JOURNAL OF MANAGEMENT STUDIES

Journal of Management Studies 46:2 March 2009
doi: 10.1111/j.1467-6486.2008.00801.x

The Role of Alliance Network Redundancy in the Creation of Core and Non-core Technologies

Wim Vanhaverbeke, Victor Gilsing, Bonnie Beerkens and Geert Duysters

Hasselt University, Belgium; Tilburg University, The Netherlands; Eindhoven University of Technology, The Netherlands; UNU-Merit, The Netherlands

ABSTRACT This paper studies the effect of a focal firm, and its partners' local alliance actions, on the creation of technological innovations by the former. More specifically, we study how two types of redundancy in a focal firm's ego network affect its ability to create new technologies in its technology core areas (exploitation) and/or non-core areas (exploration). We analyse this empirically in three different industry settings: chemicals, motor vehicles, and pharmaceuticals. One of our key findings is that individual firms can indeed boost both types of innovative output by shaping the degree of redundancy in their local alliance network, but that the way in which this should be done differs between the creation of core and non-core technologies. Next, we find that it is very useful to unpack the rather abstract notion of redundancy into more specific types of redundancy in ego networks. Overall, these findings reflect an action-oriented view on the role of individual firms in collaborative networks, which may complement the dominant view in the alliance literature emphasizing the role of the overall network structure and firms' network position within it.

INTRODUCTION

In recent 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 through direct or indirect relationships. Traditionally, alliance research has been preoccupied with the study of why and when alliances are formed (Duysters et al., 2001). In addition, researchers have analysed with 'whom' firms are likely to form alliances (Bae and Gargiulo, 2003; Gulati, 1995a; Gulati and Gargiulo, 1999; Walker et al., 1997). More recently, several scholars have dealt with the question regarding which specific network positions enable firms to achieve the highest level of performance

Address for reprints: Wim Vanhaverbeke, Department of Business Studies, Hasselt University, Agoralaan, Building D, 3590 Diepenbeek, Belgium (wim.vanhaverbeke@uhasselt.be).

(e.g. Gulati, 1999; Hardy et al., 2003; Hite and Hesterly, 2001; Uzzi, 1996, 1997). Here, the debate has been inspired by the seminal works of Coleman (1988) and Burt (1992), and focuses on the question whether firms should concentrate on developing dense networks of 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). According to this view, the replication of existing ties leads to the emergence of highly cohesive groups of firms, which facilitates the development of trust, commitment, and the 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 a 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, 2001).

In this debate, empirical contributions have generated a mixed bag of findings. In this respect, there is an increasing consensus that a 'contingency approach' might be most effective. In other words, the efficiency of a certain network structure depends on the environmental conditions in which firms operate (Ahuja, 2000; Bae and Gargiulo, 2003; Burt, 1997; Podolny, 2001; Reagans and Zuckerman, 2001). In this paper, we extend this contingency approach by arguing that the efficiency of a certain network structure is also related to the type of innovation activity that firms undertake. We propose introducing the distinction between explorative and exploitative learning (March, 1991) as an important contingency factor. Whereas explorative learning is associated with experimentation and novel technologies, exploitation is concerned with the refinement and extension of existing technologies. Although there is increasing consensus in the literature that the efficiency of a network structure is contingent on the type of learning for which firms strive (Ahuja, 2000; Burt, 1997; Podolny, 2001), there is still little empirical evidence to back up this claim. In order to fill this void, we consider these two learning activities within the context of technological innovation and study the effect of network structure on each activity's resulting output. As we will argue and as our empirical findings indicate, the innovative output of these two types of learning each requires different network structures.

In the literature, we find different levels of analysis that have been considered regarding this network structure role. 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. He emphasized that apart from relational embeddedness, a firm's effectiveness in a network also depends on two other mechanisms, i.e. 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 (Ahuja, 2000; Duysters et al., 2003; Granovetter, 1992). In line with this view, scholars have taken on an overall network perspective, which has brought a better understanding of how a particular structure of direct and indirect ties contributes to a firm's innovation (e.g. Ahuja, 2000). However, although a focal company can control its own direct ties, it is usually far beyond its ability to control the establishment of alliances between its alliance partners let alone between its partners' partners, etc. Therefore, in contrast with most of the work in this area, we will focus on the particular set of actions of the network that surrounds focal organizations. This forms the so-called 'ego network' that, by and large, falls within ego's direct sphere of influence. Here, we will build on the work by Bae and Gargiulo (2003) and focus particularly on local density (at the ego-network level) rather than on global (network wide) density, as the former has been found to have a more profound influence on focal firm performance than global density (Garcia-Pont and Nohria, 2002; Garcia-Pont et al., 2007; Rowley et al., 2000).

In sum, this study analyses how network structure – from a local action perspective – affects a firm's performance when creating new technologies in core technology areas (exploitation) and/or non-core areas (exploration). For our study, we combine a cognitive perspective, rooted in the literature on learning and innovation, with a social structural perspective with its origins in the sociological literature on networks. Combining these two strands of literature is also an important contribution of this paper, as the literature to date has predominantly focused on the role of social factors regarding alliance formation and the role of network embeddedness (Gulati, 1998), whereas a cognition-based understanding of these processes has been largely ignored (Moran, 2005; Nooteboom, 2004).

This paper is structured as follows. In the next section we develop our theory, based on which we formulate four hypotheses that specify how local action in technology alliance networks affects a firm's technological innovation. We then proceed by testing these hypotheses and by presenting the main findings from data on three different industry settings: chemicals, motor vehicles, and pharmaceuticals. The final section summarizes and discusses the results and provides suggestions for further research.

THEORETICAL BACKGROUND AND HYPOTHESES

In order to develop our theory and hypotheses, we combine a cognitive view and a social structural view. We develop this combined perspective in two steps. First we take a cognitive stance and discuss a few key notions with regard to the creation of technological innovations. Next, we take a social structural view and consider how inter-firm collaboration may affect this process of creating technological innovations. Here, we particularly focus on the role of redundancy, as one of the central notions in social network theory, and analyse how it affects the creation of technological innovations. Following these two steps, we then analyse how redundancy in the focal firm's local network (or ego network) may differentially affect the creation of new core technology and non-core technology. Based on that, we formulate four hypotheses.

The Creation of Technological Innovations

One of the central notions in the literature on learning and innovation is 'diversity' (Nelson and Winter, 1982; Nonaka, 1994), which is considered a crucial condition for the creation of (technological) innovations. Diversity refers to the heterogeneity of resources or knowledge and thus yields the potential for novel combinations to emerge (Nooteboom, 2004; Schumpeter, 1939). Regarded in this way, new technology is considered as originating from the (re)combination of diverse parts of knowledge and/or experiences (Nelson and Winter, 1982). While diversity increases the number of possible recombinations, too much diversity creates a problem. The greater the degree of diversity between two people or firms, the more difficult it becomes to understand each other and the more difficult it becomes to exchange knowledge and (re)combine it (Miller et al., 2007; Sampson, 2007). The important implication that follows is that firms have to reconcile two potentially conflicting tasks (Nooteboom et al., 2007). On the one hand, firms need to develop access to heterogeneous sources of knowledge, as combining these sources yields a potential for the development of new technology. On the other hand, they need to ensure that such novel knowledge, once accessed, is also adequately absorbed (Cohen and Levinthal, 1990). In other words, the creation of a technological innovation implies a balancing act between accessing novelty and its efficient absorption. This dual task is relevant for both exploration and exploitation, although it operates somewhat differently in each of the two (Nooteboom et al., 2007).

As pointed out by March (1991), exploration reflects an entrepreneurial search process for opportunities in areas that are new to the company. Within the context of technological innovation, this entails expanding into new domains and yields technological innovations in areas that are novel to the firm. It entails non-core technology that reflects a firm's future business and revenue streams, and thus determines its continuity in the longer term. To generate such technology requires, in particular, an emphasis on the acquisition of novel insights. In contrast, exploitation can be characterized as adding to the existing knowledge base and competence set of firms without changing the nature of their activities (March, 1991). In comparison with exploration, exploitation requires a deeper understanding of specific information rather than a wider grasp of more general information (Rowley et al., 2000). Exploitation entails the deepening of a firm's core technologies and yields technological innovations in areas with which the firm is familiar. It leads to further improvements in the core technology, which strengthens a firm's existing business and current revenue streams, enhancing its competitiveness in the short term. This deepening of its core technologies requires that a firm has a very precise understanding of novel insights.

In sum, the creation of technological innovations in areas that are non-core to the company (exploration) specifically requires an emphasis on novelty value relative to its capability to absorb the technology. In case of the creation of innovations in core areas (exploitation), a stronger emphasis on absorption is required. As we will argue, a firm's alliance network is instrumental in both types of innovations, as it will aid not only accessing novel sources of knowledge, but also understanding and applying the acquired new insights. We will now study this in more detail by considering the role of redundancy in a firm's alliance network.

A Firm's Network of Technology-Based Alliances: The Role of Redundancy

As has been elucidated in the literature, one of the key functions of an alliance network is that it provides access to different sources of knowledge. It brings together a variety of skills and experience, thus bearing a potential for novelty (Grant and Baden-Fuller, 2004; Hagedoorn and Duysters, 2002; Inkpen, 2000; White, 2005). This potential for novelty originates from the fact that knowledge, values and behaviour are more homogenous within groups than between groups, so that firms connected across different groups have more access to alternative ways of thinking, which gives them more options for creating new combinations (Burt, 2004).[1] Consequently, to create and maintain access to novel sources of knowledge, firms need to develop ties to companies that are themselves not connected to a firm's existing group of partners. In other words, a tie will provide access to new information to the extent that it offers access to non-redundant sources of information. Such a tie spans a 'structural hole' (Burt, 1992).

On the flip side, however, making use of non-redundant ties carries two risks. Having access to novel sources of knowledge through many non-redundant ties may lead to a large volume of (highly) diverse information. This consumes time and resources that cannot be allocated to absorbing and integrating the obtained novel insights. As a consequence, abundant exploration and search through non-redundant contacts may come at the price of limited attention and resources for absorption. Second, a sole focus on searching for novelty through non-redundant ties may result in a random drift, causing a firm's knowledge base to change continuously in different and unrelated directions, making the accessed novel knowledge difficult to absorb and integrate (Ahuja and Katila, 2004; Fleming and Sorenson, 2001). In other words, both from a search costs and cognition point of view, many non-redundant ties will decrease the potential for novelty absorption.

Here, the second role of a firm's alliance network, i.e. as an instrument that can also support absorbing novel findings, comes into play. If one is not able to adequately understand novel information from a given source, one may need another partner to triangulate the received information (Gilsing and Nooteboom, 2005). More precisely, if A remains linked to both B and C, even if there is also a link between B and C, this may help A to understand C by comparing what A understands of C with what B understands of C. In other words, even if two of the focal firm's direct ties are redundant for access to sources of information, it may still need both in order to understand and absorb knowledge accessed in the other relation. Moreover, the tacit and experimental nature of technological innovation further increases firms' difficulty with recognizing and valuing the technology of potential partners if they are not connected through a common alliance partner. In this way, a firm's alliance network can enhance the firm's absorptive capacity by acting as a device for screening and interpreting novel information on such information's potential relevance and value for the firm (Leonard-Barton, 1984, 1992; Stuart, 2000). In addition, even if one does understand one alliance partner's information, one may not be able to judge the reliability of that information. Accordingly, one may need a third party as a source of triangulation (Gilsing and Nooteboom, 2005) and in this way develop a richer understanding and a better evaluation of the acquired novelty (Rowley et al., 2000). In addition, a network of redundant ties also facilitates the build-up of trust, a reputation mechanism, and coalitions to constrain opportunism (Coleman, 1988; Gulati, 1995b; Hagedoorn and Duysters, 2002). This supports the exchange of tacit knowledge and the build-up of shared absorptive capacity (Gilsing and Nooteboom, 2005).

In sum, an alliance network structure that is optimal for the generation of technological innovations needs to reconcile two conflicting demands. On the one hand, a firm's alliance network should consist of ties to non-redundant partners as they form a key source of novelty, whereas, on the other hand, it should also be built up of ties to redundant partners as these are critical in realizing the potential value of this novelty. Based on these insights into how redundancy affects the creation of technological innovations, we now further analyse how redundancy in a firm's *local* network of alliances affects the creation of core technology (exploitation) and non-core technology (exploration) respectively. In line with a few recent studies (Katila and Ahuja, 2002; Koza and Lewin, 1998; Mom et al., 2007; Rothaermel, 2001), we consider these tasks as constituting two different kinds of learning. Consequently, we anticipate redundancy in a firm's local alliance network to have a differential effect on each task.

Exploration and Exploitation: A Local Action Perspective

Following a local action view of a firm's alliance network, 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) (Bae and Gargiulo, 2003). 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 adds a direct link with another company that has many direct links with firms with which the focal company is not connected, this newly added direct link may be very efficient, as it facilitates the bridging of a structural hole. On the other hand, if an alliance partner establishes alliances with firms that are already tied to the focal firm, these ties may be considered redundant. In other words, some of the actions of a focal firm's alliance partners may be beneficial, while other actions may have possibly negative effects for the focal firm. Negative actions of alliance partners may lead to subsequent reactions by the focal firm in an attempt to neutralize its alliance partners' moves.[2] This provides an inherently dynamic setting in which both direct and indirect types of links are considered important. Owing to the general lack of empirical literature on the particular effects of local actions in alliance networks, we propose an approach that focuses on the effects of those particular actions on a focal firm's innovative performance.

The appropriate network level to analyse the focal organization and its alliance partners' combined set of actions is the so-called 'ego network' (Bae and Gargiulo, 2003; Garcia-Pont and Nohria, 2002; Rowley et al., 2000). Rowley et al. (2000) argue that local density (on the ego-network level) rather than global (network-wide) density influences the focal firm's performance. We therefore go beyond the network level, and descend to the level of the ego network. This provides us with a micro-level analysis of local actions and enables us to reveal the specific impact of these actions on the innovative performance of companies. More specifically, we seek to clarify how the creation of new partnerships by a focal firm or by its direct partners influences the degree of redundancy in its network and how this affects the creation of new technological innovations in a firm's core areas, as the output of exploitative learning, and/or as in its non-core areas, as the output of explorative learning.

When considering a firm's ego network – see Figures 1 and 2 – there are basically two possibilities for the formation of new partnerships to affect the degree of redundancy. A

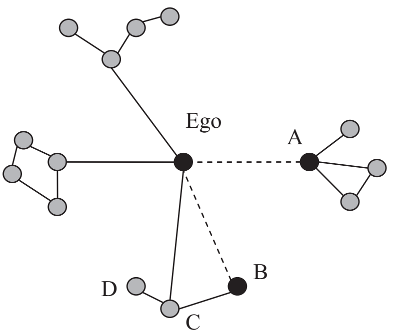

Figure 1. An ego-network perspective
Ego, focal firm.
A, alliance partner who provides access to non-redundant information.
B, alliance partner who only provides access to redundant information due to the existing alliance between the ego and partner C.

first possibility is that two partners become connected, which had hitherto been unconnected, as in Figure 1, A and B. This results in an increase in redundancy in a firm's *total* ego network. A second possibility is that already connected partners form additional ties so that their connectivity increases further, as B and C in Figure 1. This leads to an increment in the degree of redundancy within a *part* of ego's network but leaves redundancy in its total network unchanged. This distinction is important for two reasons. First, it unpacks the rather abstract notion of redundancy by showing that in an ego network, different types of redundancy can be present. Until now, the distinction in types of redundancy was between redundancy in an ego network (e.g. network efficiency) and in a global network (e.g. structural equivalence). Here, we argue that in an ego network, two different types of redundancy can also operate and that they may have a different impact on a firm's technological innovativeness. Second, the locus for initiating a connection between two partners differs between the two possibilities. Regarding the first possibility, the focal firm can take action, as it can stimulate its unconnected partners to collaborate or (try to) inhibit them from doing so. Regarding the second possibility, this lies outside the focal firm's influence, as it is up to its partners to increase the redundancy in a local part of the focal firm's network.

When comparing these two ways in which redundancy can be increased, it is important to bear in mind that the first possibility (connecting hitherto unconnected partners) differs from the second possibility (further connecting already connected partners), as in the former case redundancy in ego's *total* network increases – whereas the second possibility leaves this kind of redundancy untouched and only increases redundancy among already connected partners. Given these differences, we expect each type of redundancy to have a differential effect on the creation of core technology and non-core technology. We will consider each type in more detail.

Possibility 1: Connecting hitherto unconnected partners. If all of the focal firm's partners are unconnected, it will receive different pieces of knowledge and information. Although these alliances may give the firm access to a great deal of novelty, the different pieces of information may be (highly) unrelated. In this way, ego (the focal firm) may risk an information overload and be unable to attach meaning to this information in a sensible way. By connecting some of these unconnected partners, it can accomplish some degree of coherence in the supply of knowledge and information. This may provide ego with information that is potentially more meaningful, which can aid him in absorbing this novel information. Furthermore, following Coleman (1988), an increase in redundancy instils some degree of trust so that possibilities of opportunism are more constrained. This facilitates communication and enhances the exchange of tacit knowledge, which spurs the establishment of a shared, mutual understanding between partners (Gilsing and Nooteboom, 2005). Consequently, an increase in redundancy among ego's direct partners reduces the risk of information noise and enhances the supply of high-quality and fine-grained information (Hagedoorn and Duysters, 2002; Rowley et al., 2000; Shannon, 1957).

This increase in redundancy specifically serves the creation of core technology, as a very precise and detailed understanding of information forms a key prerequisite for this activity (Gilsing and Nooteboom, 2005; Rowley et al., 2000). Furthermore, redundancy among ego's partners supports the development of trust-based governance (Larson, 1992; Uzzi, 1997) and alleviates the risks associated with opportunistic behaviour (Williamson, 1985). This feature also seems particularly desirable for the deepening of core technology, as the focal firm will typically need to exchange highly sensitive technological knowledge. This knowledge is sensitive because it relates directly to its core products and markets, reflecting short-term revenue streams. Collaboration with trusted partners may therefore enable ego to control outgoing spillovers and to diminish the risk of freeridership (Gilsing and Nooteboom, 2005). However, these advantages of a redundant structure come at a price, since it also decreases the likelihood that redundant partners have something new to tell. This limited novelty value does not seem to constitute a major liability for the creation of core technology, as the major focus here is on the deepening of the innovating firm's existing fields of expertise (Nooteboom et al., 2007; Rowley et al., 2000).

In contrast, as far as the creation of non-core technology is concerned, some degree of coherence in the supply of novel information is required in order to mitigate the risk of information overload and to enhance the ability to absorb it (Sidhu et al., 2004). A further increase, however, will lead to a decline in the novelty value. This will be a major liability when the focal firm intends to innovate in non-core areas, as the major focus is here on moving beyond existing areas of expertise into novel domains. Furthermore, as pertaining to a redundant structure, the potential for trust-based governance and for the conveying of rich and more specific information may be somewhat less important – relative to the deepening of core technologies – if one's knowledge base is broadened into new, non-core areas (Nooteboom et al., 2007; Rowley et al., 2000).

Based on the arguments as discussed above, we can conclude that increasing redundancy among a focal firm's direct partners is especially interesting in respect of exploitation. It is also instrumental for exploration, but only up to a certain point, beyond which its negative effects begin to dominate. This leads us to our first two hypotheses.

Hypothesis 1: The creation of redundancy by connecting hitherto unconnected partners is positively related to a firm's exploitative technology innovation.

Hypothesis 2: The creation of redundancy by connecting hitherto unconnected partners is curvilinearly related (inverted U-shape) to a firm's exploratory technology innovation.

Possibility 2: Connecting locally connected partners. A second possibility is formed when already connected partners, residing in a part of ego's network, further increase their mutual connectivity. See B and D in Figure 1. Although ego can control its own direct ties, it usually has no or only limited power to control the establishment of new alliances between its alliance partners (Bae and Gargiulo, 2003). Ties among alliance partners tend to increase the density of the network surrounding ego. This may result in the formation of strong, densely connected cliques consisting of firms that are all mutually connected, which enhances their mutual knowledge exchange and the build-up of trust. This will facilitate communication among these partners, aid them in triangulation, and strengthen the absorptive capacity within this part of the network (Gilsing and Nooteboom, 2005; Lane and Lubatkin, 1998). For the focal firm, an increase in redundancy in such a local part of its network may bring a further improvement in the coherence and reliability of the information as received from this part of its alliance network, but at the price of this information's declining novelty value. In this respect, given the importance of high-quality and specific information for the creation of core technology, we anticipate that such an increase will have a positive effect. However, when the redundancy among such partners increases even further, there will be little room for additional gains in coherence and reliability. In fact, the local partners may become overly involved in one another's activities and run the risk of ignoring novel information beyond their small local 'cluster' (Duysters and Lemmens, 2003; Uzzi, 1997). This has a detrimental effect on novelty value, resulting in no further new information emerging from their collaborative efforts.

In other words, an increase in redundancy among locally connected partners may be beneficial for the creation of core technology but only up to a certain point. However, beyond this point, a decrease in novelty value will start to dominate, which will ultimately have a negative effect on the ability to create new, core technology. For the creation of new, non-core technology, we expect an increase in redundancy among locally connected firms to have a negative effect because of its strong emphasis on novelty value. Hence, our third and fourth hypotheses:

Hypothesis 3: There is an inverted U-shaped relationship between increasing redundancy among locally connected partners and a firm's exploitive technology innovation. At lower levels of redundancy the relationship is positive, whereas at higher levels the relationship is negative.

Hypothesis 4: Increasing redundancy among locally connected partners is negatively related to a firm's exploratory technology innovation.

DATA, VARIABLES AND MODELLING

Data

In order to test the hypotheses, we constructed a panel dataset which consists of the alliance and patenting activities of companies in the chemicals, automotive, and pharmaceutical industries. We limited the sample to public firms to ensure the availability and reliability of the financial data. In order to minimize the influence of survivor bias, we sampled firms from a list of all publicly held firms doing business in the three industries from the start of the sample period. Next, we checked this sample for parent companies and affiliates, using Dun & Bradstreet's *Who Owns Whom*. If the listed companies belonged to the same parent company, we combined the different affiliates with the parent firm. After checking for duplicates, 116 independent companies were included in the sample. We refer to these independent companies as 'focal firms', to distinguish them from their partners. In line with other studies on alliance networks, we selected this sample by ranking them according to industry sales in each of the three industries at the beginning of the sample period. This sampling method is also in line with other studies on technology alliance networks (Ahuja, 2000; Gulati, 1995a; Gulati and Gargiulo, 1999; Sampson, 2007). These firms were observed over a 12-year period, from 1986 until 1997. The sample is unbalanced because of merger and acquisitions during the period of observation.

The alliances data were generated from the MERIT-CATI database, which contains worldwide information on over 13,000 cooperative technology agreements involving some 6000 different parent companies. The data bank contains information on each agreement and some information on companies participating in these agreements. In the CATI database, only those inter-firm agreements are collected that contain some arrangements for transferring technology or joint research. Mere production or marketing joint ventures are excluded. In other words, our analysis is primarily related to technology cooperation. The most important data sources for this databank are a large number of trade and technology journals for a broad range of technology fields. Technology alliances are cooperative agreements between independent (industrial) partners to transfer technology or to undertake joint research. Technology alliances take the form of contractual agreements or equity joint ventures. Collection of the data in the CATI database has been very consistent since 1975,[3] but it is not possible to 'claim' full coverage since firms are not required to report the establishment of alliances[4] (see also Ahuja, 2000; Gulati, 1995a; Gulati and Gargiulo, 1999; Sampson, 2007).

All alliance network measures were calculated on the basis of the alliance matrices that were constructed from the MERIT-CATI alliance data. These matrices are required to calculate the redundancy variables that are instrumental in testing the four hypotheses. An alliance matrix was constructed for each year for each of the three sectors; these matrices contain 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 were made. First, different types of alliances were not considered separately. Consequently, there is only one adjacency matrix per industry-year. Second, the 'strength' of strategic alliances (e.g. a joint venture is a 'stronger' tie than a joint development agreement) was not weighted as has been done by some other authors (see Contractor and Lorange, 1988; Gulati, 1995a; Nohria and Garcia-Pont, 1991). The third choice relates to the length of the period during which the existing alliance portfolio is likely to have an influence on the current technological performance of a company. We chose 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, 1995a). The life-span of alliances is usually assumed to be no more than five years (Kogut, 1988, 1989).

All patenting data were retrieved from the US Patent Office Database in respect of all the companies in the sample, also those based outside the USA. Working with US 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, p. 434).[5] Especially in industries where companies operate on an international or global scale, US patents may be a good proxy for companies' worldwide innovative performance.

The financial data on the companies in the three sectors were gathered from Worldscope, COMPUSTAT, and from annual reports. Data on annual revenues were converted into Euros. Furthermore, we included the nationality of each company and its age as additional control variables.

Variable Definition and Operationalization

Dependent variable. In this study, technological innovation is measured by the weighted number of patents successfully applied for by a firm in a given year. Consequently, to calculate 'weighted patent counts', each patent is weighed according to the subsequent citations that it receives, the assumption being that more important patents receive more citations. Weights are thus determined by the number of forward citations (Trajtenberg, 1990). Although the use of weighted patents as an indicator of innovative output or performance has been criticized on different grounds (for an overview see Griliches, 1990; Lichtenberg and Griliches, 1989; see also Lanjouw and Schankerman, 2004), they are generally viewed as an appropriate measure of innovative performance at the company level (Ahuja and Katila, 2001; Basberg, 1987; Cohen and Levinthal, 1989; Hagedoorn and Duysters, 2002; Sampson, 2007).

Next, the weighted patent counts were used to derive the two dependent variables. The technological profile of focal firms was computed to determine whether a new patent in the year of observation had to be categorized as 'exploitative' or 'explorative'. A technological profile was created by adding the patents that a firm received in each patent class during the five years prior to the year of observation.[6] A new patent was considered to be 'explorative' when the innovating company had not filed for a patent successfully in the primary patent class to which the new patent belongs during the previous five years. We chose the year when the company filed for a patent rather than the year when it was granted, as the innovation in the company is realized once the company files for a patent rather than when it is granted. Since knowledge remains relatively new and unexplored for a firm immediately after patenting, patent classes keep their explorative 'status' for three consecutive years.[7] All the classes in which a company had successfully filed for a patent during the previous five years and successfully applied for a patent in the year of observation were considered 'exploitative' patent classes. This method of distinguishing exploitative and explorative patents is almost identical to the one used by Katila (2003) and to Ahuja and Lampert's (2001) concept of 'novel technologies'.

The dependent variables exploitative and exploratory technology innovation were then composed by adding all the patents that had been successfully applied for in the year of observation in the explorative and exploitative patent classes respectively.

Independent variables. We had to operationalize two redundancy measures to test the four hypotheses. The first independent variable estimates the extent to which the direct ties of a focal firm's ego network are redundant. Since we only examined ego networks with first-level alters (i.e. its direct alliance partners), traditional measures of redundancy did not apply. Such measures take into account larger parts of the network, or the entire network itself. Therefore, a redundancy-measure was developed that applies to ego networks, i.e. *egonet redundancy*. This measure calculates the proportion of direct ties that are redundant given the ego network. It only considers one tie to a weak component clique as non-redundant (Bae and Gargiulo, 2003). A weak component clique is a group of alliance partners that are all connected to the focal firm, and each partner can reach the other partners in a number of steps without going through the focal firm (Wasserman and Faust, 1994). The latter can thus reach all its alliance partners in such a weak component clique through any partner, making all other partners 'redundant'. Consider the ego network of Elf-Aquitaine in 1987, represented in Figure 2a. This ego network contains five weak component cliques, i.e. {A–B–C–D}, E, F, G and H. Elf-Aquitaine could reach A through B in the weak component clique {A–B–C–D}, and B could be reached through A. Therefore, only one of these contacts is considered non-redundant.

To calculate the *egonet redundancy* measure (see Table I for the Elf-Acquitaine numerical example), we first needed to measure the number of direct ties, t_i, linking the focal firm to its alliance partners in the ego network. This is the focal firm's degree centrality (Freeman, 1979).[8] Figure 2b indicates direct ties in solid lines. Next, we needed to calculate the number of non-overlapping weak component cliques in the focal firm's ego network, c_i. The solid lines in Figure 2c show five weak component cliques in 1987 and three in 1995. To calculate how many direct ties were redundant, we subtracted the number of weak component cliques, c_i, from the total number of direct ties of the ego network t_i. However, the number of redundant direct ties only makes sense when related to the network size. Therefore, we divided the number of redundant direct ties by the total number of direct ties, t_i. Thus, the formula for egonet redundancy is:

$$egonet\_redundancy_i = \frac{t_i - c_i}{t_i} \tag{1}$$

where i is the focal firm, t_i is the number of direct ties in the ego network of the focal firm i, and c_i is the number of components in its ego network. The minimum value of this variable is zero and it tends asymptotically to one. Increasing values indicate increasing redundancy.[9]

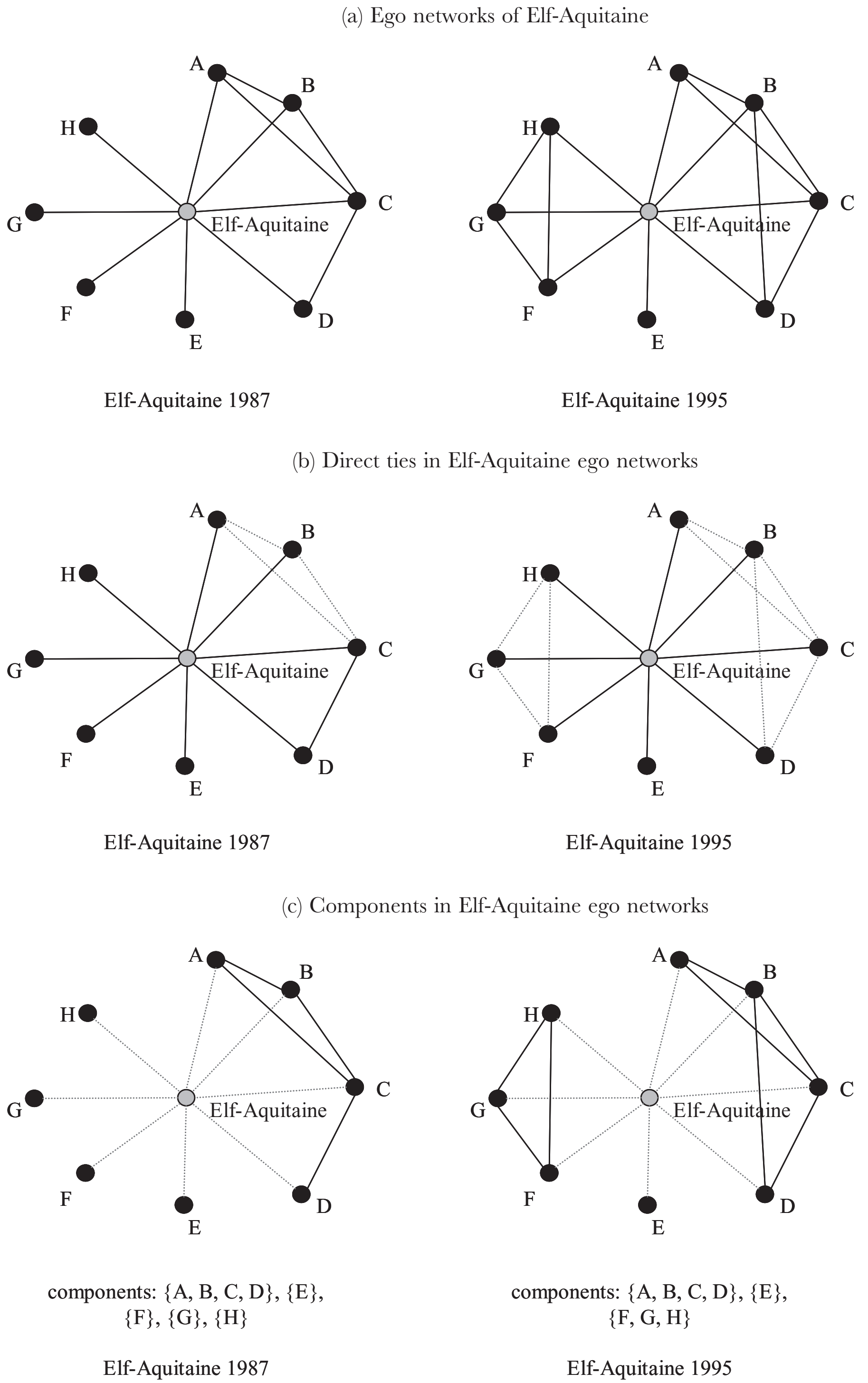

Figure 2. Elf-Aquitaine networks

Table I. Explaining component density and egonet redundancy in the Elf-Aquitaine example

		1987	*1995*
Number of direct ties	t_i	8	8
Number of components	c_i	5	3
Number of indirect ties	v_i	4	8
Maximum within-clique ties (see below:	$\sum_{n=1}^{c}(s_{ci}-2)!$	3	4
Component density	$component\_density_i = \frac{(v_i - t_i + c_i)}{\sum_{c}^{c=1}(s_{ci}-1)!}$	0.333	0.750
Egonet redundancy	$egonet\_redundancy_i = \frac{t_i - c_i}{t_i}$	0.375	0.625

			1987		*1995*	
	s_{1i}	$(s_{1i}-2)!$	4	3	4	3
	s_{2i}	$(s_{2i}-2)!$	1	0	1	0
	s_{3i}	$(s_{3i}-2)!$	1	0	3	1
	s_{4i}	$(s_{4i}-2)!$	1	0		
	s_{5i}	$(s_{5i}-2)!$	1	0		
Maximum within-clique ties	$\sum_{n=1}^{c}(s_{ci}-2)!$			3		4

The second independent variable *component-density* measures the average 'density' of the weak component cliques in an ego network. Increasing ties between partners in a weak component clique represents increasing density. Consider Figure 2c. In order for {A–B–C–D} to form a weak component clique, we need at least three ties connecting A to B, B to C and C to D. All the ties beyond this minimum number needed to connect the partners within a clique to increase the density of the weak component clique. We will refer to these ties as within-clique ties. To calculate the average component density of an ego network, we took the sum of the actual number of within-clique ties of all the components of the ego network and divided this by the sum of the *maximum possible* number of within-clique ties of all the components. The *maximum possible* number of within-clique ties per component is $(s_{ci} - 2)!$, where s_{ci} is the size of each component in the ego network of ego firm i. The formula to calculate *component density* is:

$$component\_density_i = \frac{(v_i - t_i + c_i)}{\sum_{c}^{c=1}(s_{ci}-2)!} \quad (2)$$

where i is the focal firm, v_i is the number of indirect ties in the ego network of the focal firm i, t_i is the number of direct ties in this ego network, c_i is the number of components, and s_{ci} the size of each component in this ego network.

The values of *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. A numerical example is provided in Table I. Focusing on the 1995 network in Figure 2c, we find that the maximum within component ties (denominator is 2) is 4. The nominator equals 3, as there are eight indirect ties (five in {A–B–C–D} and three in {F–G–H}), eight direct ties, and three weak components. The resulting value for 'component density' is 0.75. Full connectivity in component {A–B–C–D} would result in nine indirect ties, bringing 'component density' to its maximum value of 1.

Control variables. To control for differences between industries, *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 in the three industries.

Two other types of dummy variables were used. A first variable indicates in which economic block the company is headquartered. Following the Triad concept of the world economy (Ohmae, 1985), 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. Moreover, Asian and European firms may be less inclined to patent in the USA even when the three industries under consideration are widely recognized as global industries. Annual dummy variables were also included to capture changes in the propensity of firms to patent their innovations over time.

Furthermore, we included an organizational variable, the natural logarithm of 'corporate annual sales', as a proxy for firm size. Larger firms have more financial means and greater technological and other resources to invest in R&D than smaller firms. Therefore, large firms will have a higher innovation output than small firms, the assumption being that there is a positive correlation between technological input and output (Pakes and Griliches, 1984). However, as returns diminish when R&D investments increase, the growth in patents is usually not proportional to the increase in firm size. Furthermore, small(er) firms seem to be less inclined to adapt their alliances if there are governance misalignments (Arino et al., 2008), which may make it more difficult for them to keep on reaping learning benefits from their collaborative efforts over time. Technological capital, i.e. patents received in the five years previous to the year of observation, was also used as a control variable. Technological capital measures the technological competence of a company (Narin et al., 1987). Studies on R&D depreciation (Griliches, 1979, 1984) suggest that knowledge capital depreciates sharply, losing most of its economic value within five years. Thus, a moving window of five years is an appropriate time-frame for assessing the technological impact in high-tech industries (Ahuja, 2000; Henderson and Cockburn, 1996; Podolny and Stuart, 1995; Stuart and Podolny, 1996). Owing to technology's cumulative character, 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 is therefore expected between previous technological capital and technological learning.

Next, the age of a company was also included as a control variable. Ever since Schumpeter (1939), there has been an unresolved and ongoing debate in the literature on 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. Finally, we also controlled for firms' R&D activities. R&D expenditure is expected to be positively related to patenting (Ahuja and Katila, 2001; Hagedoorn and Cloodt, 2003; Hall and Ziedonis, 2001). To separate R&D effects from size effects (Hall and Ziedonis, 2001), we used R&D intensity (the firm's R&D expenditure divided by its annual sales) instead of R&D expenditures as a proxy for a firm's investments in the innovation process. It seems reasonable to expect the internal innovation efforts of the organization to have a positive impact on the effectiveness of the innovation strategy of the organization. Therefore, we expect R&D intensity to have a positive effect on patent activity.

Model Specification

The dependent variables are count variables and take only non-negative integer values – i.e. the weighted number of exploitative or explorative patents a firm successfully 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). However, Poisson regressions assume that the mean and variance of the event count are equal. This assumption is likely to be violated since overdispersion usually occurs in (weighted) patent count data. Overdispersion is particularly relevant in the case of unobserved heterogeneity, i.e. the possibility that identical firms on the measured characteristics are still different on unmeasured characteristics.[10] Unobserved heterogeneity may be the result of differences between companies in their innovation generating capabilities, and, consequently, also in their propensity or ability to patent. Such unobserved heterogeneity, if present and not controlled for, can lead to overdispersion in the data. Including the sum of the patents for which the firm has successfully filed in the five years before the year of observation (moving window approach) as an additional variable is a common method of controlling for unobserved heterogeneity (Heckman and Borjas, 1980). Additionally, overdispersion requires the use of a negative binomial estimation. A statistical test for overdispersion (Gourieroux et al., 1984) indicates that the negative binomial estimation provides a significantly better fit for the data than the more restrictive Poisson model. Negative binomial regression accounts for an omitted variable bias, while simultaneously estimating heterogeneity (Cameron and Trivedi, 1986; Hausman et al., 1984).

We chose for a random-effects specification of the negative binomial regression to control for unobserved heterogeneity (Greene, 2003). The Hausman test (Hausman, 1978) was not significant in all models, indicating that it is safe to use a random-effects specification. The application of a random-effects negative binomial estimation addresses concerns of heterogeneity, and allows us to include covariates that tend to be fairly time invariant, such as the type of industry and national origin.

Differences in patenting behaviour between different years are captured by including annual dummy variables in the model. These may capture the ever-growing importance of intellectual capital or changing macroeconomic conditions. The propensity to patent may also be partly determined by the nationality of the companies or the industry to which they belong. To correct for a potential simultaneity bias, we lagged the independent variables and control variables such as firms' financial measures (revenues, and R&D expenditures), age, as well as technological capital by one year.

RESULTS

Table II describes the variables used in the regressions. Table III provides the descriptive statistics and the correlations between all the variables for the 100 firms and the 912 observations in the sample. The correlation coefficients between the independent variables are relatively low, except for component density and egonet redundancy (–0.60). However, the VIF (variance inflation factor) value, which is a more advanced measure of multicollinearity than simple correlations, was calculated for component density (Stevens, 1992). The VIF value for component density was way below the critical level, indicating that egonet redundancy and component density can simultaneously be included in the models.

Table II. Definitions of dependent and independent variables

Variable name	*Variable description*	
Exploitative technology innovation	Citation weighted count of the number of patents a firm successfully filed for in year t within patent classes in which it was active in the five years prior to year t	Dependent variable
Exploratory technology innovation	Citation weighted count of the number of patents a firm successfully 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 $t-1$ (range between 0 and 10)	
(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 (range between 0 and 10) in $t-1$	
(Component density)^2	Squared term of previous variable	
Technological capital	Count of the number of patents that a firm successfully filed for during the previous five years ($t-5$ to $t-1$)	
Age	The number of years since a company is founded in $t-1$	
Firm size (ln revenues)	Natural logarithm of the total sales of the firm in $t-1$	
R&D intensity	Total R&D expenditures divided by sales in $t-1$	
Year	Dummy variable indicating a particular year (1986–97)	
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	
USA	Dummy variable set to one if the firm is headquartered in the USA	

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 III. 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 Exploitative technology innovation	69.446	125.638	0	1059													
2 Explorative technology innovation	7.864	12.542	0	132	0.32												
3 Ego redundancy	2.568	2.810	0	91.66	0.16	0.12											
4 (Ego redundancy)^2	14.487	20.97	0	84.03	0.10	0.08	0.95										
5 Component density	8.044	3.368	0	10	−0.23	−0.18	−0.60	−0.55									
6 (Component density)^2	76.051	39.524	0	100	−0.22	−0.17	−0.64	−0.59	0.99								
7 Firm size (ln revenues)	7.949	2.517	−1.570	11.912	0.42	0.26	0.32	0.31	−0.26	−0.30							
8 Technological capital	352	616	0	5110	0.95	0.32	0.15	0.08	−0.23	−0.23	0.43						
9 R&D-intensity	0.177	0.185	0	0.651	−0.06	−0.04	−0.02	−0.04	−0.06	−0.04	−0.40	−0.06					
10 Age	74	47	0	239	0.13	0.00	0.09	0.05	−0.05	−0.08	0.40	0.13	−0.15				
11 Car manufacturer	0.282	0.450	0	1	0.01	0.03	0.26	0.31	−0.21	−0.21	0.37	0.00	−0.09	0.04			
12 Chemical company	0.288	0.453	0	1	0.07	0.00	0.12	0.06	−0.06	−0.08	0.11	0.07	−0.10	0.17	−0.46		
13 European-based firm	0.223	0.416	0	1	−0.24	−0.06	0.15	0.12	−0.04	−0.07	0.02	−0.21	0.07	−0.08	0.13	0.09	
14 USA-based firm	0.432	0.496	0	1	0.03	0.04	−0.25	−0.23	0.10	0.13	−0.21	0.04	0.02	−0.09	−0.17	−0.15	−0.46

Table IV(a) provides an overview of the results of the regression analysis, explaining the determinants of the creation of core technology in the period 1986–97. Table IV(b) presents the results of the determinants of non-core technology as the dependent variable. Model 1 represents the basic model in which only the control variables are introduced. Some results are worth mentioning. The coefficient of firm size is positive and significantly related to the innovative performance. Since the independent variable is the natural logarithm of the revenues, the coefficient can be considered an elasticity: increasing firm size results in increasing innovative output but at a decreasing rate as firm size grows, since the coefficient is smaller than one. This is in line with previous research (Acs and Audretsch, 1991; Henderson, 1993). It is worthwhile mentioning that the effect of firm size is significantly larger ($p < 0.001$) for exploitation compared to exploration, indicating that decreasing returns to scale are much larger in the case of explorative learning. This reflects the idea that small firms have relatively less problems exploring new technological areas successfully than large firms do. This finding is in line with the organizational learning literature: established organizations have difficulties in exploring new technological areas, as they inhibit experimentation and favour specialization along existing technological trajectories (Ahuja and Lampert, 2001; Levinthal and March, 1993; March, 1991). Next, we find a positive and significant relation between the existing technological capital and a firm's innovative performance. This indicates that the current technological position of a company is shaped by the path it has travelled, due to the cumulative character of technology (Teece et al., 1997). When companies build on their past developed knowledge investments, we expect a higher innovation rate for firms with strong technological capital. We do not find a significant difference in the impact of this variable on the creation of core and/or non-core technology. This indicates that the accumulated knowledge base is equally important for the creation of both core and non-core technologies.

Furthermore, R&D intensity also improves the innovative performance when companies deepen their competencies in their existing knowledge domains. However, there is no direct link between R&D intensity and the exploration of new technological fields. This remarkable finding might be explained by the fact that, on average, there is no linear relation between an increase in R&D and the explorative learning of firms. The bulk of the R&D investments in a company targets incremental innovations to improve the existing technologies, products, and processes. R&D investments in more explorative, long-term oriented innovations at the periphery of a firm's technology core only account for a minor part of R&D expenditures. Moreover, subject to the financial slack and strategic priorities of the top management, investments in explorative research fluctuate strongly over time.

Age has a negative effect on the exploitative learning of innovating firms. Hence, older firms have more problems in coming up with high quality innovations in their existing technology areas. However, we do not find any significant relationship between age and explorative innovations. The fact that age does not affect explorative learning can be explained by two compensating factors. On the one hand, young firms are less conditioned by their existing technology base than older firms and will explore new technologies more easily than their older counterparts. On the other hand, young firms have to deepen their core technologies first in order to be competitive before they can 'diversify' into new technologies. Conversely, older firms have accumulated the required competencies over time and incentives to diversify when their core markets tend to mature.

As for regional dummy variables, there are significant differences between the three economic blocks. Finally, there are also significant differences between the three industries.

Model 2 introduces the linear term for the 'egonet redundancy' variable. In line with Hypothesis 1, the coefficient is positive for exploitation, implying that an increase in redundancy in the direct contacts of a focal firm's network stimulates the creation of new core technology. In contrast, there is no significant linear relationship between egonet redundancy and the exploration of new technological areas.

Model 3 introduces the squared term for egonet redundancy. In the case of exploitative learning, the quadratic term is not significant, which is in line with Hypothesis 1, which predicts a linear and not a curvilinear relationship. In the case of exploration, we find a curvilinear relation between the redundancy in the direct ties of a focal firm and its explorative learning, which is in line with Hypothesis 2. Hence, higher levels of redundancy always improve exploitation, whereas redundancy also increases exploration but only up to a certain point. Beyond this point, the decline in novelty value begins to have a negative effect on the creation of new, non-core technology.

Model 4 adds 'component density' as a regressor. This variable has no effect on exploitative learning, which is in line with Hypothesis 3, which predicts a curvilinear relationship. With regard to exploration, the coefficient has the expected negative sign although it lacks significance. Model 5 adds the squared term of component density to test for a curvilinear relation. Here we find that increasing redundancy in a part of ego's network has the expected curvilinear relationship in respect of exploitative learning. This corroborates Hypothesis 3. In contrast, we find that component density has no significant effect – neither linear nor curvilinear – on explorative learning. In other words, Hypothesis 4 cannot be confirmed. We discuss these results in more detail in the following section.

DISCUSSION AND CONCLUSION

Owing to the lack of empirical literature on the particular effects of local actions in alliance networks, we have developed an approach – based on Bae and Gargiulo (2003) – that studies the effect of those particular actions on a focal firm's ability to create new technology in its core areas and/or non-core areas. More specifically, we have studied how redundancy in a focal firm's network structure affects its ability to create new knowledge in core and/or non-core technological areas. Here, we have focused on two types of redundancy in the ego network of innovating firms. The first type reflects 'ego redundancy': these alliances connect two partners or groups of partners of the focal firm that were otherwise not linked. The other type is 'component density': these alliances between partners do not increase the redundancy in ego's total network, but increase the redundancy within a separate group of partners. Given these differences, we anticipated that each type of redundancy would have a differential effect on the creation of core technology and non-core technology respectively. This idea was corroborated by the

Table IV. Determinants of exploitative and exploratory technology innovation, 1986–97

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*
(a) Exploitative technology innovation					
Egonet redundancy		0.028***	0.059**	0.063**	0.061**
		(0.010)	(0.0274)	(0.028)	(0.029)
(Egonet redundancy)^2			–0.005	–0.005	–0.006
			(0.004)	(0.004)	(0.004)
Component density				0.004	0.071**
				(0.007)	(0.035)
(Component density)^2					–0.006**
					(0.003)
Control variables					
Firm size (ln sales)	0.612***	0.605***	0.609***	0.609***	0.613***
	(0.045)	(0.045)	(0.046)	(0.046)	(0.046)
Technical capital/100	0.024***	0.021***	0.022***	0.022***	0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
R&D intensity	0.270***	0.260***	0.259***	0.261***	0.266***
	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)
Age	–0.006***	–0.006***	–0.006***	–0.006***	–0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Car manufacturer	–1.289***	–1.352***	–1.316***	–1.312***	–1.321***
	(0.170)	(0.174)	(0.176)	(0.176)	(0.176)
Chemical industry	0.484***	0.452***	0.407**	0.416**	0.414**
	(0.159)	(0.160)	(0.163)	(0.164)	(0.164)
Europe	0.268	0.239	0.257	0.256	0.281
	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)
USA	1.357***	1.340***	1.339***	1.346***	1.349***
	(0.151)	(0.153)	(0.152)	(0.153)	(0.151)
Constant	–4.517***	–4.441***	–4.496***	–4.537***	–4.604***
	(0.382)	(0.379)	(0.383)	(0.391)	(0.392)
Year dummy variables	Included	Included	Included	Included	Included
Observations (firm-year)	667	667	667	667	667
Number of firms	74	74	74	74	74
Log-L	–4,689.32	–4,685.74	–4,684.98	–4,684.85	–4,681.98
LR-test		7.16***	1.52	0.26	5.74**
(b) Exploratory technology innovation					
Egonet redundancy		0.011	0.1826***	0.177***	0.176***
		(0.086)	(0.047)	(0.049)	(0.049)
(Egonet redundancy)^2			–0.006***	–0.023**	–0.023***
			(0.305)	(0.006)	(0.006)
Component density				–0.005	0.281
				(0.013)	(0.067)
(Component density)^2					–0.003
					(0.006)
Control variables					
Firm size (ln sales)	0.336***	0.333***	0.344***	0.327***	0.325***
	(0.049)	(0.049)	(0.048)	(0.048)	(0.048)
Technological capital/100	0.023***	0.023***	0.023***	0.023***	0.022***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)

Table IV. *Continued*

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*
R&D intensity	0.066	0.061	0.039	0.037	0.0038
	(0.110)	(0.111)	(0.118)	(0.118)	(0.012)
Age	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001	(0.001)
Car manufacturer	0.335**	0.343**	0.336**	0.332**	0.333**
	(0.147)	(0.157)	(0.248)	(0.158)	(0.158)
Chemical industry	0.724***	0.667***	0.660***	0.659***	0.661***
	(0.132)	(0.138)	(0.137)	(0.137)	(0.144)
Europe	0.425***	0.461***	0.416***	0.416***	0.410***
	(0.141)	(0.145)	(0.144)	(0.144)	(0.145)
USA	1.117***	1.118***	1.133***	1.131***	1.129***
	(0.120)	(0.127)	(0.125)	(0.125)	(0.125)
Constant	−4.978***	−5.149***	−5.209***	−5.156***	−5.160***
	(0.405)	(0.427)	(0.48)	(0.444)	(0.444)
Year dummy variables	Included	Included	Included	Included	Included
Observations (firm-year)	667	667	667	667	667
Number of firms	74	74	74	74	74
Log-L	−3,226.47	−3,226.21	−3,218.88	−3,218.82	−3,218.69
LR-test		0.52	14.66***	0.12	0.26

Notes: Standard errors in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

empirical findings. The results in Table IV show that egonet redundancy has a linear effect on the creation of core technology. There is an inverted U-shape relation in respect of non-core technology. Component density has a curvilinear effect on the creation of core technology but has no effect on the development of non-core technology. Overall, these results clearly indicate that innovating firms' actions to structure their ego network, and egonet redundancy in particular, have a significant effect on both types of innovative output. Given the fact that ego network redundancy largely lies within a focal firm's sphere of influence, contrary to its component density, these findings indicate that individual firms can indeed improve their innovativeness by shaping the degree of redundancy in their local alliance network. Overall, this points to the usefulness of an action approach for developing a more action-oriented view on the role of individual firms in collaborative networks. Such a view could serve as a complementary perspective to the traditional view on alliance networks, with its emphasis on the overall network structure and firms' network position (Bae and Gargiulo, 2003, 2004; Garcia-Pont and Nohria, 2002).

Furthermore, these findings indicate that the creation of new technology forms a balancing act between building and maintaining access to novelty, on the one hand, and nurturing shared absorptive capacity, on the other hand. Whereas novelty access is provided for by non-redundant partners in a focal firm's alliance network, the corresponding ability to absorb novel technology is enhanced by redundancy in its network.

By influencing the degree of each type of redundancy, firms can further boost the creation of both core and non-core technology respectively. Here we have considered how each type of redundancy impacts the creation of the two types of new technology separately.

This also raises the question regarding how far a focal firm can make use of its local network structure with a view to boosting the two types of technology *jointly*. Following our findings, the best way forward seems to be the following: most important is to increase redundancy among ego's direct ties (i.e. egonet redundancy) up to the optimal level for exploration – 3.8 on a scale from 0 to 10 (calculation based on Model 5 in Table IV(b)). In this way, ego can benefit – in respect of both activities – from an increase in coherence in supplied information and from a diminished risk of information overload. However, beyond the optimal level, a focal firm should be careful, as a decrease in novelty value becomes a serious problem for exploration here. Although exploitation could still benefit from such an increase, a more sensible strategy is to increase the network density between a focal firm's partners to create stronger group coherence and better information flows between them, thus improving the former's innovation rate in core technologies. However, there is only a positive effect for lower component density levels. When partners are already well connected to each other (high component density levels), the impact of a further increase has a negative effect on exploitation. Firms can develop a strategy of stimulating tie density between partners because exploration is not negatively affected by changes in component density. This is, admittedly, more difficult than increasing egonet redundancy, as it lies beyond ego's direct sphere of influence: focal firms can only influence component density by using their power/status in the network (which only applies to more prominent firms) and through social control within densely connected groups.

In conclusion, it seems that balancing novelty access and its corresponding absorption, which follows from a cognitive perspective, also induces the need for a balancing act between local redundancy and local non-redundancy from a social structural perspective. This is an important point that has implications for various strands of literature. The learning and innovation literature, although clearly acknowledging the importance of inter-firm collaboration and 'interactive learning' processes, still has limited insights into what the associated social structural implications of technological innovation processes are (Malerba, 2004). Here, our logic and findings on the effect of network structure on both types of innovation not only reveal *how* networks structure impacts each task differently, but also *why* it does so. The balance between novelty access and absorption, and how that differs between the two types of innovative activities, should be reflected in focal firms' network structure. This insight is also highly informative to the alliance literature, which has predominantly studied how an alliance network acts as a channel for the diffusion of *existing* information and knowledge, rather than its potential for *new* knowledge creation (Owen-Smith and Powell, 2004; Sampson, 2007). Consequently, our focus on how ego's local network structure shapes the creation of core and non-core technology also provides us with a better understanding of the development of new knowledge and competencies in unfamiliar domains, which is still a largely unaddressed topic in the alliance literature (Gilsing et al., 2008; Hagedoorn et al., 2000; Nooteboom, 2004).

Furthermore, our study has an interesting new insight in respect of the ongoing debate on the validity of Burt's arguments versus those of Coleman in the social network literature. Our in-depth study of network structure from a local action perspective reveals that the creation of new technology in non-core areas seems to require a dual emphasis on non-redundant contacts and redundant contacts. This result indicates that innovating firms that pursue a mixed alliance strategy leading to intermediate levels of ego-network redundancy outperform firms – as far as the creation of non-core technology is concerned – that take on pure structural holes or network closure strategies at both ends of the continuum. Structural hole networking strategies do, of course, have the potential to tap into novel sources of technological knowledge, but due to the more tacit nature of new technology, firms might often experience too wide a gap in absorptive capacity when sourcing technology from their alliance partners (Cohen and Levinthal, 1990). Close and multiple contacts between partners might be disadvantageous in terms of novelty of information but they increase 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 (Lane and Lubatkin, 1998). In other words, it seems that – for the creation of non-core technology – both views convey some truth and may be regarded as complements instead of opposites as is stressed in the literature (Ahuja, 2000; Hansen, 1999; McEvily and Zaheer, 1999; Rowley et al., 2000).

In contrast, for the creation of core technology, a network closure strategy seems to work well with regard to a focal firm's network of direct ties. One of the most successful firms to employ this strategy is the METRO group, one of the world's biggest retailers. With its innovative Future Store Initiative, METRO successfully launched a partner programme aimed at innovation and knowledge sharing among its partners. The Future Store Initiative consists of an alliance of 58 innovative companies that jointly develop new technology-based products for the retail sector. This initiative has evolved into a very strong and productive knowledge network in which learning effects have greatly increased for the companies involved, as well as for METRO. The central coordination is in the hands of METRO, which facilitates face-to-face and electronic communication among its partners. This has led to a dense network of motivated partners that enhances the contributions of partners and reduces their incentive to free-ride (see De Man, 2008).

This study has several limitations. First, there is the standard concern whether we can draw general conclusions based on data from established firms in three industries. Second, we only focused on the redundancy of the information in the ego network of firms' alliance networks. 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). Similarly, some authors have found that the strength of ties (or types of alliances) is an important explanatory factor in understanding the network structure of social capital (e.g. Burt, 2000; Nicolaou and Birley, 2003; Podolny and Baron, 1997). Furthermore, we did not pay attention to the cognitive distance between a company and its partners although, in contrast to exploitative learning, partners should undoubtedly differ in technology profile for explorative learning. This raises the question of what the optimal 'cognitive distance' between alliance partners should be when involved in exploitative or explorative learning (Nooteboom et al., 2007). This, in turn, suggests that determining the conditions for exploration and exploitation could be characterized in terms of the relative absorptive capacity between alliance partners (Lane and Lubatkin, 1998).

The current study offers several opportunities for further research. First, there is a multitude of alliance types, each of which has a different tie strength. Introducing tie strength as an explanatory variable can enrich our understanding of the role of redundancy in ego networks. Similarly, different types of partners and the heterogeneity among partners are other variables that could be introduced to refine the current analysis (Faems et al., 2005; Rothaermel and Deeds, 2004).

Second, exploration and exploitation have been operationalized in different ways in the literature (see Gupta et al., 2006 for an overview). Our definition of exploitation and exploration focuses on the distinction between core and non-core technologies. This operationalization is in line with March's (1991) definition and comes close to the operationalization used by Katila (2003) in which exploration is determined in terms of entering new patent classes. Other studies define exploitation and exploration in terms of citations to a firm's prior patents in new, successfully applied patents (Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001; Rothaermel and Deeds, 2004). The two approaches are complementary and it would be interesting to analyse the impact of operationalizations on the role of redundancy in previously unconnected and connected partners within the two views of exploration.

Finally, density and redundancy can be defined at different network levels and not only at the ego-network level. Density at the overall network level may influence the exploration of new technologies (Gilsing et al., 2008). In a similar vein, cliques of firms – dense parts of the network that are larger than ego networks – are likely to play a role in explaining the innovativeness of firms (Baum et al., 2003; Gulati and Gargiulo, 1999; Rowley et al., 2004, 2005). Blending different network levels in the analysis may reveal that the impact of ego-network redundancy is contingent on the density and structure at the clique or overall network level.

In conclusion, our combined cognitive and social structural perspective has proven to be an important addition to the literature thus far, as we have complemented the dominant focus on the role of social factors regarding alliance formation and the role of network embeddedness (Gulati, 1998) with a cognition-based understanding of these processes (Moran, 2005; Nooteboom, 2004). In this way, we have been able to study how two types of redundancy in a firm's ego network affect its ability to be innovative in its core technologies (exploitation) and/or in its non-core technologies (exploration). In the literature, redundancy has traditionally been analysed without taking into account whether partner firms were previously connected to each other or not. We find empirical evidence that it is important to distinguish between redundancy that links as yet unconnected partners together (ego redundancy) and redundancy that intensifies the relations among partners that were already linked to each other (component density). Both types of redundancy play a different role in increasing the innovativeness of firms when they deepen their knowledge in core technologies or when they broaden their knowledge base in non-core technologies. The role of redundancy in a broader network has been debated by Burt (1992) and Coleman (1988). In this article, we have shown that firms can boost their technological innovativeness by shaping the two types of redundancy in their local alliance network. Hence, our study argues convincingly that not only the alliances with its partners but also the degree of different types of redundancy among its partners determine a firm's technological innovativeness. This reflects a more action-oriented view of the role of individual firms in collaborative networks, which has been ignored by the alliance literature so far. Such an action-oriented view informs firms how to orchestrate their networks in such way that they can extract more value out of it (Dhanaraj and Parkhe, 2006). This approach also requires alliance network scholars to develop a renewed interest in the management and organization of alliance networks (Bamford et al., 2003; Gomes-Casseres, 1996), as an action oriented approach can only lead to more innovation through skilful alliance portfolio management.

ACKNOWLEDGMENTS

We thank the editorial team and three anonymous reviewers, Niels Noorderhaven, René Belderbos, Rajneesh Narula and the seminar participants at the Eindhoven Center of Innovation Studies for helpful comments and suggestions on earlier versions of this paper. We also thank Ad Van den Oord for his assistance in setting up the database. All remaining errors and omissions are entirely our own.

NOTES

[1] Quoting Burt: 'People who stand near the holes in a social structure are at a higher risk of having good ideas' (Burt, 2004, p. 349).

[2] This is echoed in Burt (2001) where a distinction is made between positive and negative third parties.

[3] This long time-span allows us to circumvent left-side censoring problems, as the observation period in this study only starts in 1986.

[4] Additional information on this data bank can be found in Hagedoorn (1993) and Hagedoorn and Schakenraad (1994).

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

[6] A moving window of five years is the appropriate time-frame for assessing the technological impact (Ahuja, 2000; Henderson and Cockburn, 1996; Podolny and Stuart, 1995; Stuart and Podolny, 1996). Studies on R&D depreciation (Griliches, 1979, 1984) suggest that knowledge capital depreciates sharply, losing most of its economic value within five years. The classes were determined at a two-digit level, which resulted in approximately 400 classes.

[7] We also constructed the variable 'explorative patents', which was based on maintaining the explorative status for five years to test the robustness of our results. Changing the dependent variable 'explorative' patents in this way did not affect the empirical results.

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

[9] Ego redundancy is related to the 'bridging ties' concept of McEvily and Zaheer (1999). Bridging ties link a focal firm to other companies that are not otherwise accessible to this firm (they connect a focal firm to sources of information and opportunities that are not available from other network contacts). In respect of 'bridging ties', low (high) values indicate low (high) non-redundancy – exactly the opposite of 'proportion density'. We find a correlation of −0.63 between bridging ties and ego-network redundancy, indicating that, similar to the method used in this paper, bridging ties are a measure of (non-)redundancy.

[10] 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.

REFERENCES

Acs, Z. and Audretsch, D. B. (1991). 'Innovation in large small firms: an empirical analysis'. *American Economic Review*, **78**, 678–90.

Ahuja, G. (2000). 'Collaboration networks, structural holes, and innovation: a longitudinal study'. *Administrative Science Quarterly*, **45**, 425–55.

Ahuja, G. and Katila, R. (2001). 'Technological acquisitions and the innovation performance of acquiring firms: a longitudinal study'. *Strategic Management Journal*, **22**, 197–220.
Ahuja, G. and Katila, R. (2004). 'Where do resources come from? The role of idiosyncratic situations'. *Strategic Management Journal*, **25**, 887–907.
Ahuja, G. and Lampert, C. M. (2001). 'Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions'. *Strategic Management Journal*, **22**, 521–43.
Arino, A., Ragozinno, R. and Reuer, J. J. (2008). 'Alliance dynamics for entrepreneurial firms'. *Journal of Management Studies*, **45**, 147–68.
Bae, J. and Gargiulo, M. (2003). *Local Action and Efficient Alliance Strategies in the Telecommunications Industry*. INSEAD Working Paper No. 2003/20/OB.
Bae, J. and Gargiulo, M. (2004). 'Partner substitutability, alliance network structure, and firm profitability in the telecommunications industry'. *Academy of Management Journal*, **47**, 843–59.
Bamford, J. D., Gomes-Casseres, B. and Robinson, M. S. (2003). *Mastering Alliance Strategy: A Comprehensive Guide to Design, Management and Organization*. San Francisco, CA: Jossey-Bass.
Basberg, B. L. (1987). 'Patents and measurement of technical change: a survey of the literature'. *Research Policy*, **16**, 131–41.
Baum, J., Shipolov, A. V. and Rowley, T. J. (2003). 'Where do small worlds come from?'. *Industrial and Corporate Change*, **12**, 697–725.
Borgatti, S. P., Everett, M. G. and Freeman, L. C. (2002). *Ucinet 6 for Windows*. Harvard, MA: Analytic Technologies.
Burt, R. S. (1992). *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press.
Burt, R. S. (1997). 'The contingent value of social capital'. *Administrative Science Quarterly*, **42**, 339–65.
Burt, R. S. (2000). 'The network structure of social capital'. In Sutton, R. I. and Straw, B. M. (Eds), *Research in Organizational Behavior*. Greenwich, CT: JAI Press, 22, 345–423.
Burt, R. S. (2001). 'Bandwith and echo: trust, information, and gossip in social network'. In Casella, A. and Rauch, J. E. (Eds), *Networks and Markets: Contributions from Economics and Sociology*. New York: Russell Sage Foundation, 30–74.
Burt, R. S. (2004). 'Structural holes and good ideas'. *American Journal of Sociology*, **110**, 349–99.
Cameron, A. and Trivedi, P. (1986). 'Econometric models based on count data: comparisons and applications of some estimators and tests'. *Journal of Applied Econometrics*, **1**, 29–53.
Cohen, W. M. and Levinthal, D. A. (1989). 'Innovation and learning: the two faces of R&D'. *Economic Journal*, **99**, 569–96.
Cohen, W. M. and Levinthal, D. A. (1990). 'Absorptive capacity: a new perspective on learning and innovation'. *Administrative Science Quarterly*, **35**, 128–52.
Coleman, J. S. (1988). 'Social capital in the creation of human capital'. *American Journal of Sociology*, **94**, 95–120.
Contractor, F. and Lorange, P. (Eds) (1988). *Cooperative Strategies in International Business*. Lexington, MA: Lexington Books.
De Man, A. P. (2008). *Knowledge Management and Innovation in Networks*. Cheltenham: Edward Elgar.
Dhanaraj, C. and Parkhe, A. (2006). 'Orchestrating innovation networks'. *Academy of Management Review*, **31**, 659–69.
Duysters, G. and Lemmens, C. E. A. V. (2003). 'Cohesive subgroup formation: enabling and enforcing factors in strategic technology alliance networks'. *International Studies on Management and Organisation*, **33**, 49–68.
Duysters, G. M., Guidice, R., Sadowski, B. and Vasudevan, A. (2001). 'Inter alliance rivalry, theory and application to the global telecommunications industry'. In Hughes, M. (Ed.), *International Business and its European Dimensions*. London: Macmillan, 151–70.
Duysters, G. M., Hagedoorn, J. and Lemmens, C. E. A. V. (2003). 'The effect of alliance block membership on innovative performance'. *Revue d'Économie Industrielle*, **103**, Special Issue on 'La Morphogénèse des Réseaux', 59–70.
Faems, D., Van Looy, B. and Debackere, K. (2005). 'Interorganizational collaboration and innovation: toward a portfolio approach'. *Journal of Product Innovation Management*, 238–50.
Fleming, L. and Sorenson, O. (2001). 'Technology as a complex adaptive system: evidence from patent data'. *Research Policy*, **30**, 1019–39.
Freeman, L. C. (1979). 'Centrality in networks: conceptual clarification'. *Social Networks*, **1**, 215–39.
Garcia-Pont, C. and Nohria, N. (2002). 'Local versus global mimetism: the dynamics of alliance formation in the automobile industry'. *Strategic Management Journal*, **23**, 307–21.

Garcia-Pont, C., Canales, J. I. and Noboa, F. S. (2007). *Subsidiary Strategy: The Embeddedness Component*. IESE Business School Working Paper No. 699.

Gilsing, V. A. and Nooteboom, B. (2005). 'Density and strength of ties in innovation networks: an analysis of multimedia and biotechnology'. *European Management Review*, **2**, 179–97.

Gilsing, V. A., Nooteboom, B., Vanhaverbeke, W., Duysters, G. M. and van den Oord, A. (2008). 'Network embeddedness and the exploration of novel technologies: technological distance, betweenness centrality and density'. *Research Policy*, forthcoming.

Gomes-Casseres, B. (1996). *The Alliance Revolution*. Harvard, MA: Harvard Business School Press.

Gourieroux, C., Monfort, A. and Trognon, A. (1984). 'Pseudo maximum likelihood methods: applications to Poisson models'. *Econometrica*, **52**, 701–20.

Granovetter, M. (1992). 'Problems of explanation in economic sociology'. In Nohria, N. and Eccles, R. G. (Eds), *Networks and Organizations: Structure, Form and Action*. Boston, MA: Harvard Business School Press, 25–56.

Grant, R. M. and Baden-Fuller, C. (2004). 'A knowledge accessing theory of strategic alliances'. *Journal of Management Studies*, **41**, 61–84.

Greene, W. H. (2003). *Econometric Analysis*, 5th edition. Upper Saddle River, NJ: Prentice Hall.

Griliches, Z. (1979). 'Issues in assessing the contribution of research and development to productivity growth'. *Bell Journal of Economics*, **10**, 92–116.

Griliches, Z. (Ed.) (1984). *R&D, Patents and Productivity*. Chicago, IL: University of Chicago Press.

Griliches, Z. (1990). 'Patent statistics as economic indicators: a survey'. *Journal of Economic Literature*, **27**, 1661–707.

Gulati, R. (1995a). 'Social structure and alliance formation patterns: a longitudinal analysis'. *Administrative Science Quarterly*, **40**, 619–52.

Gulati, R. (1995b). 'Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances'. *Academy of Management Journal*, **30**, 85–112.

Gulati, R. (1998). 'Alliances and networks'. *Strategic Management Journal*, **19**, 293–317.

Gulati, R. (1999). 'Network location and learning: the influence of network resources and firm capabilities on alliance formation'. *Strategic Management Journal*, **20**, 397–420.

Gulati, R. and Gargiulo, M. (1999). 'Where do inter-organizational networks come from?'. *American Journal of Sociology*, **104**, 1439–93.

Gupta, A. K., Smith, K. G. and Shalley, C. E. (2006). 'The interplay between exploration and exploitation'. *Academy of Management Journal*, **49**, 693–706.

Hagedoorn, J. (1993). 'Understanding the rationale of strategic technology partnering: inter-organizational modes of cooperation and sectoral differences'. *Strategic Management Journal*, **14**, 371–85.

Hagedoorn, J. and Cloodt, M. (2003). 'Measuring innovative performance: is there an advantage in using multiple indicators?'. *Research Policy*, **32**, 1–15.

Hagedoorn, J. and Duysters, G. M. (2002). 'External sources of innovative capabilities: the preference for strategic alliances or mergers and acquisitions'. *Journal of Management Studies*, **39**, 167–88.

Hagedoorn, J. and Schakenraad, J. (1994). 'The effect of strategic technology alliances on company performance'. *Strategic Management Journal*, **15**, 291–311.

Hagedoorn, J., Link, A. L. and Vonortas, N. (2000). 'Research partnerships'. *Research Policy*, **29**, 567–86.

Hall, B. H. and Ziedonis, R. H. (2001). 'The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979–1995'. *Rand Journal of Economics*, **32**, 101–28.

Hansen, M. T. (1999). 'The search-transfer problem: the role of weak ties in sharing knowledge across organization subunits'. *Administrative Science Quarterly*, **44**, 82–111.

Hardy, C., Phillips, N. and Lawrence, T. B. (2003). 'Resources, knowledge and influence, the organizational effects of interorganizational collaboration'. *Journal of Management Studies*, **40**, 321–47.

Hausman, J. (1978). 'Specification tests in econometrics'. *Econometrica*, **46**, 1251–71.

Hausman, J., Hall, B. and Griliches, Z. (1984). 'Econometric models for count data with an application to the patents-R&D relationship'. *Econometrica*, **52**, 909–38.

Heckman, J. J. and Borjas, G. J. (1980). 'Does unemployment cause future unemployment: definitions, questions, and answers from a continuous time model of heterogeneity and state dependence'. *Econometrica*, **48**, 247–83.

Henderson, R. (1993). 'Underinvestment and incompetence as responses to radical innovation: evidence from the photolithographic alignment equipment industry'. *Rand Journal of Economics*, **24**, 248–70.

Henderson, R. and Cockburn, I. (1996). 'Scale, scope and spillovers: the determinants of research productivity in drug discovery'. *Rand Journal of Economics*, **27**, 32–59.

Hite, J. M. and Hesterly, W. S. (2001). 'The evolution of firm networks: from emergence to early growth of the firm'. *Strategic Management Journal*, **22**, 275–87.
Inkpen, A. C. (2000). 'Learning through joint ventures: a framework of knowledge acquisition'. *Journal of Management Studies*, **37**, 1019–43.
Katila, R. (2003). *Innovative Product Portfolios by Navigating Markets and Technology*. Wharton Technology Mini-conference, Stanford University, CA.
Katila, R. and Ahuja, G. (2002). 'Something old, something new: a longitudinal study of search behavior and new product introduction'. *Academy of Management Journal*, **45**, 1183–94.
Knoke, D. and Kuklinski, J. H. (1982). *Network Analysis, Series: Quantitative Applications in the Social Sciences*. Beverly Hills and London: Sage.
Kogut, B. (1988). 'A study of the life cycle of joint ventures'. *Management International Review*, **28**, 39–52.
Kogut, B. (1989). 'The stability of joint ventures: reciprocity and competitive rivalry'. *Journal of Industrial Economics*, **38**, 183–98.
Koza, M. P. and Lewin, Y. (1998). 'The co-evolution of strategic alliances'. *Organization Science*, **9**, 255–64.
Lane, P. J. and Lubatkin, M. (1998). 'Relative absorptive capacity and interorganizational learning'. *Strategic Management Journal*, **19**, 461–77.
Lanjouw, J. O. and Schankerman, M. (2004). 'Patent quality and research productivity: measuring innovation with multiple indicators'. *The Economic Journal*, **99**, 569–96.
Larson, A. (1992). 'Network dyads in entrepreneurial settings: a study of the governance of exchange processes'. *Administrative Science Quarterly*, **37**, 76–104.
Leonard-Barton, D. (1984). 'Interpersonal communication patterns among Swedish and Boston-area entrepreneurs'. *Research Policy*, **13**, 101–14.
Leonard-Barton, D. (1992). 'Core capabilities and core rigidities: a paradox in new product development'. *Strategic Management Journal*, **13**, 111–26.
Levinthal, D. A. and March, J. G. (1993). 'The myopia of learning'. *Strategic Management Journal*, **14**, Winter Special Issue, 95–112.
Lichtenberg, F. R. and Griliches, Z. (1989). 'Errors of measurement in output deflators'. *Journal of Business and Economic Statistics*, **7**, 1–9.
Malerba, F. (2004). *Sectoral Systems of Innovation*. Cambridge: Cambridge University Press.
March, J. G. (1991). 'Exploration and exploitation in organizational learning'. *Organization Science*, **2**, 71–87.
McEvily, B. and Zaheer, A. (1999). 'Bridging ties: a source of firm heterogeneity in competitive dynamics'. *Strategic Management Journal*, **20**, 1133–56.
Miller, D. J., Fern, M. J. and Cardinal, L. B. (2007). 'The use of knowledge for technological innovation within diversified firms'. *Academy of Management Journal*, **50**, 308–26.
Mom, T. J. M., Van Den Bosch, F. A. J. and Volberda, H. W. (2007). 'Investigating managers' exploration and exploitation activities: the influence of top-down, bottom-up and horizontal knowledge inflows'. *Journal of Management Studies*, **44**, 910–31.
Moran, P. (2005). 'Structural versus relational embeddedness: social capital and managerial performance'. *Strategic Management Journal*, **26**, 1129–51.
Narin, F., Noma, E. and Perry, R. (1987). 'Patents as indicators of corporate technological strength'. *Research Policy*, **16**, 26–48.
Nelson, R. R. and Winter, S. G. (1982). *An Evolutionary Theory of Economic Change*. Cambridge, MA: Belknap Press of Harvard University Press.
Nicolaou, N. and Birley, S. (2003). 'Social networks in organizational emergence: the university spinout phenomenon'. *Management Science*, **49**, 1702–25.
Nohria, N. and Garcia-Pont, G. (1991). 'Global strategic linkages and industry structure'. *Strategic Management Journal*, **12**, 105–24.
Nonaka, I. (1994). 'A dynamic theory of organizational knowledge creation'. *Organization Science*, **5**, 14–37.
Nooteboom, B. (2004). *Inter-Firm Collaboration, Learning and Networks; An Integrated Approach*. London: Routledge.
Nooteboom, B., Vanhaverbeke, W., Duysters, G., Gilsing, V. and Van den Oord, A. (2007). 'Optimal cognitive distance and absorptive capacity'. *Research Policy*, **36**, 1016–34.
Ohmae, K. (1985). *Triad Power: The Coming Shape of Global Competition*. New York: Free Press.
Owen-Smith, J. and Powell, W. W. (2004). 'Knowledge networks as channels and conduits: the effects of spillovers in the Boston biotechnology community'. *Organization Science*, **15**, 5–21.
Pakes, A. and Griliches, Z. (1984). 'Estimating distributed lags in short panels with an application to the specification of depreciation patterns and capital stock constructs'. *Review of Economic Studies*, **51**, 243–62.

Podolny, J. M. (2001). 'Networks as the pipes and prisms of the market'. *American Journal of Sociology*, **107**, 33–60.

Podolny, J. M. and Baron, J. (1997). 'Resources and relationships: social networks and mobility in the workplace'. *American Sociological Review*, **62**, 673–93.

Podolny, J. M. and Stuart, T. A. (1995). 'A role-based ecology of technological change'. *American Journal of Sociology*, **100**, 1224–60.

Reagans, R. and Zuckerman, E. (2001). 'Networks, diversity and productivity: the social capital of corporate R&D teams'. *Organization Science*, **12**, 502–17.

Rosenkopf, L. and Nerkar, A. (2001). 'Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry'. *Strategic Management Journal*, **22**, 287–306.

Rothaermel, F. (2001). 'Incumbent's advantage through exploiting complementary assets via interfirm cooperation'. *Strategic Management Journal*, **22**, 687–99.

Rothaermel, F. and Deeds, D. L. (2004). 'Exploration and exploitation alliances in biotechnology: a system of new product development'. *Strategic Management Journal*, **25**, 201–21.

Rowley, T., Behrens, D. and Krackhardt, D. (2000). 'Redundant governance structures: an analysis of structural and relational embeddedness in the steel and semiconductor industries'. *Strategic Management Journal*, **21**, Special Issue, 369–86.

Rowley, T. J., Baum, J. A. C., Shipilov, A. V., Greve, H. R. and Hayagreeva, R. (2004). 'Competing in groups'. *Managerial and Decision Economics*, **25**, 453–71.

Rowley, T. J., Greve, H. R., Hayagreeva, R. and Baum, J. A. C. (2005). 'Time to break up: social and instrumental antecedents of firm exits from exchange cliques'. *Academy of Management Journal*, **48**, 499–520.

Sampson, R. C. (2007). 'R&D alliances and firm performance: the impact of technological diversity and alliance organization on innovation'. *Academy of Management Journal*, **50**, 364–86.

Schumpeter, J. (1939). *Business Cycles: A Theoretical, Historical, and Statistical Analysis of the Capitalist Process*. New York: McGraw Hill.

Shannon, C. E. (1957). 'A mathematical theory of communication'. *Bell System Technical Journal*, **27**, 379–423.

Sidhu, J. S., Volberda, H. W. and Commandeur, H. R. (2004). 'Exploring exploitation orientation and its determinants: some empirical evidence'. *Journal of Management Studies*, **41**, 913–32.

Stevens, J. (1992). *Applied Multivariate Statistics for the Social Sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Stuart, T. E. (2000). 'Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high-technology industry'. *Strategic Management Journal*, **21**, 791–811.

Stuart, T. E. and Podolny, J. M. (1996). 'Local search and the evolution of technological capabilities'. *Strategic Management Journal*, **17**, Summer Special Issue, 21–38.

Teece, D. J., Pisano, G. and Shuen, A. (1997). 'Dynamic capabilities and strategic management'. *Strategic Management Journal*, **18**, 509–33.

Trajtenberg, M. (1990). 'A penny for your quotes – patent citations and the value of innovations'. *Rand Journal of Economics*, **21**, 172–87.

Uzzi, B. (1996). 'The sources and consequences of embeddedness for economic performance of organizations: the network effect'. *American Sociological Review*, **61**, 674–98.

Uzzi, B. (1997). 'Social structure and competition in interfirm networks: the paradox of embeddedness'. *Administrative Science Quarterly*, **42**, 35–67.

Walker, G., Kogut, B. and Shan, W. (1997). 'Social capital, structural holes and the formation of an industry network'. *Organization Science*, **8**, 109–25.

Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications*. New York: Cambridge University Press.

White, S. (2005). 'Cooperation costs, governance choice and alliance evolution'. *Journal of Management Studies*, **42**, 1383–412.

Williamson, O. (1985). *The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting*. New York: Free Press.