Benefiits and Risks of Strategic Collaboration: The Differential Role of a Firm's Network Structure in the Creation of Core and Non-core Technologies

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Abstract Most of the literature until now has emphasized and demonstrated the benefits of alliances for learning and innovation. Although it has been acknowledged that these competence-based benefits of collaboration may come at a price of elevated risks formed by knowledge spillovers and freeridership, such a governance view remains understudied. This study offers a coherent framework that combines the two perspectives and explains how a firm's alliance network structure affects both benefits as risks of collaboration and to what degree that differs between the creation of core and non-core technology. Based on an empirical test in three different industries (pharmaceuticals, chemicals and automotive), we predict and find that the differential effect of a firm's network structure on the creation of core and non-core technology depends on whether firms especially value the potential for reducing relational risks of collaboration (in case of core technology) or, alternatively, place more emphasis on competence based benefits formed by improved access to external knowledge and capabilities (in case of non-core technology). In this way, our study demonstrates that it is the combination of a competence and governance perspective that yields a more complete understanding of interfirm collaboration.
Key words risk, strategic collaboration, core technology, non-core technology

1 Introduction

A growing number of studies has shown that strategic alliances and interfirm networks are particularly relevant for innovation and the development of new technology (Hagedoorn, 1993; 2002; Ahuja, 2000; Hagedoorn and Duysters, 2002; Sampson, 2007; Gilsing et al., 2008; Padula, 2008). Alliances and interfirm networks enable the exchange of knowledge between partners that stimulate learning and facilitate its further recombination. However, the very same mechanism that brings a firm into contact with novel knowledge and proves to be instrumental in strengthening competitive advantage, may also damage it. Whereas knowledge spillovers are desirable from a competence perspective, they constitute a risk as seen from a governance perspective. Both views represent two different dimensions of collaboration (Williamson, 1999; Dosi and Marengo, 2000; Gilsing and Nooteboom, 2006). A competence view stresses the need for access to new knowledge, the combination of complementary competencies and the joint production of new knowledge. In contrast, a governance view stresses the need for managing relational risks due to opportunism and/or undesirable spillovers, which may diminish possibilities for appropriability of returns on innovation (Dhanaraj and Parkhe, 2006). In most of the literature until now, there has been a dominant focus on the competence side, whereas the governance side has been recognized but remains understudied (Gilsing and Nooteboom, 2006). In a recent study, Sampson (2007) combined the two perspectives and showed how the governance form in dyadic collaboration is not only critical for monitoring and control of opportunism but also affects in how far partners' complementary competencies can be successfully combined. In this paper we build on such a combined perspective, by looking at issues of both competence and governance, and propose that it is the combination of the two that yields a more complete understanding of interfirm collaboration.

In line herewith, this paper rests on the idea that competence-based benefits of collaboration come at a price of certain risks as seen from a governance view, formed by undesirable spillovers and freeridership. To understand this in more detail, we consider the structure of a firm's alliance network as this forms the conduit for knowledge flows: to and from the firm, to and from its partners, its partners' partners and beyond. To study the role of a firm's network structure in more detail, we follow Ahuja (2000) by considering not only a firm's local ego-based network (direct ties) but also the global network (indirect ties) as well as redundancy in the network (local and global). Considering direct ties and indirect ties is important as they may constitute not only sources of knowledge but also potential recipients of a firm's key expertise that may create a temptation to freeride. In addition, redundancy among ties is relevant as it increases the number of pathways for knowledge flows to and from direct and indirect ties as well as among them. In this way, we may develop a more comprehensive understanding of how a firm's alliance network structure affects knowledge flows in both desirable as undesirable directions. And what strategies firms can deploy so that benefits are secured while risks are mitigated.

Our focus lies on interfirm collaboration that is geared towards the creation of new technology. A key claim we make is that how a firm's alliance network structure affects the benefits and risks of collaboration differs between the creation of core technology and non-core technology. Following this, we predict and find that the differential effect of a firm's network structure on the creation of core and non-core technology depends on whether firms especially value possibilities for reducing relational risks (in case of core technology) or, alternatively, place more emphasis on competence based benefits formed by improved access to external knowledge and capabilities through collaboration (in case of non-core technology). In our empirical approach, we make use of a two-stage panel model that allows us to test for the assumption of structural exogeneity. Whereas previous studies basically leave this premise unquestioned, we argue that alliance network characteristics cannot be considered as fully exogenous variables. In fact, they may also be the outcome of prior managerial choices to stimulate the creation of new technology. In our estimations we correct for this endogeneity bias. Furthermore, we consider three different industries (pharmaceuticals, chemicals, automotive) that may enhance the generalisability of our findings.

2 Theoretical Background and Hypotheses

Central in this paper is the relationship between a firm's network structure and its creation of new core and non-core technology. This distinction between core and non-core technology relates to March's account (1991) on the difference between exploration and exploitation. Exploration entails searching for opportunities in areas that are new to the company. Within the context of technological innovation, this yields new technological innovations in areas that are novel to the firm. It leads to the creation of non-core technology that reflects a firm's future business and thus determines its continuity on the longer term (March, 1991). The creation of such technology requires an entrepreneurial search process in which firms look for more general information on developments and fields that are unfamiliar to them. 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). Exploitation entails the deepening of a firm's core technologies and yields technological innovations in areas with which the firm is intimately familiar. This leads to further improvements in a firm's core technology, which strengthens its existing business and secures short term revenue streams. In comparison with non-core technology, the creation of core technology requires a deep and precise understanding of specific information in stead of a wider grasp of more general information (Rowley et al., 2000; Gilsing and Nooteboom, 2006). Although a firm's alliance network may be instrumental for both tasks, the way in which it affects collaborative benefits and risks differs between them.

Creation of core technology represents a firm's core business and constitutes one of the key sources of competitive advantage, protecting its short term profit engines. In order to secure competitive advantage when collaborating, a key emphasis is put on the prevention of leakage of strategically sensitive knowledge to partners and indirect partners. So, in case of core technology, firms tend to attach more value to possibilities for reducing risks of collaboration relative to profiting from its benefits. In contrast, the creation of non-core technology deals with a firm's competitive advantage to secure future revenue streams. Here, avoiding knowledge leakage still remains an issue of concern but tends to be outweighed by the value attached to information benefits and resource sharing. The search for information on new areas beyond a firm's established domains of expertise implies that such information can only be acquired from external sources. As a consequence, firms have to accept here that access to new knowledge comes at a price of elevated risks of spillovers and freeridership. Moreover, as they have not developed deep pockets of knowledge yet, the risk of outgoing spillovers is small. Therefore, in case of the creation of non-core technology, firms tend to attach relatively more value to benefits relative to risks of collaboration.

As a next step, we will consider more in-depth in what specific ways a firm's alliance network structure - formed by its direct ties, indirect ties and degree of redundancy – affects benefits and risks of collaboration and to what degree that differs between the creation of core and non-core technology.

2.1 Direct ties

Technology collaboration with direct ties may provide two important benefits vis-à-vis internal development. One is that collaboration with direct partners provides access to complementary knowledge and skills. This is important as such complementary knowledge can speed up a firm's innovation process. In addition, it can serve as a test that enables firms to evaluate the quality and relevance of internally developed expertise (Powell and Brantley, 1992; Dyer and Nobeoka, 2000). A second benefit is that cooperation with direct partners may lead to reduced costs and risks for the firms involved (Ahuja, 2000; Das and Teng, 2001). When firms collaborate, the newly created knowledge becomes available to all firms involved. So, when making an investment in R&D a firm can, if collaborating with others, receive more new knowledge in return than in a stand alone scenario. In other words, R&D investments by its partner(s) may help to increase or speed up a firm's innovative output.

Although direct ties have an anticipated positive effect on a firm's innovative output, creating more of them will not always be better. In stead, increasing the number of partners may become counter productive, for three reasons. First, a large alliance portfolio creates a risk of dealing with many unfamiliar streams of knowledge that are increasingly difficult to integrate (Ahuja and Katila, 2004). Second, management attention and integration costs may grow exponentially beyond a certain number of alliances (Duysters and de Man, 2003), decreasing a firm's effectiveness in managing its alliance portfolio (Deeds and Hill, 1996). Third, the risk of spillovers or freeriders tends to grow with an increasing number of alliance partners. More partners implies more potential freeriders or at least more 'recipients' of spillovers while, simultaneously, resources and management time to monitor this need to be spread over a larger number of partnerships. Hence, we anticipate that marginal benefits of additional alliances will decrease whereas marginal costs of adding new alliances will increase (Ahuja, 2000). As a consequence, we expect an inverted-U shaped effect of the number of direct ties on the creation of core technology and non-core technology, albeit with two key differences.

As far as the creation of core technology is concerned, firms may have a strong preference for collaboration with direct partners. From a competence view, they allow firms to access and/or jointly develop specific information that is required for the creation of core technology. Here valuable, fine-grained pieces of information arrive directly at the focal firm and in this way leave little room for misinterpretation. On the governance side, direct partners are better controllable as they can be monitored directly. Moreover, direct partnerships provide room for the development of strong ties based on trust (Rowley et al., 2000), enhancing possibilities for control and limiting room for freeridership (Dhanaraj and Parkhe, 2006). In this way, collaboration with direct partners is beneficial from both a competence as governance view, leading to a strong positive effect of direct ties on the creation of core technology. Nevertheless, at high levels, direct ties will carry a negative effect as especially the risk of spillovers weighs heavily here.

Collaboration with direct partners is also beneficial for the creation of non-core technology, although to a somewhat lesser extent. Direct partners can provide a firm with more general information on new, unfamiliar domains. Nevertheless, it is not very likely that they can provide a fully comprehensive overview. Instead, they will provide more of a partial view so that solely relying on direct partners increases a danger that a focal firm misses out on key new developments in unfamiliar domains. So, one difference when compared with the creation of core technology is that the positive effect of direct ties will be smaller for the creation of non-core technology. From a governance view, the possibilities for control of direct partners are attractive although spillover risks form less of a key threat when compared with core technology. So, a second difference with creating core technology is that disadvantages of direct ties weigh less heavily. In sum, this leads to our first hypothesis:

Hypothesis 1a: Direct ties have a curvilinear effect (inverted-U shaped) effect on the creation of both core as non-core technology.

Hypothesis 1b: The positive effect of direct ties is expected to be stronger for the creation of core technology relative to non-core technology.

Hypothesis 1c: Beyo*nd the optimal number of direct ties, their negative effect is expected to be stronger for the creation of core technology relative to non-core technology.*

2.2 Indirect ties

Alliances can also be a channel of information between a focal firm and its indirect contacts, i.e. the partners of its partners (Mizruchi, 1989; Gulati, 1995a). Whereas direct ties serve as sources of both resources as information, indirect ties form primarily a source of information (Ahuja, 2000). As firms with their direct partners tend to specialize around a limited number of technologies, indirect ties can substantially increase possibilities for catching new information by acting as an information gathering and/or processing device (Ahuja, 2000). Through its indirect ties, a focal firm can receive information about relevant developments that are going on in its core and/or non-core areas. In this way, indirect partners may fulfill a 'radar' function in the sense of bringing more general information on relevant technological developments to the attention of the focal firm, far beyond its direct reach (Freeman, 1991; Ahuja, 2000), So, the benefits that a firm derives from its alliance network are not only determined by its direct ties but also by the number of indirect ties it can reach.

On the flip side, however, indirect ties may have disadvantages as well. First, the same mechanism that brings novel knowledge from indirect ties to the attention of the focal firm, also works in the opposite direction (Gulati and Garguilo, 1999). Knowledge that a focal firm develops in collaboration with a direct partner, may also unintentionally reach this partner's partner(s). In this way, ties to indirect partners may serve as a channel for the (unintended) spillover of knowledge held by the focal firm. As the tie is indirect, this may be very hard to monitor and prevent, let alone to enforce sanctions. Second, information from indirect ties may not be perfect but rather be 'noisy' in stead (Ahuja, 2000). It passes through a common partner, which may interpret and attach meaning to this information in a different way than the focal firm. In this process, fine-grained specificities may get lost and not reach the focal firm or be possibly misunderstood from his side. Given these specific benefits and risks of indirect ties, we anticipate an opposed effect on the creation of core technology relative to non-core technology.

In case of core technology creation, more indirect ties increase the likelihood of spillovers that may create a temptation on their side to freeride, with limited if any possibilities for monitoring and sanctioning this behaviour. Although indirect ties may offer additional new information, its more general nature, especially on a firm's core domains, increases the likelihood that a firm is already (well) familiar with the issues brought to its attention. In addition, this information tends to be imperfect and noisy, whereas the creation of core technology requires especially more specific, fine-grained information (Gilsing and Nooteboom, 2006). As a result, we expect the disadvantages from indirect ties to offset their benefits, yielding a negative effect on the creation of core technology.

In contrast, for the creation of non-core technology, information from indirect ties can be highly attractive as it may provide a firm with a more comprehensive overview on unfamiliar domains. In this way, the disadvantage of a partial view when relying on direct partners can be addressed as indirect ties may prevent that a focal firm misses out on key new developments. In addition, the more general and rather noisy nature of this information weighs less heavily relative to the creation of core technology whereas the risk of spillovers constitutes comparatively less of an issue. As a result, we expect a positive effect of indirect ties on the creation of non-core technology.

In sum, this leads to our second hypothesis:

Hypothesis 2a: Indirect ties have a negative effect on the creation of core technology.

Hypothesis 2b: Indirect *ties have a positive effect on the creation of non-core technology.*

2.3 Direct and indirect ties combined

By definition, direct ties serve as the bridge between the focal firm and its indirect ties. In other words, both ties operate in combination and should therefore also be considered jointly when assessing their effect on the creation of new technology. As argued, in case of core technology, information from indirect ties is generally less valuable. Furthermore, an increase in the combined number of direct and indirect ties leads to an accumulation of disadvantages, and especially enlarges spillover risks. We therefore expect that the negative effect of indirect ties on the creation of core technology becomes even stronger when the number of direct ties increases.

For non-core technology, firms highly value the large volume of information coming from direct and indirect ties although there is an increasing likelihood of overlap in the information received. Although also here disadvantages of both types of ties add up, this weighs less heavily in comparison with the creation of core technology. As a result, we predict that the positive net-effect of indirect ties remains, but that it will weaken in combination with direct ties.

In sum, this leads to our third hypothesis:

Hypothesis 3a: The effect of indirect ties on the creation of core technology will be moderated by the number of direct ties: the more direct ties, the stronger the negative effect of indirect ties.

Hypothesis 3b: The effect of indirect ties on the creation of non-core technology will be moderated by the number of direct ties: the more direct ties, the smaller the benefit of indirect ties.

2.4 Redundancy among ties

The degree of redundancy among ties relates to an ongoing debate in the literature on whether network ties should be redundant or non-redundant. According to Burt (1992a), there are costs associated with maintaining contacts and efficiency can be created in the network by shedding off redundant ties and selectively maintaining only a limited set of ties that bridge 'structural holes'. This view is at odds with the social capital theory of Coleman (1988, 1990), which claims that firms benefit most from cohesive (or redundant) ties with their alliance partners. Density (or 'closure') facilitates the role of social capital such as the build up of reputation, trust, social norms and social control. Following this debate, we consider which view has more validity when comparing the creation of core and non-core technology.

For the creation of core technology, we predict a positive effect of a non-redundant structure. From a competence perspective, more non-redundant ties increase the likelihood of providing access to unique and valuable knowledge. From a governance perspective a non-redundant structure is beneficial as it diminishes or potentially even nullifies room for spillovers between direct ties, indirect ties and beyond. Although redundant ties bring possibilities for trust and control, relying on non-redundant partners may be more attractive as it is generally better 'to prevent than to cure' in case of core technology. Furthermore, being amidst non-redundant partners increases the chance of possessing a central position that bridges structural holes. Such a position provides a firm with ample possibilities to control resource and information flows between its partners (Burt, 1992b). Although redundancy carries a potential for triangulation (Rowley et al., 2000), this may not be particularly attractive regarding core technology. Here, a firm is already highly knowledgeable and does not need to rely heavily on external absorptive capacity as shared with its partners. The more so, as it would increase the risk of spillovers in stead. So, a non-redundant structure offers clear benefits from both a competence as governance perspective.

In contrast, for the creation of non-core technology, the value of a non-redundant structure seems to be less obvious. On the one hand, a non-redundant structure provides a firm with access to novel information that can be highly valuable for the development of non-core technology. The limited room for spillovers as offered by a non-redundant structure may also be attractive, although to a lesser extent in comparison with core technology. On the other hand, a redundant structure might possibly be attractive as it could offer room for triangulation as well as the build-up of shared absorptive capacity that may be highly useful when dealing with novel information in unfamiliar fields. Furthermore, the potential for the build-up of trust as offered by redundant partners may not only constitute an alternative way to control outgoing spillovers but also create possibilities for sanctioning freeridership. As a result, we have arguments pointing in both directions for the creation of non-core technology. Nevertheless, we expect that getting access to novel information is crucial for the development of non-core technology and that, as a consequence, the benefits of *non-redundant* structure outweigh the triangulation and trust-building benefits of a *redundant* network structure. Hence, we anticipate a non-redundant structure to be valuable for the creation of non-core technology, although to a lesser extent when compared with core technology creation.

In sum, our final hypothesis is as follows:

Hypothesis 4a: Non-redundancy of a focal firm's network structure has a positive effect on the creation of core technology and non-core technology.

Hypothesis 4b: This positive effect is stronger for the creation of core technology relative to non-core technology.

3 Data, Variables and Modeling

3.1 Data

We tested the hypotheses on panel data including the alliance and patenting activities of companies that were active during the period 1987-1996 in the chemicals, automotive or pharmaceutical industries[18]. In these three industries not only R&D-investments and innovations but also technological

[18] SIC codes are respectively: 281/282 (281:Industrial Inorganic Chemicals; 282: Plastics Materials and Synthetic Resins); 3711 (Motor Vehicles & Passenger Car Bodies); 2834 (Pharmaceutical Preparations).

alliances with different partners are crucial to survive. Moreover, there is a strong appropriability regime in these industries favoring the use of patents as a legal instrument to capture value from technological breakthroughs (Breschi et al., 2000; Ahuja, 2000; Rothaermel and Deeds, 2004). As a result, patents can be considered as a good indicator for firms' innovation output. Testing the hypotheses in three different industries should provide a more reliable insight in how far the relationship between a firm's alliance network and the development of core and non-core technology remains invariant across industries, enhancing the generalisability of the results.

The database includes in total 116 focal firms in the three industries for a 12-year period, from 1986 until 1997. The panel is unbalanced because of mergers and acquisitions on the one hand and a few spin-offs and divestments on the other hand. As a result, the number of focal firms slightly varies each year: there were on average 95 publicly traded companies each year in the sample[19]. Data about technological alliances were retrieved from the MERIT-CATI database, which contains information on nearly 15 thousand cooperative technology agreements and their 'parent' companies, excluding production and marketing alliances, covering the period 1970-1996 (see Hagedoorn and Duysters (2002) for a further description). For most alliances, the MERIT-CATI database does not provide information when they are terminated. For that we have followed the assumption of a lifespan of 5 years, in line with most previous studies on technology alliances (Kogut, 1988; 1989; Bleeke and Ernst, 1995). More specifically, we chose for a moving window approach, in which alliances were aggregated over the five years prior to a given year, unless the alliance database indicated another lifespan (Gulati, 1995b)[20].

Direct ties, indirect ties and network structure measures were calculated based on the adjacency matrices that were constructed from the MERIT-CATI database about R&D based inter-firm alliances. Following an average lifespan of 5 years for the technology alliances, an alliance matrix was constructed for each year per industry, counting all the technology-based alliances that were established by the firms during the five-year period prior to the year of observation.

The patent data were retrieved from the US Patent Office Database for all the companies in the sample. Especially in industries where companies operate on an international or global scale, U.S. patents may be a good proxy for companies' worldwide innovative performance (Griliches, 1990).

The financial data of the focal firms in the three industries come from a combination of sources formed by Worldscope, Compustat and data published in companies' annual reports. Alliances are established and patents granted both on subsidiary as well as on parent company level. Therefore, we consolidated all data on the parent company level for each firm-year unit of observation, using 'Who Owns Whom' published by Dun & Bradstreet.

3.2 Variables

3.2.1 Dependent variables. To find out whether a new patent in a particular year reflects new core technology or new non-core technology, we calculated technological profiles of all focal companies in the sample. These profiles were created by adding up the number of patents a firm received in each patent class during the five years prior to the year of observation[21]. All classes in which a company had successfully applied for a patent during the previous five years, were labeled as *'core'* patent classes. Classes in which a company received a patent in the year of observation but did not receive a patent in the previous five years were considered *'non-core'* patent classes[22] [23]. Since knowledge in these

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[19] Previous studies on inter-firm alliances also focused on the industry leaders (Ahuja, 2000; Gulati, 1995b; Gulati and Garguilo, 1999).

[21] Different scholars have argued that a moving window of 5 years is an appropriate timeframe for assessing the technological impact of prior inventions (Podolny and Stuart, 1995; Stuart and Podolny, 1996; Ahuja, 2000). Studies about R&D depreciation (Griliches, 1979, 1984) suggest that knowledge capital depreciates sharply, losing most of its economic value within 5 years. The USPTO-classes were determined at three-digit level, which resulted in approximately 400 classes.

[22] Most patents are assigned multiple patent classes. In order to classify patents into either core or non-core patents we have only used the patent's main class designation ignoring the secondary class designations. Relying on the main class designation is of course a simplification. In most instances, patents are assigned to a combination of old and new patent classes, which allows for different grades of core versus non-core, instead of a dichotomous division between the two. This is a possible way for future research but goes beyond the scope of the current paper.

[23] We chose the year when the company filed for the patent rather than the year when it was granted, because the innovation already materialized when the company filed for a patent.

non-core patent classes remains relatively new for the firm immediately after it applied for a patent, we considered these patent classes as 'non-core' for a period of three years (in line with Ahuja and Lampert's (2001) concepts of novel and emerging technologies[24]).

The dependent variables 'core technology' and 'non-core technology' were constructed in two steps. First, patents were weighed according to the forward citations they receive (Trajtenberg, 1990), based on the assumption being that more important patents receive more citations. 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; 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). In order to correct for right censoring we estimated the number of citations that patents would receive over their life-span, based on the number of citations they received using Hall et al.'s (2001) simulated cumulative lag distribution tables.[25] Second, the two dependent variables were calculated by adding up weights of patents that were successfully applied for in the year of observation in core and non-core patent classes respectively[26].

3.2.2 Independent variables. Following our theoretical argument, the impact of an innovating firm's alliance network.on the creation of core and non-core technology should be decomposed into *direct ties, indirect ties* and the *redundancy of ties*.

Direct ties: This variable is proxied by the number of allies to whom the focal firm is directly connected to (i.e., the size of the ego-network)[27]. We also introduce the squared term of the number of alliance partners to test for an inverted U-shaped relationship in hypothesis 1a.

Indirect ties: The second dimension of a company's alliance network consists of the number of partners it can reach indirectly. There are different ways to operationalize indirect ties. We chose for a variable that measures the impact of indirect ties while taking into account the decline in tie strength of more distant ties. We operationalize this variable using the 'distance weighted centrality' measure, as provided by Burt (1991). The variable "… attaches weights of the form $1 - (f_i/(N+1))$ to each tie, where f_i is the total number of partners that can be reached up to and including the path distance i, and N is the total number of firms that can be reached by the focal firm in any number of steps" (Ahuja 2000: p. 438). The result is that alliance partners receive smaller weights the longer the path distance to the focal firm. This variable is calculated by adding up all alliances at several distances weighted by their path distances. Other network centrality measures such as betweenness or Bonacich centrality are valuable alternatives but they do not weigh indirect ties as Burt's measure does. We only report the findings for the distance-weighted centrality measure[28]. We mean-centered the direct and indirect tie variables to reduce the potential threat of collinearity when squared terms and interaction terms are introduced (Aiken & West, 1991).

Redundancy[29]: We chose '*network efficiency*' of a firm's ego-network as a measure of non-redundancy (Burt, 1992a: chap. 2) and is calculated by dividing the 'effective size' (a variable

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24 In order to test the robustness of the operationalization of non-core patents, we also constructed a 'non-core patents'-variable where new patents could keep this 'non-core' status for 5 years instead of 3 years. The empirical results in table 3 do not change when the dependent variables are calculated in this way.

25 The NBER citations database was used to determine patterns of citations (Hall et al., 2005). We adopted a nonlinear weighting scheme, assuming that the marginal informational content increases with the number of citations, as suggested in Trajtenberg (1990).

27 Another possibility is to use the degree centrality of the focal firm (number of alliances between the focal firm and its alliance partners).

28 We tested the robustness of the findings with betweenness and Bonacich centrality measures and obtained similar results.

29 The literature offers several possibilities to operationalize (non-)redundancy of alliances (Burt, 1992a; McEvily and Zaheer, 1999; Gulati, 1999; Ahuja, 2000; Baum et al., 2000). We refer to Borgatti et al. (1998) for an extensive analysis of network measures that can be used to formalize the notion of redundancy.

measuring the number of non-redundant ties in a firm's ego-network by subtracting the redundancy in the network from the number of partners the focal firm is connected to) by the number of partners in the firm's ego-network. This efficiency ratio ranges "…from a maximum of one, indicating that every contact in the network is non-redundant, down to a minimum approaching zero, indicating high contact redundancy and therefore low efficiency" (Burt, 1992a: p. 53)[30].

Apart from redundancy based on cohesion, redundancy can also be based on *structural equivalence* as argued by Burt (1992a, b). A variable that captures redundancy by structural equivalence has been provided by Hansen (1999). Two alliances of the focal firm are structurally equivalent to one another when these two partners are connected to the same other firms in the (overall) alliance network apart from the alliances with the focal firm[31]. Structural equivalence can then be calculated based on Euclidean distance (Wasserman and Faust, 1994: p. 367)[32]. Euclidean distances can be converted into a redundancy measure by taking the average of the Euclidean distances between pairs of direct partners (allies) of the focal company: high values for this variable indicate that the focal firm has alliances with partners that are not structurally equivalent and thus give the firm non-redundant information.

3.2.3 Control variables. There may also be other factors that affect the creation of core and non-core technology. We included three types of dummy variables. A first one indicates where the company is headquartered. Following the Triad-concept of the world economy, a company can be headquartered in North America, Asia or Europe - the default is the North America (Ohmae, 1985). Next, we included a dummy variable to indicate whether a company is a car manufacturer or a chemical firm (default is the pharmaceutical industry). Finally, we introduced yearly dummy variables to capture changes over time in the propensity of companies to patent their innovations.

Furthermore, we include three organizational variables as controls[33]. The first one is the age of the company, which may differentially affect a firm's ability to create core or non-core technology.

Next, the natural logarithm of 'corporate revenues' was included to control for the size of the focal firm. R&D intensity is another control variable. Assuming that there exists a positive correlation between technological input and output (Pakes and Griliches, 1984), we expect that firms that invest heavily in R&D will have a higher rate of innovation.

Technological diversity between the firm's partners in the alliance network is also included. If a firm's allies are active in widely different technological fields, they may remain unconnected, generating structural holes in a focal firm's alliance network (Ahuja, 2000). As a result, structural hole measures might reflect the negative impact of technological distance between its allies rather than social structural effects as postulated in hypotheses 4a and 4b. Following Yao (2003), we take the sum of each dyadic distance between a firm's direct contacts and divide the value by the total number of direct alliances of the firm.

3.2.4 Model estimation The two dependent variables are citation weighted patent counts. Using a Poisson regression is a standard approach to analyze count data models (Hausman et al., 1984; Henderson and Cockburn, 1996). However, a Poisson distribution assumes that the mean and variance of the event count are equal, an assumption which is likely to be violated as weighted patent count data usually suffer from overdispersion[34]. Hence, we use negative binomial regression models to predict innovative performance of the firms in core and non-core technologies.

Since we have panel data with repeated observations for the same firms, a bias can occur as observations for the same firm can be correlated. Within-firm correlation usually reduces the variance of

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30 Following Burt we developed different measures for (non)-redundancy. Based on cohesion we also calculated redundancy by 'proportion density' (Burt, 1983; Hansen, 1999) and 'network constraint' (Burt, 1992a).

31 Remark that redundancy measures based on structural equivalence take into account properties of the network structure that go *beyond* the characteristics of the ego-network of the focal firm.

32 Hansen (1999, p. 96) and Wasserman and Faust (1994, p. 367):

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

33 Those variables were calculated for the year prior to the year of observation.

34 We calculated the Lagrange multiplier test for overdispersion. this test the Poisson assumption (equality of mean and variance) against the negative binomial model (Cameron and Trivedi, 1986). The results indicate that the effects of overdispersion are statistically significant.

the parameters leading to an overestimation of the significance of the covariate effects. Therefore, we estimate the negative binomial model using the GEE (Generalized Estimating Equations) approach (Liang and Zeger, 1986). This estimation method does not account for unobserved heterogeneity, i.e. the possibility that firms identical on measured characteristics still differ on unmeasured characteristics. Heterogeneity among firms may stem from differences in underlying innovation capabilities, leading to differences between firms in their propensity or ability to deepen their core technologies and/or to explore new technological fields. To control for such unobserved heterogeneity, we followed the presample panel approach developed by Blundell et al.(1995); we included the prior stock of (citation weighted) core and non-core patents of the five year period prior to the year of observation. By including the values of the two dependent variables in the period immediately preceding the observation year, we construct an instrumental variable which serves as a 'fixed-effect' for the firms in the sample. In other words, presample information on the firms' prior core an non-core technological capabilities provides a basis to control for unobserved heterogeneity.

Another issue is that prior expertise in both core as well as non-core technologies may be mutually related, in line with the ambidexterity literature (Tushman and O'Reilly, 1996; O'Reilly and Tushman, 2004, 2007; Jansen et al 2005a, b). A firm's expertise in core domains forms the base for its absorptive capacity (Cohen and Levinthal, 1990) and may thus also affect the degree in which non-core knowledge is created. Likewise, newly developed knowledge, in non-core domains, may possibly also affect the further development of existing expertise in core domains. Therefore, we also included the (citation weighted) patent stock in core-technologies of the 5 year period preceding the year of observation in the regression explaining the creation of core technology. Similarly, we introduced the of the (citation weighted) patent stock in non-core technologies in the regression explaining the performance in core-technologies.

Finally, the three characteristics of alliance networks (direct ties, indirect ties and redundancy) cannot be considered as fully exogenous variables (Reagans et al., 2005). Network characteristics can be considered as the result of deliberate actions by the focal firm (and its partners). More specifically, such actions may reflect a firm's strategic choice regarding the emphasis it puts on the development of core technology and/or non-core technology. This is the classic endogeneity problem: an unobserved (omitted) variable jointly causes both the dependent and independent variable; while both significantly covary, such covariation is spurious (Reagans et al., 2005; Hamilton and Nickerson, 2003). Consequently, there are strong a priori reasons to believe that direct ties, indirect ties and redundancy are (partially) endogenously determined. Direct ties are obviously the outcome of deliberate actions of the innovating firms. They establish new alliances to improve their innovation performance, to seize the business opportunities associated with emerging technologies and to react to actions of their partners (e.g. the establishment of an alliance with a competitor of the focal firm). Firms can also influence the number of indirect contacts by choosing whether they partner with highly centralized firms or isolates. Similarly, the level of redundancy in its (ego-)network can be influenced by (not) choosing partners that have already ties with its existing partners[35].

To address the potential endogeneity problem between the creation of new technology and these network characteristics, we will adopt a two-step estimation procedure (Cassiman and Veugelers, 2002). In a first step, the three characteristics of the focal firms' alliance portfolio are regressed on all *assumed* exogenous variables. In the second step, the predicted values of the three endogenous variables are included as independent variables in the structural equations (Table 3).

4 Results

Table 1 and 2 represent respectively the description of the different variables and the descriptive statistics and correlation matrix. Correlations between the explanatory variables are ranging from low to moderate. Direct ties and structural equivalence are to some extent positively correlated to each other and to the citation weighted patent stock in core technologies[36].

Table 3 represents the results of the regression analysis using negative binomial estimations respectively for the creation of core and non-core technology. According to the two step approach to

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[35] Controlling redundancy based on 'structural equivalence' is more difficult, especially in the short term.

[36] Values for VIF tests indicate that the level of multi-collinearity between the explanatory variables in Table 3 does not exceed threshold values.

correct for endogeneity, we use the predicted values for direct ties, indirect ties and redundancy based on regressions that included, as independent variables, overall network characteristics, industry level variables such as industry level R&D, and firm level variables[37].

Models 1a and 1b represents the basic model including only control variables. Models 2a and 2b introduce the linear and quadratic term of the direct ties. Following a stepwise regression method, we introduce first indirect ties and their interaction term with direct ties in model 3a and 3b, followed by non-redundancy measures in model 5a, 5b, 6a and 6b. The results remain stable throughout the different models, indicating that the results are robust and enhancing confidence in our empirical findings. In the remainder of our analysis we only consider the full models 6a and 6b.

Hypothesis 1a is confirmed. Direct ties have the predicted curvilinear effect on both the creation of core as non-core technology. More specifically, we see that the impact for the linear term of direct ties is much stronger for core technology than for non-core technology, conform hypothesis 1b. According to model 6a, direct ties have a maximal impact on core technology at 37, ties (when indirect ties are kept at the mean level). For non-core technology this maximum is reached at 33 ties. At that point, direct ties lead to an increase in core technology creation of 125%, compared to only 37% for non-core technology. In addition, we find that beyond the optimal level, the negative effect of too many direct ties becomes evident. We also found empirical evidence for hypothesis 1c. Following models 6a and 6b we calculated the impact of direct ties at the optimum and at two standard deviations from the optimum (optimum + 2 std).[38] Figure 1 shows nicely that innovative output formed by newly created core technology declines at a much faster rate than for non-core technology, when the number of direct ties increases further. As a result, we find empirical evidence to support hypothesis 1c: moving away from the optimal number of alliances has bigger repercussions for core-technology compared to non-core technology.

Moreover, the number of technology alliances at which the innovative performance reaches its maximum is similar for the creation of core technology and non-core technology and the number is declining with increasing number of indirect ties: for core technology the optimal number of direct ties ranges from 48 to 22 respectively when indirect ties increase from 0 to 140. For non-core technology these figures range from 48 to 18. These maxima decrease because of the negative interacting term and that these maxima shift depending on the number of partners a firm can reach indirectly with its portfolio of direct ties.

Hypothesis 2 is partially confirmed. We find that the expected positive effect of indirect ties on the creation of non-core technology is clearly confirmed, conform hypothesis 2b. In contrast, hypothesis 2a predicting a negative effect of indirect ties on the creation of core technology is not confirmed as the coefficients remain insignificant. An explanation for this unexpected finding may be as follows. Although indirect ties are generally considered as less attractive for the creation of core technology, they may in some cases also offer a specific benefit. Instead of a generally passive stance towards indirect ties by waiting until these 'radars' pick up on something, firms may occasionally also take on a more active role. When confronted with a specific problem in its core domain, a firm may decide to activate its network to search for those sources that may be highly knowledgeable on the specific issue at hand (Freeman, 1982). In this way, firms can circumvent the drawback of more general information coming from indirect ties and benefit from their specific expertise. While remaining very careful in their reliance on them, this specific benefit may lead firms to make use of indirect ties on an incidental basis. Although for indirect ties, as a general rule, more importance is attached to reducing risks relative to accessing information, the value of highly specific and scarce information may occasionally outweigh the risks, leading positive and negative effects of indirect ties to cancel out in their effect on core technology creation.

Hypothesis 3a predicts that the effect of indirect ties is negatively moderated by the number of direct ties. Our findings in models 6a (???) provide evidence for hypothesis 3a in the case of the creation of core technology, predicting the combined effect of direct and indirect ties to be negative for the creation of core technology. In other words, we find that indirect ties have a negative effect on the development of core technology the larger the number of direct ties that connect the focal firm and its allies' partners. In contrast, hypothesis 3b is not confirmed since the coefficients for the interaction term

[37] These regressions can be obtained from the authors.

[38] Following model 2 we also find evidence for hypothesis 1c: The impact of the number of direct ties on core technology decreases with 8.2% when a company establishes more alliance with partners beyond the optimum (two standard deviations from the optimum). This is only 2.8% in the case of non-core technology.

are not significant in all models. The explanation for this unexpected result may be that firms attach even more value to any piece of new information in non-core domains than we anticipated, whereas they seem to worry less about potential spillovers as non-core technology is not at the heart of their cash-generating business. Seen in this way, the strategic need to develop a fully comprehensive overview on unfamiliar domains seems to outweigh the increasing risk of spillovers and the growing likelihood of overlap in information received. Figures 1 and 2 visualize how the interaction between direct and indirect ties influences firms' innovativeness, for core and non-core technologies respectively.

The figures show that the creation of core versus non-core technology requires two different alliance network strategies. In case of core technology, an optimal strategy is formed by many direct ties with a minimal number of indirect ties, yielding an increase in innovative output of more than 250%. See also figure 2. However, a company can also establish alliances with *few* partners that have themselves extensive alliance networks with other firms – this strategy is however has a lower payoff than the previous strategy. Firms should in any case avoid to combine a large network of direct partners that bring them into contact with a large number of indirect partners. The situation is quite different for the creation of non-core technology. Here, we find the optimal strategy in the back of figure 3, formed by a combination of a fairly small number of direct ties that connect the firm to a broad range of indirect partners, yielding a maximum increase in innovative output of about 150%. When comparing both figures, we can conclude that the two optimal strategies for combining direct and indirect ties differ profoundly between the creation of core vs. non-core technology: creation of core technology requires a large number of direct partners who are not connected to many other firms in the network, whereas the creation of non-core technology requires a limited number of partners that are well connected.

Hypothesis 4 specifies the effect of a non-redundant structure among a firm’s ties. Here, we find clear evidence for hypothesis 4a that predicts a non-redundant network structure to have a positive effect on the creation of core technology. This is true both on the local (ego)-network level, as measured by ‘network efficiency’, as well as on the overall alliance network level, measured by (the lack of) structural equivalence. In contrast, we do not find a significant effect in the case of non-core technology. This may not be entirely surprising as we already argued that both a redundant as non-redundant structure seem to offer value here. In line with this, it may be that some firms in our sample place more value on access to new information and control of spillovers, at the expense of possibilities for the build-up of trust and shared absorptive capacity, and therefore prefer a non-redundant structure. Whereas other firms in our sample make this trade-off into the opposite direction and thus have a preference for a redundant structure. The lack of a significant effect may be indicative of this idea, suggesting that the role of (non-) redundancy seems to be less clear cut for the creation of non-core technology.

5 Discussion and Conclusions

The key topic of this paper has been to understand how a firm’s alliance network structure affects both benefits as risks of collaboration and to what degree that differs between the creation of core and non-core technology. To understand this, we have considered three properties of a firm’s alliance network: its direct ties, indirect ties and degree of redundancy.

Key to understanding the differential effect of each of these network properties is the degree in which they offer value, or alternatively form a liability, from a competence and/or governance perspective. In case they offer value from *both* perspectives, they yield a strong *positive* effect on the creation of new technology. This explains the positive effect of direct ties before the optimal number of alliances is reached, for the creation of both core as non-core technology. In addition, this also applies to the positive effect of local and global non-redundancy on the creation of core technology. Likewise, when a firm’s alliance network property forms a liability as seen from both perspectives, they yield a strong *negative* effect on the creation of core and non-core technology. This explains the clear negative effect of direct ties beyond the optimal number of alliances, both for core and non-core technology. In addition, it explains the negative effect of indirect ties on core technology creation when jointly considered with direct ties.

However, once a structural property offers value from only one perspective whereas it forms a liability as seen from the other, some apparent differences emerge when comparing the creation of core technology and non-core technology. Indirect ties may offer information benefits for the creation of non-core technology but come at a price of elevated risks of spillovers and room for freeridership. Here, we predict and find that, for non-core technology creation, the value of indirect ties from a competence perspective outweighs their liability as seen from a governance perspective. In contrast, for core technology creation, indirect ties are particularly unattractive from a governance view, which we anticipated to outweigh the value from a competence view. The empirical results here were non-significant suggesting that in the case of core technology both effects are on par so that they cancel out each other. The difference with the strong positive effect for non-core technology is clear, suggesting that governance considerations weigh more heavily for the creation of core technology relative to non core technology.

In a similar way, this also applies to the differential effect of direct ties as a moderating variable influencing the impact of indirect ties on innovative performance. In case of core technology, they form a liability from both a competence as governance view, which was corroborated by the negative effect we found. In case of non-core technology, however, direct and indirect ties combined may offer value from a competence view but constitute a liability from a governance view. The empirical results were insignificant suggesting that both effects cancel out each other in the case of non-core technology. The difference with the negative effect in case of core technology suggests that competence considerations weigh more heavily for the creation of non-core technology relative to core technology.

Based on the above, we can draw three conclusions. First, once considerations of competence and governance converge in terms of either offering value or forming a liability – as seen from both perspectives - the differential effect of network structural properties on the creation of core and non-core technology is one of degree. Second, once a structural property offers value from one perspective whereas it forms a liability as seen from the other, its differential effect on the creation of core and non-core technology seems to become more one of kind. Third, a network property that neither offers evident value nor constitutes a heavy liability from any of the two perspectives will have no effect on the creation of new technology (i.e. local and global redundancy in relation to creation of non-core technology).

Most of the research until now has assessed the value of alliances from a competence perspective. This has yielded a growing understanding to what extent and how alliances affect interfirm learning and the creation of (technological) innovations (Powell et al., 1996; Hagedoorn, 2002; Faems et al., 2005; Padula, 2008). Our study forms an important complement to this literature by explicating how competence-based benefits of collaboration come at a price of certain risks as seen from a governance view. More specifically, we offer a coherent framework that combines the two perspectives and explains under which conditions collaborative risks may offset or even nullify the value of collaborative benefits. Seen in this way, Ahuja's (2000) conclusions do not hold when distinguishing between the creation of core and non-core technology, since each requires a different alliance network structure. In addition, the positive effect of non-redundancy on the development of core-technology contradicts the positive effect of redundancy as found by Ahuja (2000). This difference may be attributed to the fact that Ahuja has used raw patent counts as dependent variable in stead of citation-weighted patents as we did. In other words, the higher the (economic) value of new technology, the more important it becomes to protect it (in case of core technology) through a non-redundant structure.

The current study also creates options for future research. First, core and non-core technologies have been operationalized in a particular way. Another way of operationalisation could be formed by means of differences in technological distances between patent classes (Nooteboom et al., 2007). In this way, the current dichotomous approach toward core and non-core technologies could be further improved upon by a continuous approach measuring the distance to a firm's existing technology core. Second, future studies should also combine the two processes of intra- and interorganizational learning to get a better understanding of how firms should be organized internally to improve knowledge acquisition and learning from alliance partners (Holmqvist, 2003, 2004)Finally, the discussion about core and non-core technology can be easily extended to other industry contexts where (not technology but) other types of competencies drive the creation of competitive advantages. Whether firms' competitive strengths stem from technology, design, brands or business modeling, they all face the need to renew the company through new business development.

Overall, this study has shown how firms can make use of their alliance network so that benefits are secured while risks are mitigated, and how that differs between creating core and non-core technology. Following our findings, we found support for both competence-based as governance-based arguments, suggesting a complementarity between the two approaches. In this way, we have demonstrated that it is the combination of both a competence as governance perspective that yields a more complete understanding of interfirm collaboration.

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Table 1 Definitions of dependent and independent variables

Variable name	Variable description
Core technology patents variable	Citation weighted number of patents a firm filed for in year t within patent classes in which is has been dependent active in the five years prior to the given year t
Non-core technology patents variable	Citation weighted number of patents a firm filed for in year t within patent classes in which is has dependent not been active in the five years prior to the given year t
Core technology patent stock	Cumulative lagged dependent variable (core technology) for the 5 year period preceding year t
Non-core technology patent stock	Cumulative lagged dependent variable (non-core technology) for the 5 year period preceding year t
Direct ties	Number of partners to whom a focal firm is connected to (standardized variable)
Indirect ties	'Distance weighted centrality': Number of indirect ties but weighted to account for the decline in tie strength across progressively distant ties (standardized variable)
Network efficiency	'Effective size' divided by the number of partners in the focal-firm's ego-network (Burt, 1992a, p. 53)
Structural equival.	Average Euclidean distance of every pair of profiles of the direct partners of the focal firm (Hansen, 1999)
Age	The number of years since a company is founded in year t-1
Size	Natural logarithm of annual sales
R&D intensity	Natural logarithm of one plus R&D expenditures as a percentage of annual sales
Technological distance between partners	Average technological distance among a focal firms' alliance partners (Yao, 2003)
Year	Dummy variable indicating a particular year (1987-1997) (1997 is the default)
Chemical company	Dummy variable set to one if the firm is a chemical company (Pharmaceutical industry is the default)
Car manufacturer	Dummy variable set to one if the firm is a car manufacturer (Pharmaceutical industry is the default)
Europe	Dummy variable set to one if the firm is headquartered in Europe (US is the default)
Asia	Dummy variable set to one if the firm is headquartered in the Asia (US is the default)
YearDummy variable indicating a particular year (1987-1997) (1997 is the default)	

Notes: All independent and control variables are lagged 1 year to avoid simultaneity problems.
All network variables are based on alliance network representing all the technology-based alliances that were established in an industry during the five years prior to year t

Table 2 Descriptive statistics and correlation matrix

	Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Core technology patents	1777.9	2340.4	0	15239													
2	Non-core technology patents	91.6	123.3	0	1311	0.53												
3	Direct ties	14.06	14.93	1	113	0.58	0.32											
4	Indirect ties	67.68	32.49	0	177	-0.07	-0.15	-0.16										
5	Network efficiency	0.877	0.183	0	1	0.19	0.06	0.06	0.21									
6	Structural equivalence	0.420	0.164	0	0.879	0.52	0.31	0.40	-0.03	0.23								
7	Age	79.66	46.21	0	237	0.24	0.10	0.12	0.01	-0.02	0.11							
8	Firm size (ln)	8.711	1.665	0.29	11.91	0.44	0.26	0.43	-0.22	-0.07	0.33	0.36						
9	R&D-intensity (ln)	9.411	0.437	8.60	10.25	-0.06	-0.06	-0.05	0.17	0.03	-0.01	-0.14	-0.38					
10	Techn. distance partners	0.022	0.008	0	0.029	0.05	-0.04	-0.11	0.27	0.19	-0.08	0.06	-0.10	0.02				
11	Core technology pat. stock	7766	10849	0	66088	0.96	0.51	0.60	-0.07	0.19	0.52	0.24	0.44	-0.05	0.05			
12	Non-core technology pat. stock	444.1	438.6	0	2631	0.54	0.56	0.37	-0.11	0.06	0.34	0.12	0.27	-0.06	-0.07	0.60		
13	Chemical company	0.372	0.483	0	1	0.03	0.01	-0.04	-0.09	-0.04	0.00	0.16	0.08	-0.09	-0.17	0.09	0.04	
14	Car manufacturer	0.278	0.449	0	1	0.05	0.11	0.23	-0.34	-0.23	0.07	0.04	0.38	-0.07	-0.16	-0.03	0.14	-0.48
15	European firm	0.249	0.427	0	1	-0.28	-0.12	0.00	-0.09	-0.13	0.02	-0.02	0.05	0.07	-0.12	-0.26	-0.20	-0.17
16	Asian firm	0.325	0.471	0	1	-0.03	-0.07	0.01	-0.11	-0.10	-0.04	0.06	0.15	-0.07	-0.07	-0.03	-0.10	-0.01
17	Year 1986	0.082	0.274	0	1	-0.05	0.01	-0.09	-0.26	-0.03	-0.05	-0.05	-0.05	-0.02	0.01	-0.06	-0.05	0.01
18	Year 1987	0.086	0.281	0	1	-0.04	0.02	-0.06	-0.24	-0.03	0.01	-0.04	-0.02	-0.02	-0.02	-0.06	-0.03	-0.00
19	Year 1988	0.080	0.271	0	1	-0.00	0.05	-0.03	-0.08	-0.04	002	-0.03	-0.04	-0.01	0.00	-0.03	-0.00	-0.02
20	Year 1989	0.080	0.271	0	1	0.04	0.01	0.00	-0.03	-0.03	0.05	-0.02	-0.04	-0.02	-0.09	-0.02	-0.01	-0.01
21	Year 1990	0.086	0.281	0	1	-0.01	0.06	0.02	-0.01	-0.01	0.02	0.01	-0.02	-0.02	-0.08	-0.02	-0.00	-0.00
22	Year 1991	0.086	0.281	0	1	0.04	0.01	0.01	0.00	0.06	0.01	0.02	-0.01	-0.01	0.01	0.05	0.04	-0.00
23	Year 1992	0.081	0.274	0	1	0.03	-0.06	-0.01	0.03	0.07	0.00	0.04	0.02	-0.02	-0.02	0.05	0.05	-0.00
24	Year 1993	0.084	0.278	0	1	0.02	-0.02	0.02	0.01	0.03	-0.01	0.04	0.02	-0.02	0.02	0.03	0.03	-0.00
25	Year 1994	0.081	0.274	0	1	0.02	-0.02	0.01	0.09	0.02	-0.03	0.02	0.01	0.00	0.06	0.01	0.02	-0.00
26	Year 1995	0.084	0.278	0	1	0.05	0.01	0.01	0.07	-0.03	-0.02	0.01	0.04	-0.00	0.04	-0.01	-0.01	0.00
27	Year 1996	0.083	0.276	0	1	-0.00	0.01	0.05	0.16	-0.02	-0.01	-0.01	0.03	0.13	0.04	-0.01	-0.01	0.01

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Table 2 Descriptive statistics and correlation matrix (continued)

	Variable	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
14	Car manufacturer																
15	European firm	0.09															
16	Asian firm	0.12	-0.40														
17	Year 1986	-0.00	0.03	-0.01													
18	Year 1987	0.02	0.01	0.01													
19	Year 1988	0.03	-0.01	-0.00	-0.09												
20	Year 1989	-0.01	-0.00	-0.00	-0.09	-0.09											
21	Year 1990	0.01	-0.00	0.01	-0.09	-0.09	-0.09										
22	Year 1991	0.01	-0.01	0.01	-0.09	-0.09	-0.09	-0.09									
23	Year 1992	-0.00	-0.00	0.01	-0.09	-0.09	-0.09	-0.09	-0.09								
24	Year 1993	0.02	-0.02	0.02	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09							
25	Year 1994	-0.00	-0.02	0.01	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09						
26	Year 1995	-0.01	0.01	-0.00	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09					
27	Year 1996	-0.02	0.01	-0.02	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09				

Table 3 Determinants of the innovation rate of firms – 1986-1997

Core technology **Non-Core technology**

Variable Model 1 Model 2 Model 3 Model 4 Model 5 Model 6 Model 1

Model 2 Model 3 Model 4 Model 5 Model6

Direct ties

Direct ties 0.675***0.6949***0.643***0.883***0.856***0.317***0.309***0.297***0.310**0.303**

(0.092)(0.093) (0.095)(0.124) (0.124)(0.093) (0.094)(0.096) (0.125)(0.125)

(Direct ties)^2-0.190***-0.204***-0.195***-0.222***-0.215***-0.086***-0.087***-0.084***-0.087***-0.0848***

(0.020)(0.020) (0.000)(0.022) (0.022) (0.020)(0.020) (0.021)(0.022) (0.022)

Indirect ties

Indirect ties0.1870.1170.2530.1820.475**0.455**0.476**0.457**

(0.183)(0.188) (0.185) (0.190)(0.185) (0.190)(0.187) (0.192)

((Indirect ties) -0.234***-0.206***-0.247***-0.217**-0.121-0.111-0.121-0.111

* (direct ties) (0.092) (0.092)(0.092) (0.093)(0.092) (0.093)(0.092) (0.093)

(Non)-redundancy

Network efficiency0.658***0.744***0.1630.165

(0.245)(0.246)(0.247)(0.248)

Structural equivalence -0.922** -1.052***-0.0040.031

(0.400)(0.401)

(0.403)(0.405)

Control variables

Car manufacturer-0.523***-0.480***-0.417**-0.417**-0.379**-0.372**0.292** 0341***0.603***0.609***0.603*** 0.611***

(0.124) (0.126)(0.170) (0.170) (0.171)(0.171) (0.125)(0.127) (0.171) (0.171)(0.172) 0.172)

Chemical industry0.0710.1320.1830.1770.2200.2210.234**0.242**0.432***0.431***0.432*** 0.432***

(0.108)(0.109) (0.134)(0.134) (0.132)(0.135) (0.109)(0.111) (0.135)(0.135) (0.136) (0.136)

Europe-0.750***-0.932***-0.918***-0.902***-0.900***-0.880***-0.059-0.111-0.092-0.088-0.092-0.087

(0.116)(0.120) (0.121) (0.121)(0.121) (0.121) (0.117) (0.121)(0.122) (0.122)(0.122) (0.122)

Asia-0.614***-0.710***-0.649***-0.657***-0.654***-0.666***-0.371***-0.388***-0.274**-0.277**-0.274** -0.277**

(0.099) (0.101)(0.111) (0.111)(0.111) (0.111)(0.099) (0.102) (0.112)(0.112) (0.112)(0.112)

Age0.0010.0010.0000.0000.0000.000-0.001-0.001-0.001-0.001-0.001-0.001

(0.001) (0.001)(0.001) (0.001)(0.001) (0.001)(0.001) (0.001) (0.001) (0.001) (0.001)(0.001)

Firm size, 0.296***0.226***0.220***0.233***0.222***0.237***0.0550.0120.0170.0190.0170.019

(0.043) (0.045) (0.045) (0.045)(0.045) (0.045)(0.044) (0.045)(0.045) (0.045) (0.045)(0.046)

R&D intensity1.133*** 0.839**0.718**0.780**0.767**0.844**-0.187-0.504-0.568-0.554-0.567-0.550

(0.330)(0.334) (0.336) (0.336)(0.336) (0.337) (0.338) (0.346) (0.349) (0.349) (0.350)(0.350)

Techn. distance1.2230.9991.111-0.2870.119-1.5642.5512.3401.2200.8071.2200.806

Prior non-core technology1.894***1.790***1.736***1.781***1.796*** 1.848***4.504***4.408***4.331***4.339*** 4.331*** 4.340***

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(0.384) (0.385) (0.386) (0.386) (0.386) (0.387) (0.385) (0.386)
(0.387) (0.388) (0..387) (0.388)
Prior core technology0.412*** 0.367*** 0.367*** 0.365*** 0.353*** 0.347*** 0.155*** 0.132***
0.136*** 0.135*** 0.136*** 0.135***
(0.025)(0.036) (0.036)(0.036) (0.037) (0.037)(0.026)(0.036)(0.037) (0.037)(0.037)(0.038)
TrendIncludedIncludedIncludedIncludedIncludedIncludedIncludedIncludedIncludedIncludedIncludedIncluded
Constant3.566***4.421***4.416***3.762***4.737***4.047***2.832***3.303***2.982***2.832***2.983***2.838***
(0.407) (0.424)(0.442) (0.490)(0.464) (0.505)(0.412) (0.430)(0.448) (0.496)(0.470) (0.511)

Number of firms7474747474747474747474 74
Number of firms-years (obs.)662662662662662662662662662662662 662
Wald chi-squared (d.f.)1387 (21)1445 (23)1436 (25)1456(26)1438 (26)1461 (27)551 (21)546 (23)552 (25)554 (26)552(26) 54 (27)
Pearson Chi-squared (662)433.38410.24414.33417.78412.98415.01883.32887.94864.94863.48864.17 864.35

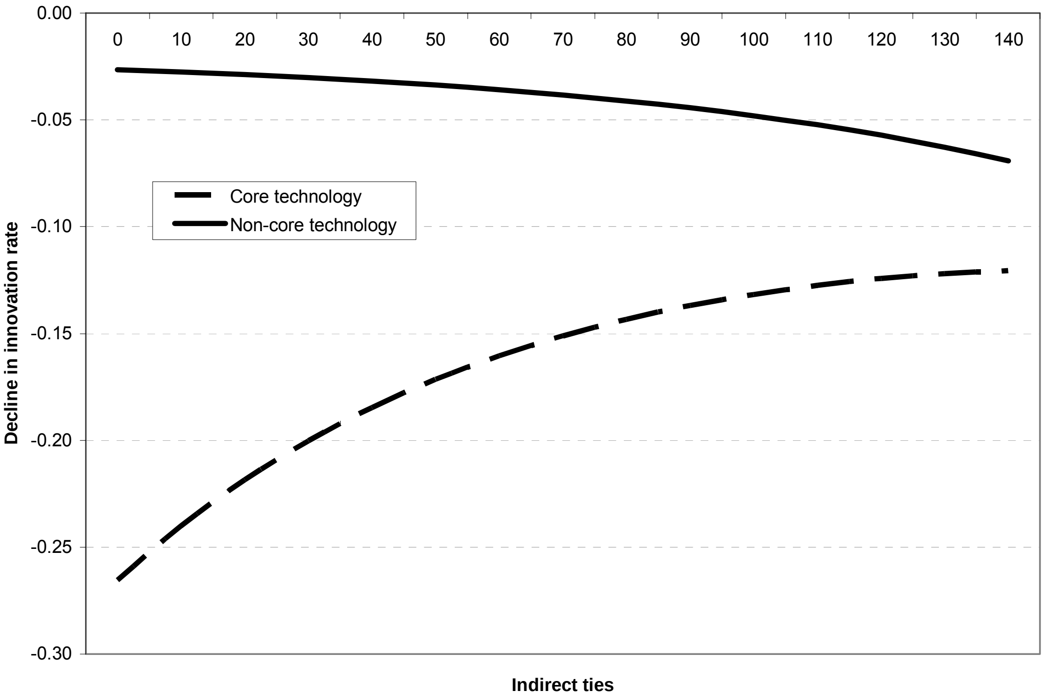
Notes: Standard error between brackets

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

Year dummy variables are included but not reported in the table.

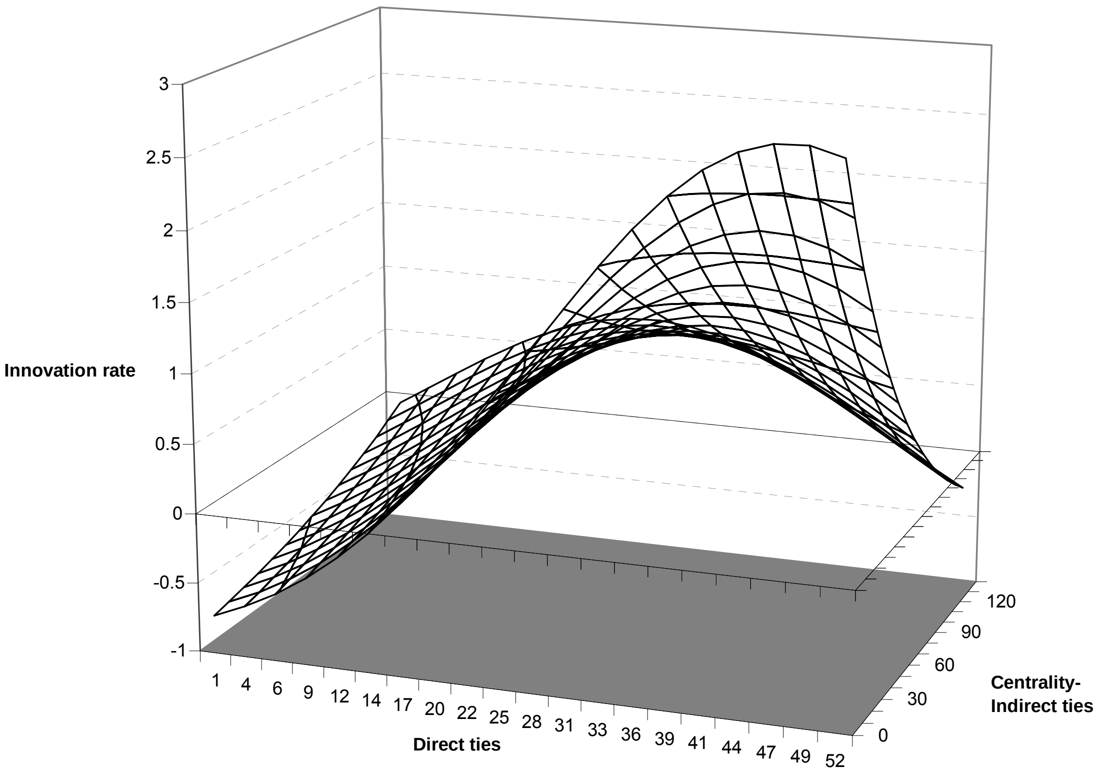
The models use a population averaged negative binomial estimators. The sample is an unbalanced panel.

Independent variables are lagged one year to avoid simultaneity problems.



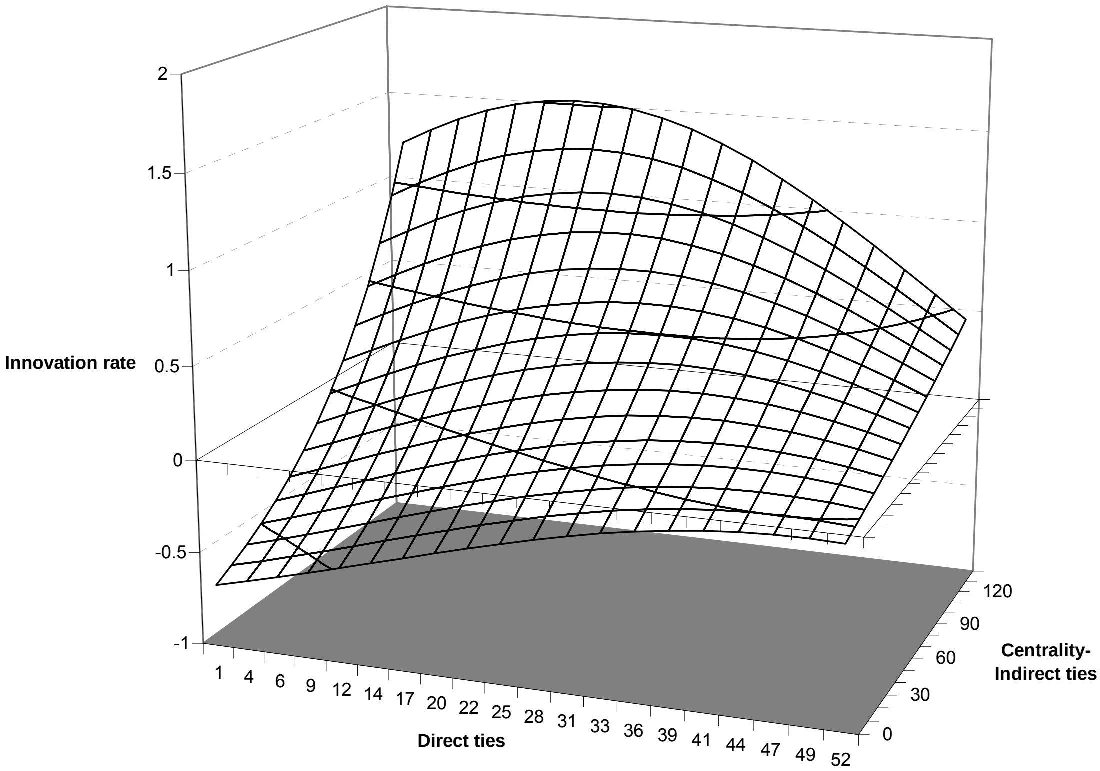
Note: Direct ties are calculated at + 2 standard deviations from the optimum for several levels of indirect ties

Figure 1 Decline in innovation rate for high values of direct ties



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

Figure 2 Innovation rate for different levels of direct and indirect ties – core technology



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

Figure 3 Innovation rate for different levels of direct and indirect ties – non-core technology