)	(2.3092)	(2.3077)
Constant	2.8328***†	2.6524***	2.6720***	2.8355***	2.8623***	2.6693***	2.8412***	2.6437***	2.7144***
	(0.3296)	(0.3368)	(0.3482)	(0.3618)	(0.3278)	(0.3372)	(0.3304)	(0.3375)	(0.3402)
alpha	1.0505***	1.0500***	1.0828***	1.10641***	1.0301***	1.0527***	1.0515***	1.0539***	1.0533***
	(0.1665)	(0.1681)	(0.1741)	(0.1702)	(0.1640)	(0.1683)	(0.1668)	(0.1687)	(0.1685)
Number of firms	74	74	73	74	74	74	74	74	74
Number of firms-years	662	662	655	662	662	662	662	662	662
Wald chi-squared	232.76	252.50	250.26	254.43	236.70	255.65	232.88	252.94	254.40
Chi-squared vs. previous nested model		126.90***	6.68***††	2.46		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.
† Significance of the likelihood test of alpha = 0. High significance indicates that the panel estimator is preferred over the pooled estimator.

represent (non-)redundancy. Contrary to hypothesis 4, the impact of this variable on the strengthening of the technology portfolio is negative and significant. The coefficient is positive but not statistically significant in table 3.3b. Again, the results are pointing in the opposite direction of the hypotheses.

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 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 improving technology performance – and especially for broadening the technology base. The coefficients in table 3.3a indicate that being part of the 'learning highway' fosters the strengthening of a firm's technology base, but not the broadening of it. The coefficient in table 3.3b is negative but not significant.

We can conclude that redundant information from alliance partners does not spur the strengthening of a focal firm's technology portfolio. On the contrary, there is evidence that non-redundancy improves the innovativeness of the company. This requires some more explanation in the next section. We found no hard evidence for a relation between (non)-redundancy and the broadening of the technology base. The coefficients in table 3.3b have the wrong signs and suggest that – contrary to hypothesis 5 – exploring new technologies might benefit from redundant ties. However, these coefficients are not significant and we have to be cautious in drawing any conclusions. The results for network hierarchy indicate that being tied up to a few dominant alliance partners has a negative impact on the innovation performance of a company.

CONCLUSION

This chapter focuses on the impact of firms' social capital on the strengthening and broadening of their technology portfolio. March (1991) argues that each company needs to balance both the exploitation of its current capabilities and the exploration of new ones 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 broadening and strengthening of the technology base are different in nature, we assume that the role of alliances and the structure of the alliance network are contingent on the type of learning: we argued that redundant information coming from alliance partners that are mutually linked to each other in dense networks improves the strengthening or deepening of the existing technological capabilities within a firm. On the contrary, non-redundant information enhances the exploration of new technological areas 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 an 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. For companies this means that one has to weight the benefits of adding another alliance to the costs of creating and managing this alliance. Gomes-Casseres (1996) has shown that there is a natural limit to the number of alliances that a company can manage successfully. We also found evidence that the optimal number of direct ties depends on the number of indirect ties (centrality in the alliance network): central players need less direct ties to get access to a broad range of actors and technologies. Furthermore, there is strong evidence that social capital has a much larger impact on the exploration of new technological fields than on the strengthening of a firm's existing technological portfolio. 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. Many companies have already adapted a strategy of constructing a "radar-screen" which consists of multiple strategic alliances. Alliances allow firms to "scan" their environment for new windows of opportunities. At relatively low costs they can get a "sneak preview" of a broad array of new technologies without investing large amounts of money. Furthermore, it allows them to tap into the technological resources of other companies in areas in which they themselves do not have an established core competency. Complementary knowledge from partners can allow companies to combine their knowledge into new technologies or products that each partner individually would not have been able to produce to create.

Indirect ties also have a beneficial effect on both types of 'learning' but the impact on the exploration of new technological fields is significantly larger. Interestingly, the empirical results show that direct ties also have a moderating effect on the impact of indirect ties (which resembles the results of Ahuja (2000a)). This suggests that companies that establish alliances with partners that are at the center of the alliance network need fewer ties than those that have ties with companies that in turn have no other alliances.

Finally, we did not find empirical evidence that firms profit from redundant ties when they are primarily interested in the refinement and strengthening of its existing technology base and competencies, while non-redundant ties are advantageous in explorative learning. On the contrary, non-redundancy improves the technological performance of the companies when they intend to strengthen their existing technological competencies. There is some evidence (but not conclusive) that redundancy spurs exploration of new technological fields. 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, but the empirical results go in the opposite direction of the argumentation in hypotheses 4 and 5. We suggested that that the exploration of new technologies requires boundary-spanning alliances. In line with Burt's (1992a, 2000) suggestion that firms can reap 'entrepreneurial' rents because of the absence of ties among their contacts, innovative firms that would like to explore new technological opportunities should therefore be engaged in non-redundant ties.

We found no support for this argument. On the contrary, non-redundant ties are beneficial for companies that aim at strengthening their technologies. So, why non-redundancy is not favorable for companies exploring new technological areas? Part of the answer has been provided by the literature: Cohen and Levinthal (1990) mentioned already that absorptive capacity is not only a question of getting access to new technologies, but also of evaluating and incorporating externally generated technical knowledge. Detecting new technologies and getting access to them is different from the evaluation and assimilation process. The question here is what firms do when they want a fuller understanding and want to move beyond 'detection phase' towards evaluation and assimilation of new technologies. In an 'explorative' setting knowledge is new and highly tacit. This requires triangulation in order to be able to understand and value the new knowledge. Such triangulation can only be obtained from redundant, multiple sources (Duysters and Hagedoorn, 2003; Gilsing, 2003; Nooteboom and Gilsing, 2004). In exploitation on the other hand, knowledge is (more) codified, there is more stability through a dominant design and contingencies can be better foreseen. More importantly, there are industry-standards, selected technical norms and so on, which decrease the need for continuous checks with existing ties. Because of this, redundancy can be reduced and must be reduced, in view of the need for efficiency and competition. These arguments are in line with our empirical results. As a result, further research should have a closer look at technological exploration in its different phases.

In contrast with most studies we calculated several variables that measure (non)-redundancy in alliance networks in different ways. The results show that redundancy can have different meanings. 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 variables 'network hierarchy' and 'pattern of partner sharing'. The negative impact of network hierarchy on both types of learning indicates that companies should avoid to be allied to one or a few dominant partners. Walker *et al.* (1997) use 'pattern of partner sharing' 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. 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 (Hansen *et al.*, 2001, Rowley *et al.*, 2000). Combining the strength of the alliances and the redundancy in the alliance network opens up new research avenues that go beyond the scope of this contribution. Rowley *et al.* (2000) made a first attempt in this direction: they suggest and find evidence that strong ties are especially important for the purpose of exploitation. The situation is different in the case a company intends to explore new technologies: the time and resources invested in strong ties (compared to weak ties) "would decrease the number of alternative contacts a firm can realistically maintain and therefore limits its reach into divergent sectors of the environment." (Rowley *et al.*, 2000: 375). The need for weak ties has been observed in industries that are characterized by rapid technological changes (Afuah, 2000). However, their analysis is hardly comparable with the one we presented here: future research might make use of the combination of the strength of ties and their degree of redundancy in order to explain their value in strengthening and broadening a company's technology base.

Furthermore, we have made a distinction between 'explorative' and 'exploitative' patents. However, exploration may cover many different issues. First, we have no indication whether or not the 'explorative' patent class in which a company was granted a patent, is in technological terms closely related to the other classes in which the company is already active. The 'proximity' of patent classes can be measured (Jaffe, 1986, 1989; Verspagen, 1997) and, as a result, one can calculate the level of exploration of a company's patents in a particular year compared to its current patent portfolio. Instead of having separate regressions for exploitative and explorative patents, one could simply measure the impact of different regressors on the 'level of exploration'. Second, we made no distinction between technologies that are new to a firm but may have been in existence earlier and those that have never been explored before by any other firm – i.e. the difference between novel technologies and nascent or emerging technologies (Ahuja and Lampert, 2001). Exploration means something different in both situations and successful alliance strategies will obviously differ. Hence, there is a need to further differentiate the notion of technological exploration.

Moreover, we did not consider different types of alliances separately and their specific effect on exploring new technological fields and on the deepening of a firms' existing set of technologies. Making a distinction between different types of alliances is likely to improve the analysis – as has been suggested in the context of 'open innovation' (Chesbrough, 2003) – but this requires the use of a different data-set.

Another possible area that deserves attention is that a firm's experience in the past with the creation of explorative patents (and not only exploitative ones) is likely to generate expertise in exploring new technological fields – compared to companies that stick to their existing technological competencies. This routine-based argument suggests that splitting up the number of patents in the past into an explorative and an exploitative part should allow us to analyze the impact of the experience of companies with 'explorative strategies' on their efficiency in exploring new technological fields. The same argument may, of course, hold for companies specializing in the strengthening of the existing technological base.

Finally, 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 (Nooteboom 1999, 2000).

CHAPTER 4

LOCAL ACTION IN TECHNOLOGY ALLIANCE NETWORKS: AN EMPIRICAL INVESTIGATION [18]

Abstract

This chapter studies the effect of local alliance action on the technological performance of companies. We go beyond the commonly used network level of analysis and focus on the ego-level aspects of strategic technology alliances. Our main focus is on the empirical outcomes of local actions with respect to technology alliances. In this chapter we aim to discern efficient strategies of local action that allow firms to become more innovative in three different industry settings; chemicals, motor vehicles and pharmaceuticals. The results of our analysis show that redundancy in an ego-network is related in a curvilinear way to innovative performance but density of networks between alliance partners negatively affects the innovative performance. Exploitative and explorative learning also seem to require a different ego-network structure.

[18] This chapter is based on a paper written with Wim Vanhaverbeke and Geert Duysters

INTRODUCTION

Over the past decades we have witnessed a rapid proliferation of strategic technology alliances. The unprecedented increase in the number of newly established alliances has led to the creation of dense alliance networks in which virtually all firms are linked to each-other by means of direct or indirect relationships. Traditionally, alliance research has been pre-occupied with the study of why and when alliances are formed (Duysters *et al.*, 2001). More recently, researchers have engaged in the analysis of with 'whom' firms are likely to form alliances (Gulati, 1995; Walker *et al.*, 1997; Gulati and Gargiulo, 1999; Bae and Gargiulo, 2003). Most scholars in this tradition have taken on an overall social network perspective in dealing with alliance formation patterns. Despite a growing number of empirical studies on network positioning strategies (e.g. Uzzi, 1996, 1997; Gulati, 1999; Hite and Hesterly, 2001) only a few of these studies actually connect network strategies and network positions to technological performance measures.

In this chapter we will fill this void by focusing on the effects of alliance formation patterns from an ego-network perspective. More in particular, we will focus on the outcomes of local alliance action on the innovative performance of the companies under study. This study will also contribute to the ongoing debate in the academic literature on the efficiency of networking strategies. The debate focuses on the discussion of whether firms should concentrate on building strong ties with preferential partners or should opt for relationships that overarch structural holes. Scholars in the first tradition often make use of 'network closure' arguments (Coleman, 1988) that argue that through the replication of existing ties highly cohesive groups of firms emerge that work together under conditions of trust, commitment and free sharing of knowledge. On the other hand, scholars taking on a 'structural holes' perspective (Burt, 1992) suggest that firms may enjoy brokerage advantages by taking advantage of opportunities that arise from bridging disconnected parts of the network (Duysters *et al.*, 2003). This allows firms to obtain non-redundant, high-yield information and facilitates information access, timing, referrals and control benefits (Burt, 1992). Empirical contributions in this debate have generated a mixed bag of findings. There is, however, increasing consensus that a 'contingency approach' might be most effective. This implies that the efficiency of network strategies is dependent on the environmental conditions in which firms operate. In order to account for these different environmental conditions we will focus our study on three different industry settings, i.e. chemicals, motor vehicles and pharmaceuticals. In contrast to most work in this area, which takes on an overall network perspective, we will focus on the particular set of actions of the network that surrounds focal organizations, the so-called ego-network (Garcia Pont and Nohria, 1999; Rowley *et al.*, 2000; Bae and Gargiulo, 2003).

In this chapter we will first derive some basic hypotheses on the effects of local action in technology alliance networks. We will then provide the empirical results followed by a discussion of the main findings and conclusions.

THEORETICAL BACKGROUND AND HYPOTHESES

The growing importance of alliance networks has induced many scholars in the field of organization science, strategic management and sociology to study the structure of these networks and their implications for firm performance. The structural and relational position of firms in alliance networks has been the focus in the majority of studies in this particular field. Inspired by seminal work of Coleman (1988), Granovetter (1985) and Burt (1992) many authors have subsequently dealt with the question of which specific structural network positions enable firms to achieve the highest level of performance. Most of the work in this area has taken on an overall network perspective that tends to neglect the endogenous micro-level dynamics of organizational action (Bae and Gargiulo, 2003). In this chapter we argue that these endogenous micro-level dynamics prove to be instrumental in building the overall network structure. In order to fill this gap in the existing academic literature we follow Bae and Gargiulo (2003) by arguing that networks are basically the outcome of the combined local alliance actions of all individual players in the network. This at first sight obvious aspect of alliance networks has received relatively little attention in the dominant network literature. The existing literature seems to take on a rather deterministic approach to network structure and positioning where firms are primarily influenced by the exogenous network structure they are part of.

In this chapter we argue that the efficiency of alliance strategies is primarily dependent on two major factors, i.e. the local actions of a focal firm (ego) and the local actions of its alliance partners (alters). Local actions can be associated with the establishment (or dissolution) of direct ties (ego-alter) whereas the local actions of the alliance partners are associated with indirect ties (alter-alter). Of course, direct and indirect ties are interrelated. If, for example, the focal firm undertakes a direct link with another company that has many direct links with firms with which the focal company has no contact, these indirect links might be very efficient because they facilitate the bridging of a structural hole. Therefore, this single direct link brings about many important indirect links to the company. On the other hand, if an alliance partner establishes alliances with firms that are already tied to the focal firm these ties might be considered to be redundant (from a structural holes perspective). Some of the actions of a focal firm's alliance partners might be beneficial to the focal company and some of the actions might have a negative effect on the focal firm's network position. Negative actions of alliance partners might lead to subsequent actions of the focal firm in order to neutralize the moves of its alliance partners.

This provides us with an inherent dynamic setting in which both types of links (direct and indirect) are considered to be important. Therefore we will focus our analysis on the effects of local actions of both the focal firms and their alliance partners on the former's innovative performance. Our main focus will therefore be on the combined set of actions of the network that surrounds focal organizations, the so-called ego-network (Garcia Pont and Nohria, 1999; Rowley *et al.*, 2000; Bae and Gargiulo, 2003). Rowley *et al.* (2000) argue that local density rather than global (network wide) density influences the performance of the focal firm. Ego-network measures are consistent with this view. We therefore leave behind the network level, and descend to the level of the ego-network, which provides a micro-level analysis of local actions and their impact on the innovative performance of companies.

Hypotheses

From an ego-network perspective, a focal company can either engage in new direct ties that are disconnected from its current network, i.e. the new tie has no direct connections to its existing set of alliance partners (A in figure 4.1), or can establish a link with a company that is already connected to at least one of its alliance partners (B in figure 4.1). From a structural holes perspective, the first tie (*Ego-A*) can be considered as a non-redundant tie that is likely to bring in novel, non-redundant information to the focal company. The latter tie (*Ego-B*) on the other hand, is considered to be redundant and does not result in the creation of new separate clusters to the ego-network.

However, closure advantages may stem from increased collective social capital that facilitates trust and improves cooperation. Through the formation of these ties cohesive subgroups

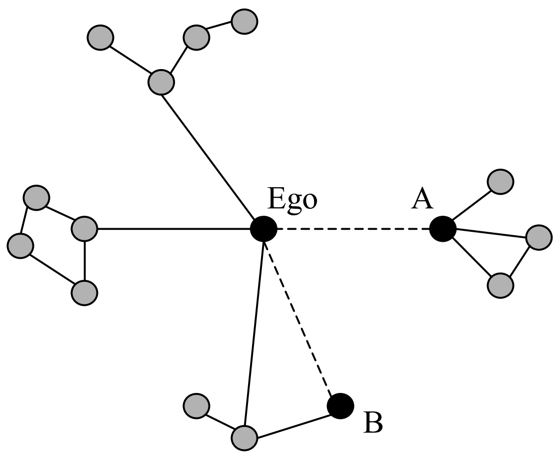

Figure 4.1 An ego-network perspective

emerge that maintain strongly cohesive ties among themselves. The firms involved in those strong ties relationships are more likely to share information or to act in concert (Knoke and Kuklinsky, 1982). As argued by Krackhardt (1992: 218) these '…. strong ties constitute a base of trust that can reduce resistance and provide comfort in the face of uncertainty'. Trust and comfort tend to facilitate information sharing and therefore can be seen as a stimulus for successful alliances.

On the other hand, scholars taking on a 'structural holes' perspective (Burt, 1992) suggest that firms may enjoy brokerage advantages because of their access to non-redundant information (Duysters *et al.*, 2003). This non-redundant or high-yield information is said to facilitate information access, timing, referrals and control benefits (Burt, 1992). In high-tech environments most new business opportunities come about as a result of new combinations of knowledge. It therefore seems to be important to link up with other clusters in the network. Firms may decide to act as a local bridge between different clusters of the network. By teaming up with a competent partner from another cluster, firms can benefit from the know-how of the complete cluster. The lack of 'social capital' might fuel opportunism though, as well as a lack of commitment among alliance partners. Liberal exchange of technological know-how is simply too difficult to facilitate in those relationships characterized by only small amounts of trust. The potential benefits of 'weak ties' might also be restricted because of resource limitations in terms of the managerial resources that firms can deploy in the search process for new partners. Matching, complementary (non-redundant) partners might be very hard to find and may easily exhaust available managerial resources.

Many of these problems are caused because information about relevant technological assets is often tacit and not readily available, and because the information provided by the potential alliance partner may be opportunistically biased. The more information asymmetry problems are faced, the more difficult the process of partner valuation will be. It is clear that in a setting where firms aim to overarch structural holes by teaming up with partners to whom the firm is unfamiliar problems associated with information asymmetry are considerably higher.

Furthermore, it is often argued that strong ties lead to increased similarity among partners. This might be a disadvantage in terms of the novelty of information exchanged. However, it might prove to be a significant advantage to the firms involved because of the potential lack of absorptive capacity among companies. In order to reap the full benefits of alliances firms need to have a sufficient degree of absorptive capacity (Cohen and Levinthal, 1990). Close contact between partners often leads to increased absorptive capacity because densely connected firms act similarly and develop similar preferences (Knoke and Kuklinski, 1982). Similarity leads to some degree of knowledge overlap between alliance partners and is therefore positively related to the absorptive capacity of partners. Structural hole networking strategies seem to be less effective because of the often too wide gap in absorptive capacity among alliance partners.

Too much overlap between alliance partners might, however, result into patterns of 'overembeddedness' in which firms face a lack of learning opportunities. In spite of the high levels of trust and commitment in these alliances too much knowledge overlap may hamper the efficient transfer of new ideas and technologies. The low informational value of the ties in a redundant ego-network is likely to have a detrimental effect on the overall learning efficiency in these networks. In other words, the information yield of the ties is likely to be low. Therefore we argue that although redundancy can be very helpful in raising the overall level of trust, commitment and absorptive capacity, the value of redundancy is likely to decrease once a certain threshold level is passed. Above this specific level, we expect that the ego-network is likely to become 'overembedded' and that the informational value of ties starts to decrease. Therefore, we expect a curvilinear relationship between the creation of redundancy in an ego-network and the innovative performance of ego. Thus:

Hypothesis 1: The creation of redundancy in an ego-network has a positive curvilinear effect (inverted-U shape) on the innovative performance of the focal company.

Whereas most of the alliance literature has traditionally focused on the effect of direct ties on company performance, there is increasing consensus among authors that indirect ties play an equally important role in determining the effects of network positioning of companies (Mizruchi, 1989; Haunschild, 1993; Gulati, 1995). In similar vein, we might argue that a firm's local action has only a partial effect on its ego-network. Although a focal company can control its own direct ties, it is often unable to control all of the alliance actions of its partners. In fact, some actions by other players might even neutralize specific moves that are made by the focal organization (Bae and Gargiulo, 2003).

Granovetter (1992) was among the first to go beyond the relational embeddedness level in which firms are characterized in terms of their direct links with other companies. Granovetter emphasized that apart from relational embeddedness firm's effectiveness in a network is also dependent on two other mechanisms; structural embeddedness and positional embeddedness. Whereas positional embeddedness focuses on the impact of particular network positions that organizations occupy in the overall structure of the network, structural embeddedness is concerned with the effects of indirect ties, or the tendency of actors around the focal firm to cooperate with each other (Granovetter, 1992; Duysters *et al.*, 2003). Those particular ties among alliance partners can either strengthen the position of ego, or can have a diminishing effect on the local action of the focal company.

Ties among alliance partners tend to increase the density of the network surrounding the focal organization. This may result in the formation of strong, densely connected cliques consisting of firms that are all mutually connected. From a closure perspective increased density often leads to the accumulation of shared social capital (Burt, 1997). Social capital encompasses many aspects of a social context, such as social ties, trusting relations, and value systems that facilitate actions of individuals located within that context (Tsai, 1998). Increased social capital decreases the chances of opportunistic behavior and facilitates trust among partners (Chung *et al.*, 2000). Structural embeddedness therefore facilitates norm creation at the network level, whereas relational embeddedness facilitates trust at the dyadic level (Rowley *et al.*, 2000). Especially in dynamic industry environments companies tend to learn as much as possible from a number of 'trusted' sources instead of optimizing their non-redundant ties (Hagedoorn and Duysters, 2002).

In spite of the noted advantages of ties among alters, authors in the structural holes tradition (e.g. Burt, 1997) have, however, pointed at the dangers of increased redundancy of information and to the effects of decreasing opportunities for information brokerage due to the establishment of ties among alters. Dense networks created by multiple ties among alters are often characterized as being redundant and inefficient (Hagedoorn and Duysters, 2002).

In high-tech environments firms might become locked-in in their own closed social system and start to suffer from 'over-embeddedness', rigidity and collective blindness (Uzzi, 1997; Duysters and Lemmens, 2003). Over-embeddedness often leads to the development of core rigidities (Leonard-Barton, 1995) and drives firms into so-called competency traps (Levitt and March, 1988). This leads to decreasing opportunities for learning and innovation (Duysters and Lemmens, 2003).

We make a distinction between two types of indirect ties in an ego network[19]; an indirect tie can be the bridge between otherwise separate clusters of alliance partners, but it can also take place within a cluster of alliance partners that would remain a cluster even when that tie was removed from the ego network[20]. The two types of indirect ties do not have the same effect on the position of the focal firm in the ego-network. When an alliance is the single bridge between two individual partners or clusters of partners, it increases redundancy in the ego-network. That effect is already analyzed in hypothesis 1. When an alliance is just reinforcing the cohesiveness within a cluster, i.e. when there are other alliances that hold the cluster together as a whole, then redundancy is not increased but the ties between partners belonging to the same cluster are strengthened.

The former forecloses possible brokerage advantages for ego; the latter increases the density within a cluster and therefore decreases the potential yield of information that can be obtained from the network. From a structural holes perspective, increasing density among the alliance partners can have a negative effect on the focal company's innovative performance. The network closure theory predicts that there should be a positive relationship between both types of indirect ties and the innovative performance of companies.

The relationship between indirect ties and innovative performance might be a bit more complex than as predicted by these opposing theories. To some extent density within a component of alliance partners can be beneficial for the innovative performance of the focal firm. Redundancy might be necessary as argued by the network closure theory. However, too much redundancy leads to 'overembeddedness' which is detrimental for the innovative performance of partnering firms (Kogut *et al.*, 1992; Uzzi, 1997). Very dense components are thus likely to suffer from marginal informational benefits. Therefore, we hypothesize:

Hypothesis 2a: Increasing cohesiveness between alliance partners in the same cluster has a negative impact on the focal firm's technological innovative performance.

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[19] This distinction is similar, but not identical, to the distinction Bae and Gargiulo (2003) make between between-cluster indirect ties and within-cluster indirect ties.

[20] A cluster of alliance partners can be formalized as a "weak component clique", i.e. a subgroup in which all members can reach each other at least indirectly without passing through the focal firm (Bae and Gargiulo, 2003, p. 11).

Hypothesis 2b: Increasing cohesiveness among alliance partners in the same cluster has a curvilinear effect (inverted-U shape) on the technological innovative performance of the focal firm.

As discussed above, empirical contributions in the Coleman/Burt debate have generated a mixed bag of findings. There is, however, increasing consensus that a 'contingency approach' might be most effective. This implies that the efficiency of network strategies is dependent on the environmental conditions in which firms operate. We would like to extent this argument by reasoning that the effects of local action are also, for a large part, dependent on the innovation strategies that firms undertake. In particular, we would like to introduce the discussion on explorative and exploitative learning (March, 1991). Whereas explorative learning is associated with experimentation and novel technologies, exploitation is concerned with the refinement and extension of existing technologies. Under conditions of explorative learning companies tend to depart from their existing knowledge base and move into resource areas where they can find tacit and novel knowledge (Levinthal and March, 1993). Exploitative learning, on the other hand, is characterized by an extension of existing know-how that entails less uncertainty and a lower degree of 'tacitness' (Hansen *et al.*, 2001). The important differences in the specific nature of both types of learning (March, 1991; Chesbrough, 2003) significantly influence the way in which a company can tap into the technological capabilities of its alliances partners (Rowley *et al.*, 2000; Ahuja and Lampert, 2001; Hagedoorn and Duysters, 2002; Vanhaverbeke *et al.*, 2003). More in particular, we argue that this contingency is reflected in differences in the value of indirect ties (Vanhaverbeke *et al.*, 2003).

In the case of explorative learning firms need to team-up with companies that are knowledgeable in those technological areas in which the focal firm has little or no expertise. When companies get involved in explorative learning they 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: 373-374). Non-redundant ties are advantageous in these broad scanning activities in order to cover a broad technological field with a minimum of alliances. As a result, companies in search for new knowledge will benefit more from non-redundant ties spanning structural holes than from dense network ties (Granovetter, 1973; Burt, 1992, 2000). Hence, redundancy is not expected to be valuable in explorative learning. Increasing density between alliance partners (without increasing redundancy) is also of no value to the focal company. The latter does not need to team up with partners that are already familiar with each other through established alliances.

In contrast, redundant ties may be beneficial for the focal company when it is primarily interested in deepening existing technological knowledge. Contrary to explorative learning, exploitative learning '…requires a deeper understanding of specific information rather than a wider grasp of general information' (Rowley *et al.*, 2000). Exploitative learning entails strengthening and refining the firm's existing core technology, which implies both high-quality, fine-grained information and trust-based governance (Uzzi, 1997; Larson, 1992). High density among the alliance partners in the ego-network provides an efficient network structure to meet these information requirements. 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). Dense ego-networks help a company to evaluate the obtained information and to get a deeper understanding of a specific technology. Furthermore, dense ego-networks serve as a trust creating mechanism alleviating the risks associated with opportunistic behavior (Williamson, 1985); trust is crucial in exploitative learning as partners exchange highly sensitive technological knowledge. Redundancy and density in the ego network are expected to have a positive impact on exploitative learning. However, as argued before, redundancy might only be valuable up to a particular level since 'overembeddedness' reduces the marginal value of additional indirect ties. Therefore, we hypothesize:

Hypothesis 3a: Redundancy in the ego-network of the focal firm is related in a curvilinear way (inverted U-shape) to exploitative learning. Increasing redundancy has a negative effect when a focal firm is involved in explorative learning strategies.

Hypothesis 3b: Increasing density among alliance partners (without increasing the redundancy level) has a positive impact on exploitative learning. Increasing density among alliance partners has a negative effect on explorative learning.

Data

In order to test our main hypotheses we constructed a longitudinal dataset which consists of alliance and patenting activities of 116 companies in the chemicals, automotive and pharmaceutical industries. These focal companies were observed over a 12-year period, from 1986 until 1997. However, due to new start-ups, mergers and acquisitions the panel is unbalanced. This specific sample was selected to include the largest companies that were establishing technology based strategic alliances in the three industries mentioned (alliance data were retrieved from the MERIT-CATI database[21]). For small or privately owned companies it is hard to obtain information on the establishment of a sufficient number of alliances. This is one of the reasons why other studies on inter-firm alliances also focus on leading companies in an industry (Gulati, 1995; Gulati and Gargiulo, 1999; Ahuja, 2000).

All network measures were calculated on the basis of 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 as well as the alliances established by other companies that belong to the industry. In constructing network measures, a number of choices have been made. First, different types of alliances were not considered separately. Second, the 'strength' of the relationships of strategic alliances was not weighted as some authors did (see Contractor and Lorange, 1988; Nohria and Garcia-Pont, 1991; Gulati, 1995). 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, 1995). The lifespan of alliances is assumed to be usually no more than five years (Kogut 1988, 1989).

[21] The data on alliances are taken from the MERIT-CATI database which contains worldwide 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.

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: 434)[22]. Especially in industries where companies operate on an international or global scale U.S. patents are a good proxy for companies' worldwide innovative performance.

For companies in the three sectors the financial data are gathered from Worldscope, COMPUSTAT and from company websites. The data contain yearly revenues, converted to the European Euro in order to standardize. Furthermore the nationality of each company and its age are included.

Variable definition and operationalization

Dependent variable

Technological innovative performance is measured by the patent intensity of a firm. This measure was chosen because it controls for firm size. Small firms generate a smaller amount of patents than larger firms. Therefore the impact of the alliance portfolio of small firms can not be compared to the impact of the alliance portfolio of large firms. Thus we need to control for firm size to standardize innovative outcome. Patent intensity enables the comparison of technological performance and technological learning of companies (Aspden, 1983; Pavitt, 1988; Acs and Audretsch, 1989; Napolitano and Sirilli, 1990; Cantwell and Hodson, 1991; Patel and Pavitt, 1991, 1995). Patent intensity is calculated by means of dividing the innovative performance of a firm, i.e. the patents that were granted in a given year, by the size of the firm, i.e. the revenues generated by that firm in the same year. In other words, the patent intensity is innovative performance controlled by firm size.

[22] See also Basberg (1987) and Griliches (1990).

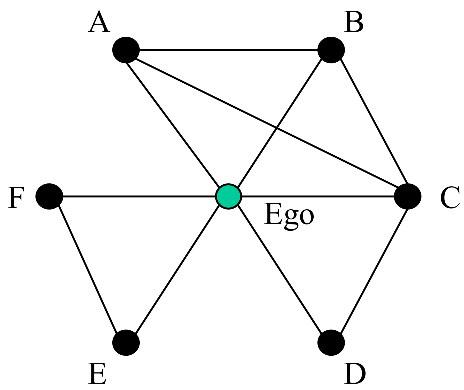

Figure 4.2a **Ego-network**

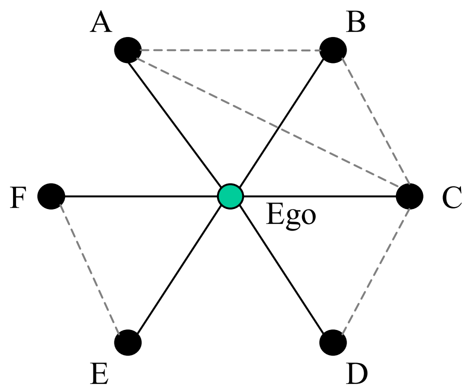

Figure 4.2b **Direct ties**

For exploitative technological performance the measure exploitative patent intensity is calculated. The number of patents a firm filed for in year t within patent classes in which it had been active in the five years prior to the given year is divided by the revenues generated by the firm in that same year to make the measure comparable to patent intensity. For explorative technological performance the number of patents a firm filed for in year t within patent classes in which it had not been active in the five years prior to the given year is divided by the revenues generated by the firm in that same year.

Independent variables

The first independent measure estimates the extent to which the direct ties of a focal firm's ego network are redundant. Since we observe ego-networks with only first-level alters (its alliance partners) traditional measures of redundancy do not apply. Traditional measures take into account larger parts of the network or the entire network itself. Therefore a redundancy-measure applying to ego-networks only was developed, i.e. egonet redundancy. This measure calculates the proportion of direct ties that are redundant given the ego-network. It considers only one tie to a weak component clique, i.e. a group of alliance partners that are themselves connected, as non-redundant. The other ties are considered to be redundant. Consider the ego-network in figure 4.2a. This ego-network contains two weak component cliques, i.e. *Ego-A-B-C-D* and *Ego-E-F*. *E* can be reached through *F* in weak component clique *Ego-E-F*, and *F* can be reached through *E*. Therefore one of these contacts is considered redundant.

To calculate the egonet redundancy measure, first we need to measure the number of direct ties linking the focal firm to its alliance partners in the ego network. This is the degree centrality of

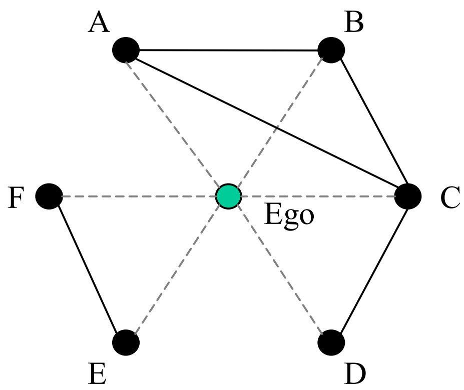

Figure 4.2c Weak component cliques

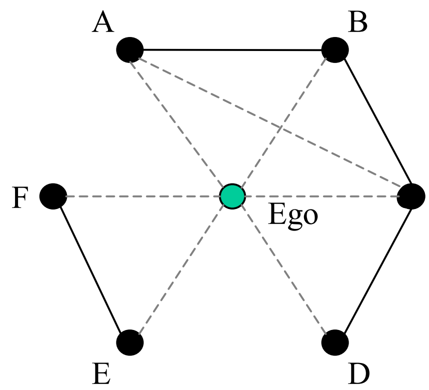

Figure 4.2d Minimum Indirect ties needed

ego (Freeman, 1979)[23]. Figure 4.2b represents direct ties in solid lines. Next, we need to calculate the number of non-overlapping weak component cliques in the focal firm's ego-network. A weak component clique is a group of alters (here the alliance partners) that are all connected to the ego (focal firm) under study, and every alter can reach the other alter in a number of steps without going through ego (Wasserman and Faust, 1994). Ego can thus reach all actors in such a weak component clique through any partner, making all other partners 'redundant'. The solid lines of figure 4.2c show the 2 weak component cliques in our example. Thus all ties to the alters in a weak component clique are redundant except for one. In other words, one weak component clique stands for one non-redundant direct tie, all other direct ties being redundant. To calculate how many direct ties are redundant we subtract the number of weak component cliques from the total number of direct ties of the ego network (since only one tie per weak component clique is non-redundant). However, the number of redundant direct ties only makes sense when related to the network size. Therefore, we divide the number of redundant direct ties by the total number of direct ties. This results in a measure with values ranging from zero to one. A low value implies there is no or little redundancy, increasing values indicate increasing redundancy.

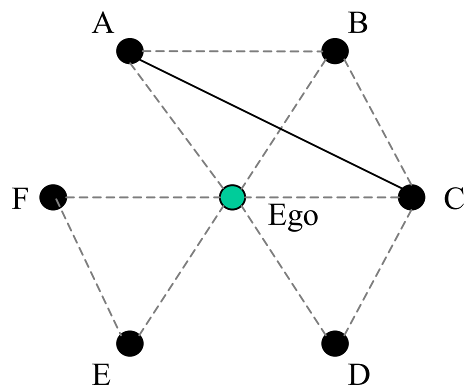

Figure 4.2e Within-clique ties

[23] This and other network variables can be calculated with the network analysis software package Ucinet 6 (Borgatti *et al.*, 2002).

The second independent variable, component-density, measures the 'density' of the weak component cliques of an ego's ego-network. First, we need to understand how a weak component clique is composed. The minimum number of ties necessary to form a weak component clique always equals the number of alters minus one. Consider figure 4.2a again. In order for *ego-A-B-C-D* to form a weak component clique, we need at least three ties connecting *A*, *B*, *C* and *D* (we do not involve ego in this calculation). Thus, in the weak component clique *ego-A-B-C-D* there are four alters, and therefore three (4-1) ties are necessary to form a weak component clique. These are shown by the solid lines in figure 4.2d. All the ties beyond this minimum number of ties needed to connect the alters within a clique are referred to as 'within-clique ties'. Thus, if a weak component clique contains *g* alters and *h* ties, there are *h*-(*g*-1) within-clique ties. In figure 4.2a there is one within-clique tie, i.e. tie *A-C* represented by a solid line. This is the real number of within-clique ties. However, the maximum possible number of within-clique ties in one weak-component clique is (*g*-2)*!*. In order to calculate the 'density' of the weak component cliques of an ego-network we add up all the real within-clique ties, and divide this by the sum of the maximum possible number of within-clique ties of all the weak-component cliques of the ego-network. The formula for component-density is:

$$compdens_i = \frac{(\ in_i - d_i + c_i\ )}{\sum_{n=1}^{c} (s_{ci} - 2)!}$$

where i is the ego firm, in_i is the number of indirect ties in the ego-network of ego firm i, d_i is the number of direct ties in the ego-network of ego firm i, c_i is the number of components of the ego-network of ego firm i, and s_{ci} is the size of each component in the ego-network of ego firm i.

The values for component-density again range from 0 to 1. High values imply that the weak-component cliques of the focal firm are characterized by high density. A value of one indicates that maximum density is reached.

Control variables

To control for differences between industries intercept dummy variables were included to indicate whether a company is a car manufacturer or chemical firm (default is the pharmaceutical industry) and to control for differences in the strategic value of innovation and patenting propensity among the three industries.

Two other types of dummy variables were used. A dummy variable indicating in which economic region the company is headquartered was used to control for regional differences. Following the Triad-concept of the world economy, a company can be headquartered in North America, Asia or Europe – the default here is Asia. Firms from a different economic region may differ in their propensity to patent. Also annual dummy variables were included to capture changes over time in the propensity of companies to patent their innovations.

Furthermore, we included an organizational variable, the natural logarithm of 'corporate sales', as a proxy for firm size. Larger firms have more financial means and vast technological and other resources to invest in R&D than smaller firms. Therefore, assuming that there exists a positive correlation between technological input and output (Pakes and Griliches, 1984) large firms will have a higher rate of innovation than small firms. However, returns diminish when investment increases. Thus, as the dependent variable patent intensity is already controlled for by firm size, we expect a negative relation between firm size and patent intensity.

Also technological capital, i.e. patents received in the five years previous to the year of observation, was used as a control variable. Technological capital measures the technological competence of a company (Narin *et al.*, 1987). Studies about R&D depreciation (Griliches, 1979, 1984) suggest that knowledge capital depreciates sharply, losing most of its economic value within 5 years. Thus, a moving window of 4 to 5 years is the appropriate time frame for assessing the technological impact in high-tech industries (Podolny and Stuart, 1995; Stuart and Podolny, 1996; Henderson and Cockburn, 1996; Ahuja, 2000). Because of the cumulative character of technology, the current technological position of a company is often dependent on its previous level of technological know-how (Teece *et al.*, 1997). A positive relation between previous technical capital and technological learning is expected. The last control variable to be included is related to the age of a company. Ever since Schumpeter Mark I and Mark II there is an unresolved and ongoing debate in the literature about the relationship between age and innovative performance. Some authors have addressed the important role of young entrepreneurial companies in the innovation process, whereas others have appraised the important role of older, large, efficient companies in this same process.

Model specification

The dependent variables take only nonnegative continuous values, i.e. the newly acquired patents in the year of observation divided by the revenues generated by that firm in the same year. For exploitative patent and explorative patent intensity the newly acquired patents were divided into exploitative and explorative classes as described above. A GLS random effects regression for cross-sectional time-series approach provides a natural baseline model for such data. The basic model can be written as follows:

$$Y_{(i.t)} = \alpha + \beta X_{(i,t)} + u_{(i)} + e_{(i,t)}$$

where $e_{i,t}$ is the standard error term with normal distribution and μ_i are independent draws from a normal distribution with zero mean and standard error σu. Random effects control for the potential non-independence of repeated observations on the same company.

RESULTS

Basic models

Table 4.1 describes the variables used in the regressions. Table 4.2 provides the descriptive statistics and the correlations between all the variables for the 100 firms and the 912 observations in the sample. Although overall there is no high correlation between the variables, component density is highly correlated (-0.60) with egonet redundancy. However, the VIF (variance inflation factor) value for component density was calculated, which is a more advanced measure for multicollinearity than simple correlations (Stevens, 1992). It is generally believed that if the VIF value exceeds the value of 10, the variable should be excluded from the analysis. However, the VIF value for component density was 1.69, and therefore egonet redundancy and component density were included simultaneously in the models.

Table 4.3a provides an overview of the results of the regression analysis using GLS random effects estimations for cross-sectional time-series for patent intensity. Year dummy variables were included in the regression but are not represented in this table. Model 1 represents the basic model

Table 4.1 Definitions of dependent and independent variables

Variable name	Variable description	
Technical learning	Count of the number of patents a firm filed for in year t within all patent classes	dependent variable
Exploitative learning	Count of the number of patents a firm filed for in year t within patent classes in which it was active in the five years prior to year t	dependent variable
Explorative learning	Count of the number of patents a firm filed for in year t within patent classes in which it was active in the five years prior to year t	dependent variable
Egonet redundancy	Share of the direct contacts that are redundant in year t-1	
$(\text{Egonet redundancy})^2$	Squared term of previous variable	
Component density	Average relative density within the components of a focal firm, i.e. the actual number of ties within a component divided by the potential number of ties, averaged over all components of the focal firm	
$(\text{Component density})^2$	Squared term of previous variable	
Cumulative patents	Count of the number of patents that a firm filed for during the previous five years (t-5 to t-1)	
Age	The number of years since a company is founded	
Firm size (ln revenues)	Natural logarithm of the total sales (x 1000 Euro) of the firm in t-1	
R&D expenditures (ln)	Natural logarithm of the total R&D expenditures (x 1000 Euro) of the firm in t-1	
Year	Dummy variable indicating a particular year (1986-1997)	
Chemical company	Dummy variable set to one if the firm is a chemical company	
Car manufacturer	Dummy variable set to one if the firm is a car manufacturer	
Europe	Dummy variable set to one if the firm is headquartered in Europe	
US	Dummy variable set to one if the firm is headquartered in the US	

Note: All network variables are based on alliance network representing all the technology-based alliances that were established in an industry during the five years prior to year *t*

Table 4.2 Descriptive statistics and correlation matrix

	Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Technical learning	0.203	1.874	0	52.885													
2	Exploitative learning	0.092	0.835	0	24.038	0.89												
3	Explorative learning	0.111	1.167	0	28.846	0.82	0.47											
4	Ego redundancy	0.250	0.281	0	0.917	-0.02	-0.02	-0.01										
5	(Ego redundancy)^2	0.141	0.208	0	0.840	-0.05	-0.05	-0.04	0.95									
6	Component density	0.810	0.336	0	1	0.00	0.01	-0.02	-0.60	-0.56								
7	(Component density)^2	0.769	0.393	0	1	0.00	0.01	-0.02	-0.65	-0.61	0.99							
8	Firm size (ln revenues)	7.949	2.517	-1.570	11.912	-0.45	-0.37	-0.41	0.32	0.32	-0.29	-0.31						
9	Cumulative patents	352	616	0	5110	-0.05	-0.04	-0.06	0.17	0.12	-0.28	-0.28	0.43					
10	Car manufacturer	0.282	0.450	0	1	-0.10	-0.09	-0.08	0.30	0.34	-0.27	-0.27	0.42	0.09				
11	Chemical company	0.288	0.453	0	1	-0.09	-0.08	-0.08	0.09	0.04	-0.03	-0.04	0.09	0.03	-0.46			
12	Age	74	47	0	239	0.01	0.05	-0.06	0.04	0.01	-0.04	-0.06	0.32	0.14	0.04	0.08		
13	European based firm	0.223	0.416	0	1	0.20	0.18	0.16	0.07	0.04	0.00	-0.02	-0.13	-0.22	0.02	0.10	-0.05	
14	US based firm	0.432	0.496	0	1	-0.07	-0.07	-0.05	-0.22	-0.19	0.12	0.14	-0.16	0.00	-0.18	-0.13	-0.09	-0.45

in which only the control variables are introduced. Some results are worth mentioning. The coefficient of firm size is negative and significantly related to patent intensity as expected. Thus increasing firm size results in decreasing innovative output. This confirms the idea that smaller firms are usually more innovative than large companies (Ahuja and Lampert, 2001). Next, we find a positive and significant relation between previous technical capital and the patent intensity of a firm. Thus previous knowledge stimulates the technological innovative performance of a firm. Knowledge accumulation building on previous knowledge is the basis for technological development. Because of the cumulative character of technology, the current technological position of a company is shaped by the path it has traveled (Teece *et al.*, 1997). When companies can build on their previously developed knowledge investments in the past should lead to a higher innovation rate in the present.

Model 2 introduces the linear term for the 'egonet redundancy' variable. The results show a positive and significant relation between egonet redundancy and patent intensity implying that redundancy in the direct ties of an ego network stimulates the technological innovative performance of a company.

In hypothesis 1 we predict a positive though curvilinear relation between the creation of redundancy in an ego-network and the innovative performance of the focal company. In model 3 we included both the linear and the squared term of egonet redundancy in the regression in order to account for the curvilinear effect. We find there is a positive and significant relation between egonet redundancy and patent intensity. This corroborates hypothesis 1. Thus redundancy in the direct ties of an ego network stimulates patent intensity. However, the significance of the squared term of egonet redundancy implies that redundancy in the direct contacts is only beneficial up to a maximum point. This point is reached when approximately 52% of the direct ties are redundant[24].

Model 4 returns to the linear model and adds 'component density' as a regressor[25]. Although egonet redundancy keeps its positive coefficient, its significance decreases and becomes weak. For component density we find a negative and weakly significant relation. Thus increasing density in the components of an ego network is not beneficial for the patent intensity of a focal

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[24] 52% = 0.4500 / 2*0.4314.

[25] In table II the correlation between component density and egonet redundancy is -0.60. This would plead against inclusion of component density in the same regression analysis as egonet redundancy. However, the VIF (variance inflation factor) value for component density was calculated, which is a more advanced measure for multicollinearity than simple correlations (Stevens, 1992). It is generally believed that if VIF exceeds the value of 10, the variable should be excluded from the analysis. However, the VIF value for component density was 1.69, and therefore component density was included in the regression.

Table 4.3a **Determinants of the patent intensity of firms, 1986-1997**

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Egonet redundancy		.1455***	.4500***	.0946*	.3947***	.3945***
		(.0472)	(.1395)	(.0544)	(.1427)	(.1426)
(Egonet redundancy)^2			-.4314**		-.4323**	-.4226**
			(.1860)		(.1893)	(.1857)
Component density				-.0830*	-.0259	-.0803*
				(.0445)	(.2055)	(.0443)
(Component density)^2					-.0502	
					(.1854)	
Control Variables						
Firm size (ln sales)	-.1745***	-.1808***	-.1789***	-.1799***	-.1781***	-.1780***
	(.0151)	(.0161)	(.0161)	(.0161)	(.0162)	(.0162)
technical capital	.0001***	.0001***	.0001**	.0001**	.0001**	.0001**
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)
Car manufacturer	.1895**	.1759**	.1843**	.1671**	.1763**	.1757**
	(.0773)	(.0828)	(.0832)	(.0833)	(.0836)	(.0837)
Chemical industry	.0296	.0184	.0118	.0156	.0092	.0092
	(.0731)	(.0770)	(.0774)	(.0774)	(.0777)	(.0777)
Age	.0021***	.0022***	.0021***	.0022***	.0021***	.0021***
	(.0006)	(.0007)	(.0007)	(.0007)	(.0007)	(.0007)
Europe .0873	.0716	.0684	.0742	.0701	.0710	
	(.0752)	(.0794)	(.0798)	(.0798)	(.0801)	(.0802)
USA	-.1026	-.0987	-.0950	-.0975	-.0940	-.0939
	(.0677)	(.0719)	(.0723)	(.0723)	(.0725)	(.0727)
Constant	1.3650***	1.3998***	1.3679***	1.4737***	1.4371***	1.4399***
	(.1338)	(.1431)	(.1443)	(.1485)	(.1498)	(.1498)
R^2	0.3022	0.3207	0.3223	0.3233	0.3250	0.3247
d.f.	894	811	810	810	808	809
Wald chi^2	177.15***	177.90***	183.48***	181.31***	186.75***	186.67***
Number of firms	100	97	97	97	97	97
Number of firm-years	912	830	830	830	830	830
Average number of obs per group	9.1	8.6	8.6	8.6	8.6	8.6

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 GLS random effects estimator. The sample is an unbalanced panel with 116 firms and 1137 firm-years (units of observation)

firm. In other words, the more alliance partners cooperate among each other within the same component (beyond the level that is strictly necessary to create a component) the less technologically innovative the focal firm becomes.

Model 5 introduces the squared term for both egonet redundancy and component density. Again the curvilinear relation for egonet redundancy is significant. However, the significance for component density disappears. Therefore, model 6 omits the squared term for component density assuming a linear relationship between component density and the innovative performance of the focal companies. In model 6 the significance for component density increases although it remains weak.

In short, hypothesis 1b is corroborated by the data. Redundancy in an ego network of a focal firm's alliance portfolio improves the innovative performance of the company up to a point, where after redundancy becomes a liability. Component density negatively affects the innovative performance of companies – although the relationship is only weakly significant. This implies that a focal company is better off to be linked to groups of alliance partners that are not or only poorly connected to each other by means of alliances. This empirical result confirms the arguments in favor of the structural holes theory as argued in hypothesis 2a (Burt, 1992).

Table 4.3b and 4.3c provide the results for the analysis of respectively exploitative and explorative learning (hypothesis 3). Again we make use of GLS random effects estimations for cross-sectional time-series. Model 1 represents the basic model including only the control variables.

It is useful to mention some of the differences between the analyses for exploitative learning and explorative learning. First, for explorative learning (see table 4.3c) the coefficient of the 'car manufacturer' dummy variable is positive and significant, while not significant for exploitative learning (table 4.3b). Therefore, car manufacturers seem to be inclined to explore more new technical domains than their counterparts in the pharmaceutical and the chemical industry, all else equal. Consequently, the stronger inclination of the car manufacturers to explore new technical domains is also the reason why we find a significant coefficient for this dummy variable in table 4.3a where all patents are taken into account.

For both explorative and exploitative learning the coefficient of the control variable 'age' is positive and significant. However, the coefficient for explorative learning is smaller than for exploitative learning. Hence, age seems to be advantageous for both exploitative and explorative technological learning but its impact is larger for exploitative learning compared to explorative learning. A possible explanation is that start-ups or young companies usually stick to their knitting in one particular technical field because they do not have the technical know-how and financial resources to diversify into other, new, technological fields. This implies that older companies profit from economies of scope and scale in R&D.

As for regional dummy variables there are no significant differences between the three economic regions for exploitative learning. However, for explorative learning European firms are doing better than Far-East and US based companies, while the latter still have a lower level of explorative learning than Far-East based companies. This is a bit surprising given the technological lead and entrepreneurial resilience of the US economy: another possible explanation for this empirical result is that companies in these three industries in Europe and the Far East had to diversify their innovation efforts into technical fields in the period 1986-1997 whereas their American counterparts had already done that before.

Model 2 in table 4.3b adds 'egonet redundancy' as a regressor to the analysis. The coefficient is positive and significant implying that some redundancy in the direct contacts of a focal's ego network stimulates the deepening of firms' current technological portfolio. We also introduced component density as a single regressor. The sign is negative, which means that increased cooperation between a focal firm's alliance partners is detrimental for the deepening of its current knowledge base. However, the negative coefficient was not significant and the Wald chi2 decreased to a level below that of the basic model. Therefore we decided not to include this model in table 4.3b.

When both variables are introduced in model 3[26] 'egonet redundancy' keeps its positive sign and the value of the coefficient does not change drastically. 'Component density' has a negative sign but is not significant at all. Therefore, we omit this variable again in model 4.

Model 4 introduces the squared term for egonet redundancy. The linear term is positive and significant, whereas the squared term is negative and significant. Thus there exists a curvilinear relation between the redundancy in the direct ties of a focal firm and exploitative learning. These results corroborate hypothesis 3a. The optimal point is at approximately 49%[27]. The same was done for component density. The linear and squared term were introduced in a separate regression (not displayed in table 4.3b). However, no significant results were found, and the Wald chi2 decreased compared to models 2 and 3. Model 5 adds both the linear term and the squared term for component density but both coefficients are not significant. As a result, we stick to model 4.

Model 2 in table 4.3c introduces 'egonet redundancy' into the regression with explorative learning as the dependent variable. The coefficient is positive and highly significant. We also introduced the

[26] For the inclusion of component density with a high correlation with egonet redundancy see note 22.

[27] From model 4: 49% = 0.2622/ (2*0.2692).

Table 4.3b Determinants of the exploitative patent intensity of firms, 1986-1997

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Egonet redundancy		.0723** (.0299)	.0696** (.0345)	.2622*** (.0881)	.2614*** (.0902)
$(\text{Egonet redundancy})^2$				-.2692** (.1176)	-.3035** (.1198)
Component density			-.0044 (.0282)		.1842 (.1296)
$(\text{Component density})^2$					-.1729 (.1169)
Control Variables					
Firm size (ln sales)	-.0778*** (.0104)	-.0828*** (.0112)	-.0827*** (.0112)	-.0811*** (.0112)	-.0819*** (.0112)
technical capital	.0001** (.0000)	.0001** (.0000)	.0001* (.0000)	.0001* (.0000)	.0000* (.0000)
Car manufacturer	.0625 (.0569)	.0573 (.0607)	.0568 (.0612)	.0614 (.0610)	.0645 (.0614)
Chemical industry	-.0090 (.0542)	-.0126 (.0569)	-.0127 (.0573)	-.0175 (.0573)	-.0171 (.0575)
Age	.0014*** (.0005)	.0014*** (.0005)	.0014*** (.0005)	.0014*** (.0005)	.0014*** (.0005)
Europe	.0696 (.0558)	.0634 (.0588)	.0634 (.0591)	.0624 (.0591)	.0585 (.0594)
USA	-.0487 (.0505)	-.0456 (.0535)	-.0456 (.0538)	-.0428 (.0538)	-.0435 (.0540)
Constant	.6346*** (.0952)	.6649*** (.1018)	.6688*** (.1048)	.6411*** (.1027)	.6376*** (.1056)
R^2	0.2273	0.2454	0.2455	0.2456	0.2484
Wald chi^2	92.01***	95.83***	95.40***	101.06***	103.04***
Number of firms	100	97	97	97	97
Number of firm-years	912	830	830	830	830
Average number of obs. per group	9.1	8.6	8.6	8.6	8.6

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 GLS random effects estimator.

Table 4.3c Determinants of the explorative patent intensity of firms, 1986-1997

Variable	Model 1	Model 2	Model 3	Model 4
Egonet redundancy		.0777***		.0362
		(.0287)		(.0333)
Component density			-.0816***	-.0661**
			(.0235)	(.0273)
Control Variables				
Firm size (ln sales)	-.0718***	-.0730***	-.0729***	-.0730***
	(.0059)	(.0060)	(.0061)	(.0061)
technical capital	.0001***	.0001***	.0000***	.0000***
	(.0000)	(.0000)	(.0000)	(.0000)
Car manufacturer	.0735***	.0586**	.0580**	.0534**
	(.0250)	(.0265)	(.0268)	(.0267)
Chemical industry	.0072	-.0038	-.0016	-.0052
	(.0230)	(.0238)	(.0241)	(.0239)
Age	.0005**	.0005**	.0005**	.0005**
	(.0002)	(.0002)	(.0002)	(.0002)
Europe	.0489**	.0429*	.0433*	.0430*
	(.0238)	(.0245)	(.0250)	(.0246)
USA	-.0378*	-.0352*	-.0379*	-.0359*
	(.0206)	(.0214)	(.0218)	(.0215)
Constant	.5492***	.5496***	.6341***	.6156***
	(.0504)	(.0526)	(.0579)	(.0591)
R^2	0.2438	0.2541	0.2569	0.2586
Wald chi^2	211.50***	212.17***	213.28***	217.79***
Number of firms	100	97	97	97
Number of firm-years	912	830	830	830
Average number of obs per group	9.1	8.6	8.6	8.6

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 GLS random effects estimator.

squared term of egonet redundancy as a second regressor (not displayed in table 4.3c) but this hardly improved the model as the squared term was not significant.

Model 3 introduces component density as a single regressor. The coefficient for this variable is negative and highly significant. Again, we introduce the squared term of component density in a separate regression, but the variable has no significant coefficient and therefore this model is not included in table 4.3c. Thus, while we do not find a significant impact of component density in the case of exploitative learning, this variable has clearly negative impact on explorative learning. Having partners that are densely connected to each other hampers explorative learning. Hence, this type of learning is improved when allies are only loosely coupled to each other.

Next, the egonet redundancy variable and the component density variable were introduced simultaneously into model 4[28]. The significance of egonet redundancy disappears, while the negative coefficient for the component density variable remains significant. Hence, for explorative learning we only find a positive and significant effect for egonet redundancy when we do not account for component density. However, model 4 performs better than model 2, thus we believe that redundancy on the ego-network level has no effect on the exploration of new fields.

The differences in the optimal network structures between explorative and exploitative learning are clear. Redundancy in the direct ties of a focal company's network stimulates exploitative learning up to a maximum point. Beyond that threshold increasing redundancy has a negative impact on exploitative learning. This corroborates hypothesis 3a for exploitative learning. This is not the case for explorative learning: Redundancy has no effect on explorative learning. Increasing density or cohesion between the allies of the focal firm has no significant effect on exploitative learning, while this does have a significant negative effect on explorative learning. Hence, hypothesis 3b is corroborated for explorative but not for exploitative learning.

Finally, we should explain why there is no support for the hypothesized negative impact of redundancy on explorative learning. Most likely the answer has to be sought in the very nature of explorative learning. Redundant ties are likely to be detrimental for firms that intend to discover new and promising new technological areas with a minimum of alliances. However, is exploration merely discovering new technological areas? In order to apply for a patent in a new patent class (= explorative patent) companies not only have to detect and evaluate new technologies but they also have to absorb it and turn it into new innovations (patents). The question here is what firms do when they want a fuller understanding and want to move beyond 'light exploration'. In such a setting knowledge is new and highly tacit. This requires triangulation in order to be able to

[28] For the inclusion of component density with a high correlation with egonet-redundancy see note 22.

understand and value the new knowledge (Gilsing, 2003). Such triangulation can only be obtained from redundant, multiple sources. Moreover, given the tacitness of knowledge, it is difficult if not impossible to use contracts as governance instruments, creating a need for trust-based governance. Hence, the need for triangulation in exploration is crucial and requires multiple, redundant contacts in order to reduce information noise. Therefore, redundancy might be beneficial for companies that search for innovations in new technological areas.

DISCUSSION AND CONCLUSION

In this chapter we have investigated the effects of local action in technology alliance networks on the innovative performance of focal companies. The overall results show that local action does indeed have a significant effect on the level of technological innovative performance of companies. This seemingly obvious result has, however, been largely neglected in the existing academic literature. The majority of the existing alliance literature has focused on network positions as positions that are primarily influenced by the overall network structure as opposed to being shaped by local action. The first approach is to a large extent deterministic, the second one is more voluntaristic in nature. The outcome of the empirical analysis in this chapter is an important finding because it shows that individual firms can decide, for a large part, on their position in an alliance network.

We focus on two types of indirect ties in the ego-network of innovating firms. The first type increases ego-redundancy: these alliances connect two partners or groups of partners of the focal firm that were not linked otherwise. The other type increases component density: these alliances between partners do not increase the redundancy in the ego network, but increase the density within a group of partners. The results (table 4.3a) indicate that the distinction between the two types of indirect alliances is important to understand the effect of alliance networks on the technological innovative performance of companies. With respect to the closure versus structural hole debate about efficient networking strategies the results for the ego-redundancy measure indicate that firms pursuing an alliance strategy based on redundant ties seem to outperform firms that take on a structural holes-related strategy. This result can be explained by the fact that the tacit nature of technology requires firms to have a sufficient degree of absorptive capacity (Cohen and Levinthal, 1990) in order to benefit from the know-how of alliance partners. Close contact between partners often leads to increased absorptive capacity because densely connected firms act similarly and develop similar preferences (Knoke and Kuklinski, 1982). Similarity leads to some degree of knowledge overlap between alliance partners and is therefore positively related to the absorptive capacity of partners. Structural hole networking strategies seem to be less effective because of the often too wide gap in absorptive capacity among alliance partners.

The relationship between ego-redundancy and the innovative performance of companies is not linear but curvilinear. After a certain threshold the impact of redundancy on innovation performance becomes negative; the marginal value of an additional alliance between alliance partners is lower than the additional cost of setting up the alliance. Thus, after a certain threshold level is reached firms start to suffer from overembeddedness and the informational value of ties starts to decrease. Firms that are too similar tend to suffer from decreased strategic opportunities through the lack of information access, timing, referrals and control (Burt, 1992: 62)

The results (table 4.3a) furthermore show that growing density levels within groups of alliance partners has a negative effect on the innovative performance of the focal firm. Redundancy in the direct ties plays a role but how dense partners are linked to each other plays no role at all. This is an interesting finding, because it is frequently argued, in line with the network closure theory (Coleman, 1988; Bourdieu and Wacquant, 1992) that dense, clique like networks of partners stimulates the innovative performance. We find, however, that increasing density levels within groups of partners has no beneficial effect.

Finally, we examined the effect of ego-redundancy and component-density on explorative and exploitative learning. The two types of learning differ considerably from each other and the optimal network structure to spur exploitative learning is clearly not optimal in the case of explorative learning. We hypothesize a curvilinear relation (inverted U-shape) between redundancy in the ego-network of the focal firm and its exploitative learning, but increasing redundancy is expected to have a negative effect in the case of explorative learning. Similarly, increasing density within groups of alliance partners is hypothesized to have a positive impact on exploitative learning and a negative effect for explorative learning. The results indicate that exploitative and explorative learning require different network structures. However, the expected effects are not always corroborated by the results: exploitative learning benefits from increasing redundancy up to a certain level (curvilinear effect) whereas component density has no effect at all. On the contrary, explorative learning is not affected by network redundancy but increasing density between partners is detrimental for its success.

We suggested in hypothesis 3a that ego redundancy should have a negative effect on explorative learning. The fact that the empirical analysis shows a positive (but not always significant) sign indicates that explorative learning is not confined to the detection and evaluation of new technologies only. Firms can apply for explorative patents, as defined in this chapter, if they discovered and evaluated new technological areas. However, since we defined explorative learning in such a way that a technological field remains its explorative status for an extended period of time, the generated new insights based on the understanding of the newly acquired technology also serves as explorative learning. In such setting, when companies move beyond 'light exploration' and desire a fuller understanding of a new technological area, knowledge is new to the firm and usually highly tacit. This requires triangulation in order to understand and value the new knowledge. Such triangulation and possibly hedging can only be obtained from redundant, multiple sources. This explains the unpredicted positive, though not always significant, sign for the effect of egonet redundancy on explorative learning.

Naturally this study has its limitations. First, we focused on the redundancy of the information in the ego-network of firms' alliance networks only. 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 paid no attention to the cognitive distance between a company and its partners although it is beyond doubt that, opposite to the case of exploitative learning, partners should differ in technology profile in explorative learning. This raises the question of what the optimal 'cognitive distance' should be between alliance partners when involved in exploitative or explorative learning (Nooteboom 1999, 2000). Finally, benefits stemming from alliances might be limited through resource limitations in terms of the managerial and financial resources that firms can deploy in the search process for new partners. Matching, complementary partners might be very hard to find and may soon exhaust available resources. Many of these problems are caused because information about relevant technological assets is often tacit and not readily available. Also the information provided by the potential alliance partners may be opportunistically biased. The more information asymmetry problems are faced, the more difficult the process of partner valuation will be. This is clearly the case when companies enter new technological areas: problems associated with information asymmetry are considerably higher when a company is teaming up with partners that have a complete different knowledge base.

CHAPTER 5

CONCLUSION

The three previous chapters provide different analyses of the effect of alliance network structure positions on the technological learning of firms. More in particular, we intended to give an answer on the following research question:

What is the effect of particular alliance networking strategies on the degree of technological learning of firms?

This research question was split up into three sub-questions. Each of the preceding chapters dealt with one of the sub-questions. Chapter two analyzed how internal learning and external learning mutually affect a firm's technological performance. In chapter three we tried to find the effect of networking strategies on explorative and exploitative learning. The role of local alliance action on the technological performance of a company was discussed in the fourth chapter.

Instead of dealing with these research questions one by one, we will put the findings of the analyses in a portfolio perspective.

OPTIMAL ALLIANCE PORTFOLIOS

As mentioned before, firms can no longer rely on their internal development of technological capabilities. Rather, firms need to complement their internal R&D with an alliance portfolio to keep up with the rapid pace of technological change. The results of the empirical research of the three previous chapters provide some preliminary guidelines for firms on how to build an optimal alliance portfolio. Next, we will try to translate the findings of the empirical analyses into a number of dimensions that are crucial for the management of an alliance portfolio.

Balancing internal and external learning

The first step towards building an alliance portfolio is determining in how far a particular company needs external resources for learning. The results from the analysis in chapter two show that there are two optimal strategies for combining internal and external learning. The first strategy emphasizes the internal development of strong technological resources combined with a small alliance portfolio; the other strategy focuses on the establishment of an extensive alliance network supported by a minimal internal development of technological knowledge. Hence, there is no single optimal strategy to follow. Different optimal strategies exist that can co-exist in one and the same industry.

However, we also found support for differences in the effect between internal and external learning for different sizes of the existing technological and social capital. For low degrees of internal technological capabilities and/or small alliance portfolios an increase in either one of both types of capital will increase a company's rate of innovation. Therefore, at low levels technological and social capital are found to mutually reinforce each other's impact on the technological performance of a company. With increasing levels of both types of capital on the other hand, we found strong empirical support for the change in interaction between both types of capital. At high levels, technological and social capital become substitutes: companies can rely on a focus on either type of capital to come up with a strong technological performance. Furthermore, there is evidence that companies can overextend their alliance portfolio: the innovative performance rapidly decreases when the portfolio is becoming too large.

As a result, firms need to make an inventory of their existing technological knowledge as well as the existing set of alliances, and explore the possibilities of extending (or shrinking) the alliance portfolio up to an optimal level.

"Optimal" portfolio size

The empirical analyses in the previous chapters indicate that companies that established many alliances in the past develop routines and alliance management skills which in turn lead to higher innovative output. However, since overembeddedness is a potential problem companies need to build an alliance portfolio up to an optimal level. We find strong evidence, both in chapter two and three, that portfolio size matters indeed. However, parallel to the findings of Gomes-Casseres (1996) we find there is an optimum of alliances a firm can manage successfully, after which the added value of an extra alliance diminishes and decreases the effectiveness of the portfolio as a whole. Furthermore, we make a distinction between optimum size of the alliance portfolio for firms that prefer to concentrate on exploitative learning, i.e. strengthening the existing knowledge base, and firms that wish to focus on explorative learning, i.e. broadening the existing knowledge base.

The analyses indicate that the optimum level of the alliance portfolio is smaller for exploitative learning than for explorative learning. Since companies depend to a larger extent on partners for explorative learning – companies have less developed internal technological know-how about these explorative technological areas and exploration is usually related to tacit knowledge that can only be transferred by means of a close interaction with partners – more ties are necessary in the case of explorative learning. Moreover, we found that the impact of social capital on explorative learning is larger than on exploitative learning.

However, this optimum size is also dependent on the number of indirect ties. In chapter three we find evidence that indirect ties have a positive impact on both exploitative and explorative learning. This implies that information can be acquired through partners from players with whom a firm is not connected. However, we also find that the number of direct partners has a moderating effect on the effectiveness of the number of indirect partners. Therefore direct ties may substitute indirect ties, and vice versa. Thus, firms with partners that are well-connected to the rest of the network may be equally successful to firms with a larger set of partners that are less well-connected to the rest of the network. This implies that the optimum portfolio size grows as the number of indirect partners diminishes. As a result, innovating companies have the possibility to choose between many ties to companies that are not central in the alliance network themselves and a small number of ties with companies that are in the 'pack' of it.

Hence, the optimum portfolio size is dependent on a number of factors. First, the chosen learning strategy determines to a large extent what the optimum is. Exploitative learning requires a smaller number of alliances than explorative learning. Second, the connectedness of the partners determining the centrality of the focal firm in the overall alliance network influences the optimum size as well. Well connected partners lower the optimal number of alliances for both explorative and exploitative learning.

The results of the previous chapters only show some stylized facts about the optimum size of the alliance portfolio for an 'average' company. In reality this optimum size depends on a whole range of parameters. For example, the size of the firm itself matters to a great extent, putting limits on the resources available, both financial and managerial, to build an alliance portfolio as well as on the capabilities to internalize the knowledge that is received through the alliances. The optimum size also depends on the industry and the economic region in which the companies are located (different national systems of innovation). Firms may have different management styles through which they are inclined to establish alliances or opt for licensing or M&As. Hence, a direct translation of the empirical results into management prescriptions is not possible, but they nevertheless give valuable information on how management should take optimum size of the portfolio into account, how exploration and exploitation ask for a different approach, and how direct ties always have to be considered jointly with indirect ties.

Indirect ties

The analysis in chapter three shows that indirect alliances are a good tool for companies to scan the environment for new ideas and technologies. The observed impact of indirect ties is significantly larger in case a company is involved in exploring new technological fields than when a firm deepens its existing technology base. Hence we may conclude that firms focusing on explorative learning should find partners that have themselves an extensive network of partners. These 'highly connected' partners are vital in providing information about other companies that might possess relevant technologies for the focal firms. This is particularly interesting in explorative learning since the focal firm does – in comparison with exploitative learning – not know much about the interesting and relevant technological competencies and the companies that have expertise in these areas.

However, the results of the previous chapters also indicate that it is advantageous when a focal firm's partners are mutually connected to each other to some extent compared to a situation where its partners are exclusively connected to other firms in the network that have no direct connection with the focal firm.

Redundancy

A next question in the formation of an alliance portfolio is the degree to which partners, both direct partners and indirect partners, should be redundant in the information provided. This is again dependent on the learning strategy a firm wishes to pursue as well as on the type of redundancy.

Redundancy can be considered on different levels. We can distinguish between redundancy based on cohesion and redundancy based on structural equivalence. Redundancy based on cohesion occurs between two actors, i.e. when they are themselves connected to each other, whereas redundancy by structural equivalence occurs when two actors are connected to the same others, thus providing the same information to the focal firm.

In chapter three we test with different measures for the effectiveness of both types of redundancy and non-redundancy on exploitative and explorative learning. Contrary to our expectations, most measures point to non-redundancy enhancing exploitative learning. For explorative learning we did not find conclusive results, although the results point tentatively towards redundancy spurring the broadening of the knowledge base. It is also important to mention that some variables show divergent results for the two types of learning while other variables – like network hierarchy – indicate that the effect goes in the same direction for both of them. A variable like 'pattern of partner sharing' indicates (contrary to most other results) that redundancy fosters exploitative learning, not explorative learning. In chapter four we introduce yet another measure of redundancy, which is also based on cohesion. However, this redundancy measure differs from the others in that it adds the components of the ego-network as a new dimension of redundancy The analysis in chapter four finds that redundancy is positively and curvilinearly related to a firm's exploitative patent intensity. Some redundancy in the partners of the ego-network therefore stimulates the deepening of the technology base, but only up to a maximum. We did not find a significant result for the effect of redundancy between direct partners and explorative learning.

In short, we have mixed results for the impact of redundancy on both exploitative and explorative learning. There are significant differences between exploitative and explorative learning, but the signs of the coefficients are not always as expected. From these different findings we may conclude though that redundancy is a subtle concept that has many dimensions as explored by the different 'redundancy' variables in chapters three and four. There are more dimensions to redundancy which need to be considered in the measurement of its effects than was assumed so far in the hypotheses. The question why non-redundancy is not favorable for companies exploring new technological areas as was suggested by the hypotheses in chapter three could be raised. One possible explanation is that detecting new technologies and getting access to them is different from the evaluation and assimilation process. The question here is what firms do when they want a fuller understanding and want to move beyond 'detection phase' towards evaluation and assimilation of new technologies. In an 'explorative' setting knowledge is new and highly tacit. This requires triangulation which can only be obtained from redundant, multiple sources (Duysters and Hagedoorn, 2003; Gilsing, 2003; Nooteboom and Gilsing, 2004). In exploitation on the other hand, knowledge is (more) codified, there is more stability through a dominant design and contingencies can be better foreseen. Because of this redundancy can be reduced. These arguments are in line with our empirical results. As a result, further research should have a closer look at technological exploration in its different phases. We probably have looked too narrowly at the first phases where companies detect and get access to new technologies. Assimilation and integration of new technologies most likely require more redundant network structures. This is clearly an interesting area for future research.

Technological capabilities partners

So far, we explained different aspects of the alliance network structure which are important in explaining an optimal alliance portfolio. Stuart (2000) suggests that not only the network structure but also the characteristics of the focal firm's alliance partners matter.

In the second chapter we tested for one such characteristic, i.e. the previous technological capabilities of the partners. We used the patent portfolio of the partnering companies and tested for its effect on the innovative performance of the focal companies. The measured effect was not significant. However, this may be caused due to the fact that we used a measure that averages the innovative performance of all the partners in the network. A more refined measure will probably be more effective in order to test for a relation between the success of the alliance partner's innovative performance and the focal firm's performance.

In the third chapter we used the average technological distance between the partners of the focal firm as a control variable. Ahuja (2000a) argues that larger technological diversity between the firm's partners generates structural holes in a focal firm's alliance network. Moreover, 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). In this way, structural hole measures might reflect the negative impact of technological distance between its allies rather than social structural effects. The results suggest that partnering with companies that have a similar technological profile is likely to play a stimulating role in external technology acquisition within technological areas in which the company already has some expertise. When a company intends to strengthen its existing technology base it should carefully choose partners with similar technology profiles. However, we did not find that technological distance has an impact on the broadening of companies' technology base. Explorative learning is almost by definition more experimental and uncorrelated technology profiles of a company's partners will not harm the innovative performance of the focal firm. We may conclude that it is advantageous to carefully select alliance partners who have a similar technology profile when a company intends to strengthen 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.

In short, we discussed that internal learning and external learning should be matched. At low levels, they mutually reinforce each other, at higher levels they become substitutes. Next, we discussed four dimensions of an alliance portfolio. The portfolio size is, irrespective of the available resources within the company, dependent on the chosen learning strategy as well as on the extent to which the partners are connected. Indirect ties are a useful means to scan the environment for new ideas and technologies, thus enhancing explorative learning. As for redundancy we can conclude that it is a multi-dimensional concept. There exists no simple one-to-one relationship between (non) redundancy and the strengthening or broadening of the technology base. The relationship seems to be more complex and it should be unraveled into different sub-concepts. We distinguished – parallel with Burt's (1992) concept of network constraint – two dimensions, i.e. density and hierarchy. They clearly have a different effect on technological performance. Group membership (operationalized by 'pattern of group membership', Walker *et al.* (1997)) also seems to play a role in determining the technological innovative performance of companies. This is in line with recent research about the impact of block membership on companies' technological performance (Lemmens, 2003). Increasing technological distance is detrimental for exploitative learning, while the difference in technology base between partners is not important in explorative learning.

The results of the analyses cannot directly be translated into management lessons about the optimum composition of an alliance portfolio. Portfolio composition, scale and scope economies in building an alliance portfolio, the renewal of a portfolio that gradually becomes obsolete through external technological trends or disruptive technologies: they are all topics that are extremely interesting. However, we did not spend attention to it because we had to restrict our attention to a few narrow research topics. In the next section we will discuss some limitations of this thesis.

Methodological issues

We use panel data in the three chapters and the unit of observation is the 'firm-year' in each one of them. This has a number of consequences. First, we used rough measures for the overall technological innovative performance as dependent variables in the tests. The number of new patents (exploitative or explorative) and the patent intensity give us an indication of how alliance portfolios enhance the technological learning of companies. However, these measures did not provide us with an idea of the distribution or internal composition of the alliance portfolios. Some groups of alliances might be much more important than others for the competitive advantage of a firm. So far, we did not differentiate different groups of alliances from each other which may be necessary to have a full understanding of alliance portfolio management.

Whereas we used patents extensively in our study, both in the dependent variables and in the independent variables, we did not put weights to the importance of these patents. This would, however, be more accurate, since not every patent contributes to learning in the same way. With the use of patent citations, i.e. the citation of one patent to the other to indicate on what knowledge the new patent is based, we could measure the 'importance' of a patent. A company in the possession of an often cited patent will have highly relevant technological knowledge in-house. Therefore this firm may be more attractive as a potential alliance partner than other firms. Thus, dependent variables based on the quantity of patents can be refined by weighting the patents.

Next, we only could take care of averaged independent variables. Take technological distances between partners as an example. Although the average of technological distances between partners may be the same for two focal companies, the distribution (or variance) of these technological distances may be very different. Our study draws conclusions based on the average of technological distances but it is clear that also other characteristics of the partners and their technological profiles might be interesting dimensions to study.

As for the measures we used, there are some more possibilities to improve our current study. First of all, the dichotomous nature of our exploitative learning/explorative learning dependent variable confines our methods of analysis. A continuous variable measuring the extent to which knowledge accumulation is exploitative or explorative would allow for more types of regression methods. So far, we had no indication whether or not the 'explorative' patent class in which a company was granted a patent, is in technological terms closely related to the other classes in which the company is already active. The 'proximity' of patent classes can be measured (Jaffe, 1986, 1989; Verspagen, 1997) and one can calculate the level of exploration of a company's patents in a particular year compared to its current patent portfolio. Instead of having separate regressions for exploitative and explorative patents, one could simply measure the impact of different regressors on the 'level of exploration'. Furthermore, we made no distinction between technologies that are new to a firm but may have been in existence earlier and those that have never been explored before by any other firm – i.e. the difference between novel technologies and nascent or emerging technologies (Ahuja and Lampert, 2001). Exploration means something different in both situations and successful alliance strategies will obviously differ. Another possible area that deserves attention is that a firm's experience in the past with the creation of explorative patents (and not only the total number of patents) is likely to generate expertise in exploring new technological fields – compared to companies that stick to their existing technological competencies. This routine-based argument suggests that splitting up the number of patents in the past into an explorative and an exploitative part should allow us to analyze the impact of the experience of companies with 'explorative strategies' on their efficiency in exploring new technological fields. The same argument may, of course, hold for companies specializing in the strengthening of the existing technological base.

Conceptual issues

Central to the topic of discussion in this thesis is external learning. In chapter two the reinforcing and moderating effect between internal and external learning on technological performance is studied. Chapters three and four build further on this argument by examining how network positions resulting from the external learning of a set of companies influence the learning process of these firms. Therefore, external learning is a common theme in the three chapters of this thesis. However, we limited the study to the effects of alliances exclusively. There are more ways of external technological knowledge acquisition, however. Traditionally, mergers and acquisitions were regarded another potential way of acquiring knowledge externally. Research has shown, though, that mergers and acquisitions did not always result in the efficient knowledge transfer (Vanhaverbeke *et al.*, 2002; Hennart and Reddy, 1997). Recently attention has been drawn to new forms of corporate external venturing. This implies companies set op a venture capital fund to stimulate employees to take up internally developed ideas and develop them further in a new venture. However, the VC-financing is also used increasingly for small investment in emerging technologies (educational investments in research labs, explorative research at universities, or start-ups). This allows companies to have an early view on new, emerging technologies that may be relevant for the firm. These small investments create options for the firm to spin in the external venture when the idea proves to be successful. It is considered an excellent way to overcome rigidness of large companies to depart from 'common practice'. Next, companies do not need to take the risk of changing their strategy as long as the success of a new idea is uncertain. Hence, companies profit more and more from the choice between different modes to explore and absorb externally developed technologies. Alliances are only one mode to acquire externally developed technologies and the choice is certainly no longer one between strategic alliances and M&As (Chesbrough, 2003; Van de Vrande *et al.*, 2004)

Next, we made no distinction between the different types of alliances. We do not distinguish between equity and non-equity alliances, or any other typology that might have refined the analysis. We do believe though that such a classification would be useful when studying firm's learning strategies. Exploitative learning will require a different composition of alliance portfolios with respect to alliance types than does explorative learning. We focused only on 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 (Hansen *et al.*, 2001; Rowley *et al.*, 2000). Combining the strength of the alliances and the redundancy in the alliance network opens up new research avenues that go beyond the scope of this thesis. Rowley *et al.* (2000) suggest and find evidence that strong ties are especially important for the purpose of exploitation. They argue that weak ties are advantageous in case a company intends to explore new technologies. The need for weak ties has been observed in industries that are characterized by rapid technological changes (Afuah, 2000). Future research might make use of the combination of the strength of ties and their degree of redundancy in order to explain their value in strengthening and broadening a company's technology base.

Relative network positions of the focal firm and its partners may result in an interesting study as well. Again we believe that both types of learning require different sets of relative network positions. The relative positions of the focal firm and the partnering firms may have an effect on the technological learning of the focal firm. A centrally positioned firm has different opportunities as well as different requirements for an alliance portfolio, compared to a firm which operates in the periphery of the same alliance network. Also, the strategy a firm wishes to pursue determines to a great extent the requirements of a portfolio. Two equally positioned firms will have different results if their alliance portfolio differs in network positions of partners. When the focal firm is centrally positioned and has alliance partners that are also centrally positioned this might lead to different results than when an equally centrally positioned firm chooses to team up with peripheral players. Similarly, focusing on the technology profiles of both the focal firm and the partners may be considered as a natural extension of our research (see also Yao, 2003)

Another issue we neglected to take into account in our study is the stages of the technology life cycle in which companies under study operate. Neither did we take into account the development stage (embryonic, growth, mature, aging) of the industries at study. We believe, however, that different stages of the technology life cycle put different demands on the portfolio structure of a company as well as influence the network structure in which the company operates.

The neglect of the development or evolution of industries brings along another issue, namely disruptive technologies. These have an effect on the evolution of alliance networks (Gulati and Gargiulo, 1999). As such, disruptive technologies play a role in the technological capability process as well. Firms need to react to technological continuities in order to maintain or possibly build a competitive position. Various authors picked up the topic of corporate strategies related to disruptive technologies (Tushman and Andersen, 1986; Bower and Christensen, 1995; Christensen and Overdorf, 2000; Christensen *et al.*, 2000). Also, a number of authors dealt with the evolution of networks (Gulati and Gargiulo, 1999; Baum *et al.*, 2002). However, both groups of authors neglected the effect of technological discontinuities on alliance networks.

Future research on the dyadic level (dyad-year as unit of observation) could also complement the firm level analysis about the relationship between technological resources and alliance networks. An analysis on the dyadic level allows us to focus on the question how the probability of the formation of new alliances is affected by (the difference between) the existing technological capital of the allying companies. Hence, this opens up the possibility to explore the opposite causality – from technology performance to alliance network structuring – as has been suggested in the introduction of this thesis.

We have already mentioned that technological distance among partners as well as between the partners and the focal firm are likely to play a role in the structuring of the alliance network (Yao, 2003). It might be interesting to observe in how far technology and the technological profiles of players determine the network structure of an industry. Next, do technology profiles determine network positions? Companies with a large stock of technological resources are highly attractive as potential alliance partners if companies enter alliances to get access to other firms' technology. Also, a company with specialized technological know-how may become interesting as this know-how becomes increasingly important in a sector, thus moving a peripheral player to a more central network position. This is in particular true in situations where new, disruptive technologies emerge and force companies to reshape their alliance portfolio. And can a firm obtain a desired network position by reshaping its technology profile? This view is based more on the attractiveness of players within an industry than on the conscious partner selection of the focal firm itself though. This is part of ongoing research about disruptive technologies and the evolution of network structure as has been explored by Vanhaverbeke *et al.* (2003).

The above presumed effect of the technological profile of a company on network structure combined with the findings of this thesis that network structure has an effect on learning implies technological learning, technology profiles and network structure should be modeled dynamically. Simple one-directional models are no longer sufficient in such settings. This also means that the modeling of the empirical research will take a different shape, where structural equation modeling (e.g., LISREL) may be one way to explore these multiple interactions between companies.

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SAMENVATTING

Technologische innovatie is de laatste decennia steeds belangrijker geworden voor bedrijven. Om competitief te zijn op de wereldmarkt dienen bedrijven continu te innoveren. Nieuwe technologieën zijn echter zodanig complex geworden, dat bedrijven steeds vaker samenwerking met partners zoeken om tot innovatie te komen. Allianties verlagen het risico van innovatie doordat partners kosten kunnen delen, en vaak het tempo van innovatie verhogen (time-to-market). Daarnaast hebben bedrijven niet altijd alle benodigde kennis in huis, en het combineren van complementaire kennis met partners kan leiden tot de beoogde innovatie die anders nooit bereikt zou worden. Ook kunnen allianties een frisse kijk op zaken bieden, of fungeren als een radarfunctie voor het vinden van nieuwe ideeën of technologieën. Om een leidende rol te kunnen spelen in de wereldwijde economie combineren bedrijven derhalve hun technologische kennis.
Dit alles heeft geresulteerd in een sterk groeiend belang van strategische technologie allianties, en het ontstaan van innovatie netwerken van bedrijven. Samenwerken is echter niet altijd even gemakkelijk. Voor bedrijven is het vaak moeilijk te bepalen met wie samen te werken. Partnerkeuze is inherent aan netwerkpositionering, met andere woorden, door zorgvuldig te kiezen met wie samen te werken kan een bedrijf zelf bepalen welke positie het inneemt in het innovatie netwerk. De belangrijkste onopgeloste vraag in de literatuur is echter hoe netwerkpositionering het innovatievermogen in bedrijven beïnvloedt. Hier is tot op heden weinig onderzoek naar gedaan, en vormt het onderwerp van dit proefschrift. Met andere woorden, in dit proefschrift wordt een antwoord gezocht op de volgende vraag: wat is het effect van alliantie netwerkstrategieën op de technologische performantie van bedrijven?

Om te komen tot een antwoord op deze centrale vraag zullen drie aspecten aan de orde komen. Allereerst is het voor bedrijven belangrijk om de afweging te maken tussen het intern ontwikkelen van technologische kennis, of het (extern) samenwerken met bedrijven om tot innovatie te komen. Pas wanneer op deze vraag een antwoord is gegeven kunnen we kijken naar de vraag hoe bedrijven optimaal gebruik kunnen maken van deze extern geacquireerde technologische kennis. Derhalve zal als tweede aspect van de centrale vraag worden gekeken naar de optimale positionering van een bedrijf in een innovatienetwerk met als doel de bestaande kennis te verbreden of te verdiepen.

Hierbij wordt vaak een deterministische kijk op zaken genomen. In de literatuur zien we dat bedrijven relatief weinig invloed kunnen uitoefenen op het netwerk in zijn geheel. Bedrijven hebben echter wel de mogelijkheid om een bepalende rol in hun directe omgeving te spelen. Daarom zal als derde en laatste aspect nogmaals worden gekeken naar netwerkpositionering, echter op een egonetwerk niveau. Dit betekent dat niet meer het netwerk in zijn geheel, met alle indirecte contacten (contacten van partners), in beschouwing zal worden genomen, maar zal worden gekeken naar de effectiviteit van netwerkstrategieën op het beïnvloedbare niveau van de directe partners.

Bovengenoemde deelvragen zijn empirisch onderzocht met behulp van twee longitudinale datasets. Deze datasets bevatten informatie over de alliantieactiviteit en patentactiviteit van de bestudeerde bedrijven. Het eerste deel van het onderzoek is verricht in de ASIC-industrie (applicatie gerichte geïntegreerde chips) een tak van de micro-elektronica industrie die zich bezig houdt met het op maat maken van chips naar klantenwens. De verzamelde data hebben betrekking op 99 ASIC-gerelateerde bedrijven die geobserveerd werden in de periode tussen 1988 en 1996. Het tweede deel van het onderzoek is uitgevoerd op een dataset met 116 bedrijven in de chemische industrie, de auto industrie en de farmaceutische industrie, die geobserveerd werden over een periode van twaalf jaar, van 1986 tot 1997.

Het eerstgenoemde aspect, de relatie tussen interne R&D en externe acquisitie van technologie, is in hoofdstuk twee empirisch onderzocht. Hierbij wordt gebouwd op ‘path-dependency’ theorie van het bedrijf (Teece *et al.*, 1997). Het voortbouwen op bestaande technologische kennis (technisch kapitaal) werd afgezet tegen het succes van een alliantieportfolio (sociaal kapitaal) in de internationale ASIC-industrie in de periode 1988-1996. Sterk empirisch bewijs werd gevonden voor het wederzijds versterkend effect van sociaal en technisch kapitaal bij lage niveaus van bestaande technologische kennis en alliantie portfolio’s. Bij hogere niveaus van bestaande technologische kennis en grotere alliantie portfolio’s werken beide vormen van kapitaal als substituten.

Een andere belangrijke empirische bevinding is het bestaan van twee mogelijke evenwichten die vertaald kunnen worden als optimale strategieën voor bedrijven om te innoveren: de eerste bestaat uit een sterke focus op interne ontwikkeling van technologische vaardigheden ondersteund door een kleine alliantie portfolio. De tweede optimale strategie bestaat uit de opbouw van een sterk alliantie portfolio ondersteund door een lage mate van interne ontwikkeling van technologische capaciteiten. Beide strategieën kunnen naast elkaar bestaan in een industrie.

Verder werd empirisch bewijs gevonden dat het experimenteren met nieuwe technologieën, zowel nieuw voor het bedrijf als nieuw voor de industrie, leidt tot verhoogd innovatief succes in de daarop volgende jaren.

Om een antwoord te vinden op het tweede hoofdaspect van dit proefschrift, hoe bedrijven zich dienen te positioneren om te komen tot optimale innovatie, wordt technologisch performantie opgedeeld in het verbreden van technologische kennis (exploratie) en het verdiepen van technologische kennis (exploitatie). Bij exploitatie zoeken bedrijven naar partners die aanvullende kennis in huis hebben of R&D kosten willen delen. Daardoor kan er een versnelling plaatsvinden in termen van time-to-market en kosten *(Teece, 1986)*. Een vereiste om samenwerking succesvol te laten verlopen is een bepaalde mate van gezamenlijke overlappende kennis, waardoor bedrijven duidelijk kunnen communiceren en de doelstelling helder gesteld kan worden (Hansen *et al*., 2001). Exploratie behelst het zoeken naar nieuwe technologische opportuniteiten. Hier krijgen partners te maken met kennis die nieuw is, waarbij problemen op voorhand onbekend zijn, en de kennis nog niet te expliciteren is. Resultaten kunnen niet voorspeld worden, wat het gehele proces (en de einduitkomst) erg onzeker maakt. In plaats van te concentreren op een van beide strategieën, dienen bedrijven een balans te vinden tussen exploratie en exploitatie (March, 1991; Chesbrough, 2003).

Dit onderzoek is ingebed in de sociale netwerkliteratuur. Binnen deze academische stroming wordt al jarenlang een discussie gevoerd tussen aanhangers van twee scholen die beide een verschillend belang hechten aan de redundantie van contacten. Allereerst zijn er de aanhangers van Burt, die argumenteert dat contacten die onderling niet verbonden zijn (direct of indirect) unieke informatie zullen opleveren. Aanhangers van deze theorie vinden dat een bedrijf zich zodanig dient te positioneren dat het in staat is om door alliantievorming delen van het netwerk met elkaar te verbinden die op geen andere manier met elkaar verbonden zijn. Dit zou leiden tot een optimale efficiëntie in de spreiding van relaties.
Coleman's theorie neemt het tegenovergestelde standpunt in. Aanhangers van deze school beweren dat onderling verbonden contacten juist leiden tot wederzijds vertrouwen, o.a. door de sociale controle die hieruit voortvloeit. Er is kortom geen of nauwelijks ruimte voor opportunistisch gedrag. Daarnaast gaan bedrijven eenzelfde richting uit 'denken', wat meer zekerheid geeft over het succes van een technologie die nog in de kinderschoenen staat. Immers, wanneer meer bedrijven aan eenzelfde technologie werken, dan is de kans dat deze technologie steun krijgt groot. De laatste jaren heeft zich een contingentiestandpunt ontwikkeld dat er voor pleit dat beide theorieën

toepasbaar zijn, afhankelijk van de omstandigheden waaronder ze worden toegepast. Ditzelfde standpunt wordt ook in dit proefschrift ingenomen.
Bovengenoemde discussie impliceert dat bedrijven een keuze dienen te maken tussen het overbruggen van structurele gaten in het netwerk, of het creëren van sterk samenhangende relaties om profijt te trekken van sociale controle in het netwerk. Met andere woorden, bedrijven dienen keuzes te maken over wanneer en hoe gebruik te maken van redundante en niet-redundantie relaties bij het extern acquireren van technologie.

Het effect van sociaal kapitaal (het gebruik van redundante en niet-redundante contacten) op beide typen technologisch performantie (kennisverbreding en kennisverdieping) is gemeten met behulp van een longitudinale dataset die de grootste spelers in de chemische industrie, auto-industrie en farmaceutische industrie bevat. Er is sterk bewijs gevonden voor het bevorderende effect van zowel direct als indirecte contacten op technologische performantie van bedrijven. Echter, het effect voor exploratie is significant hoger.
Ook wordt een matigend effect van directe contacten op indirecte contacten gevonden. Dit impliceert dat naarmate een bedrijf meer directe contacten heeft, het effect van de indirecte contacten kleiner wordt. Dit heeft alles te maken met het absorptievermogen van een organisatie. In feite leidt dit er toe dat een bedrijf kan kiezen tussen twee optimale alliantieportfolio strategieën: een kleine set van partners die zelf een groot netwerk van allianties hebben, of een grote set van partners die zelf kleine netwerken hebben.

Het derde aspect dat onderzocht wordt in dit proefschrift is netwerkpositionering op egonetwerk niveau. Dit niveau is grotendeels genegeerd in de netwerk literatuur en het overige academische werk. Echter, vanuit bedrijfsstrategisch standpunt is juist dit niveau van groot belang. Het is namelijk niet vanzelfsprekend dat de partners van een bedrijf de informatie die zij van hun contacten (dus de indirecte contacten van het bestudeerde bedrijf) binnenkrijgen ook zullen doorspelen naar het bestudeerde bedrijf. Vooral in multinationals zal de informatie die voortvloeit uit de ene alliantie een lange tijd nodig hebben tot het terecht komt bij de werknemers die deelnemen in een andere alliantie. Daarnaast kan een bedrijf niet altijd overzien met welke contacten een partner samenwerkt, laat staan dat een bedrijf hierop invloed kan uitoefenen. Dit alles pleit ervoor om netwerkpositionering ook op egonetwerk niveau te bekijken.

Ook bij het bestuderen van dit niveau werd gewerkt met de dataset voor bedrijven in de chemische industrie, de auto industrie en de farmaceutische industrie. De resultaten van de empirische analyse duiden op een curvilineaire relatie tussen redundantie op het egonetwerk niveau en innovatievermogen van een bedrijf. Dit betekent dat een toenemende mate van redundantie een positief effect heeft op innovatieve performantie van bedrijven tot een bepaald niveau. Daarna gaat toenemende redundantie het innovatievermogen negatief beïnvloeden. Behalve redundantie in de directe contacten is ook het effect van verbondenheid van partners onderling op de innovatieve performantie van bedrijven gemeten. Een toenemende mate van verbondenheid beïnvloedt het innovatievermogen negatief, maar niet altijd significant. Dit gaat in tegen de bovengenoemde leer van Coleman die claimt dat compacte groepen van goed verbonden partners juist innovatiever zouden zijn dan andere bedrijven.

Deze resultaten voor de algehele technologische performantie van bedrijven zijn later uitgesplitst naar het verbreden van technologische kennis en het verdiepen van technologische kennis. Er is bewijs gevonden dat deze twee typen van technologische ontwikkeling verschillende vormen van netwerk strategie vereisen. In het geval van het verdiepen van bestaande kennis dient een bedrijf met name aandacht te schenken aan de redundantie van de directe contacten. Wederom werd een positieve maar curvilineaire relatie gevonden tussen redundantie en verbreden van kennis, wat bevestigt dat redundantie een positief effect heeft tot een bepaald maximum. Daarna gaat redundantie de technologische verdieping nadelig beïnvloeden. De verbondenheid van partners heeft geen invloed op het verdiepen van kennis. Voor het verbreden van kennis werd een heel ander verband gevonden. Redundantie in de directe contacten bleek geen significante invloed te hebben, terwijl verbondenheid van partners het verbreden van kennis nadelig beïnvloed.

In zijn algemeenheid kunnen we concluderen dat door bestudering van de effecten van alliantie netwerkstrategieën op technologische performantie van bedrijven dit proefschrift zowel een conceptuele als empirische bijdrage heeft geleverd aan het academische werk en de praktijk van bedrijven die zoeken naar een optimale balans voor hun innovatiestrategieën.

ABOUT THE AUTHOR

Bonnie Beerkens was born in Wessem on January 6th, 1975. After completion of the HAVO at Scholengemeenschap St. Ursula in Horn, she studied Logistic Management at Vervoersacademie, Fontys Hogeschool in Venlo for one year. Thereafter she started with International Business Studies at the University of Maastricht, Faculty of Economics and Business Administration where she specialized in Organization and Strategy. She also studied at Keim Yung University, Daegu, South-Korea for half a year, as part of an exchange program. In 1998 Bonnie graduated with a final thesis on ‘Technology Strategy and Industry Evolution’. In that same year she began working as a teacher at the University of Maastricht. Bonnie started her PhD at the Eindhoven University of Technology, Faculty Technology Management, department Organisation Strategy en Marketing in 1999. Currently she is working as a full time academic researcher at the contract center of the faculty Technology Management at the Eindhoven University of Technology.

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