ECOLE DES HAUTES ETUDES COMMERCIALES DE PARIS

Ecole Doctorale « Sciences du Management/GODI » - ED 533
Gestion Organisation Décision Information

" Intraorganizational Networks, Interorganizational Collaboration and Firm Innovation "

THESE
présentée et soutenue publiquement le 5 septembre 2014
en vue de l'obtention du

DOCTORAT EN SCIENCES DE GESTION

Par

Mattheus Cornelis GOOSSEN

JURY

Président du Jury : **Monsieur Stéphane SAUSSIER**
Professeur des Universités,
IAE - Université de Paris I Panthéon-Sorbonne – France

Co-Directeurs de Recherche : **Monsieur Pierre DUSSAUGE**
Professeur, HDR
HEC Paris – France

Monsieur Corey C. PHELPS
Professeur Associé,
Desautels Faculty of Management, McGill University – Canada

Rapporteurs : **Monsieur Emmanuel LAZEGA**
Professeur des Universités,
Institut d'Etudes Politiques de Paris – France

Monsieur Srikanth PARUCHURI
Professeur Associé,
Smeal College of Business,
The Pennsylvania State University, Pennsylvania – USA

Suffragant : **Madame Denisa MINDRUTA**
Professeur Assistant,
HEC Paris – France

Ecole des Hautes Etudes Commerciales

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

Innovation is core to firm financial performance and long-term organizational survival (Cefis & Marsili, 2005; Roberts, 1999). Increasing levels of competition in industrial environments drive organizations into a continuous cycle of efficiency improvements and cost reduction, but innovation provides an opportunity to break this sequence. The introduction of new products or production processes gives firms an opportunity to improve their financial performance (Schumpeter, 1942). A firm's innovative capability – the capability to successfully pursue innovation – is therefore an important antecedent for firm competitive advantage (McGrath, Tsai, Venkataraman, & MacMillan, 1996).

A vast body of literature has revealed the importance of collaboration among actors to explain firm innovative performance (Borgatti & Foster, 2003; Brass, Galaskiewicz, Greve, & Tsai, 2004; Phelps, Heidl, & Wadhwa, 2012; Swan, Newell, Scarbrough, & Hislop, 1999). This literature has shown how various characteristics (number, type, strength, structure) of collaborative relationships among actors influence their ability to obtain, preserve and exploit knowledge and information, which is reflected in creativity and innovativeness (Van Wijk, Jansen, & Lyles, 2008). The large majority of this literature falls within three types of studies. First, scholars from the field of organizational behavior have focused on the impact of interpersonal networks on individual-level performance (e.g. Burt, 2000; Obstfeld, 2005). Second, scholars from the field of management and organization have looked at the consequences of business unit relationships for the performance of teams, departments or business units (e.g. Hansen, 1999; Tsai, 2001). Third, strategic management scholars have extensively investigated the effects of interorganizational relationships on organizational performance and innovation (e.g. Ahuja, 2000a; Phelps, 2010).

Whereas this research has provided a comprehensive understanding of the networks and innovation relationships at each level – individual, team/unit, and firm – very few studies have assessed potential multilevel effects. This is an important limitation to this line of research since innovation is ultimately the outcome of multilevel processes, i.e. individual and collective processes occurring at a microlevel and a macrolevel (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013; Payne, Moore, Griffis, & Autry, 2011; Rothaermel & Hess, 2007). In a multilevel network conceptualization, actors at a lower level form a network that itself becomes a node at a higher level (Harary & Batell, 1981; Moliterno & Mahony, 2011). For instance, persons form social ties with their colleagues at the individual level, which results in an intraorganizational network, while their firm participates in alliances and joint ventures at the interorganizational level, which results in an interorganizational network. In such nested networks, nodes are no longer cohesive entities but become networks themselves. Applying a multilevel lens to networks and innovation research challenges past studies in three important respects.

To begin, the majority of studies on network structure and innovation have limited themselves to a microlevel analysis: the effects of network structure on a single actor in that network. While one may expect that effects at the microlevel (i.e. for the individual actor) are similar at the macrolevel (i.e. for all actors combined), there are reasons to question this assumption. For instance, a network brokerage position is often related to increased innovation. In such a position, where an employee connects otherwise unconnected colleagues, s/he can combine diverse knowledge from different sources (Burt, 2000; Fleming, Mingo, & Chen, 2007). However, network brokerage has strong adverse effect on a broker's colleagues and reduces their performance (Bizzi, 2013). So what may be good for individual performance, at the microlevel, may not automatically be advantageous for organizational performance, at the macrolevel.

Second, there is an incomplete understanding of the processes mediating intrafirm network structure and firm innovation. A small number of studies have empirically investigated the effects of macrolevel network structure on macrolevel innovation (Provan, Fish, & Sydow, 2007). These studies demonstrate that connections increase firm innovation, but also obtained confounding results regarding the effects of network clusters and network cohesion. For instance, while Carnabuci and Operti (2013) find positive effects for network cohesion on the reuse of knowledge in new innovations, Guler and Nerkar (2012) conclude that global cohesion hurts firm innovation. Similarly, organizational learning literature obtained varying results regarding the role of network clusters. Whereas some studies find that network clusters increase organizational learning (e.g. Cowan & Jonard, 2004), other studies do not confirm this role of clusters (Fang, Lee, & Schilling, 2010). One plausible explanation for these inconsistent results may be related to competing mediating processes. Two important processes that mediate the relationship between network structure and firm innovation are knowledge sharing and retention. If network characteristics have varying or opposing effects on knowledge sharing and retention, the final effect on firm innovation becomes unpredictable.

Third, research on networks and innovation has not yet explored potential joint-level network effects. Joint-level effects are the combined effects of a lower-level and a higher-level network on an actor's innovation. For firm innovation, this refers to the characteristics of its intraorganizational collaboration network among its employees and its interfirm collaboration network of alliances and joint ventures (Brass et al., 2004). Both networks have independent consequences for firm innovation, but it is very likely that there are also multilevel and joint-level effects since organizations are nested systems (Hitt, Beamish, Jackson, & Mathieu, 2007). Thus, one should examine both networks simultaneously to fully grasp their influence on firm innovation (Phelps et al., 2012). For example, a well-connected intraorganizational network may stimulate intrafirm knowledge sharing and reduce a firm's dependency on other firms. Conversely, collaborating with other organizations may be more effective if the focal firm has a stronger intraorganizational network. Multilevel research on networks and innovation is essential to better comprehend the effects of networks, how they jointly influence innovation, and when they are complementary and substitutionary.

In short, past literature on networks and innovation has not adequately addressed the importance of levels of networks and their individual and joint effects on firm innovation. First, the effects of network structure on innovation may depend on the level of observation: individual actors or entire networks. Second, the effects of networks on innovation are poorly understood because mediating processes are hardly examined. Third, organizations are part of a multilevel network that is like to have joint effects on firm innovation. The aim of this dissertation is to address these limitations by integrating networks at various levels and assessing their effect on processes that explain the network and innovation relationship. I do so by answering the following question: *how do firm intraorganizational and interorganizational networks, independently and jointly, influence firm innovation?*

To answer this question, I focus on two levels of networks: intraorganizational networks of employees within firms and interorganizational networks between firms. These intraorganizational networks consist of collaboration networks among scientists working in the research and development departments of an organization. Their collaboration on R&D projects leads to communication and interaction that facilitate the flow of information and knowledge, and ultimately affects to innovation (Brown & Duguid, 1991; Paruchuri, 2010; Singh, 2005). Interorganizational networks are composed of organizations that establish interfirm partnerships for innovative purposes. Such interorganizational collaboration leads to knowledge spillovers between firms and forms an important source of innovation (Ahuja, 2000a; Hamel, 1991; Shan, Walker, & Kogut, 1994). The motivation for these two levels is twofold. First, innovation is the outcome of a recombinant search process, i.e. a process in which existing knowledge components (expertise, skills, technologies, etc.) are put into new combinations or configurations (Fleming, 2001). Since each employee has at least some unique knowledge or expertise, individual employees perform a critical function in the recombinant innovation process (Grant, 1996; Ployhart & Moliterno, 2011). Second, whereas knowledge and information are frequently shared among employees within an organization, it is less eagerly shared between employees of different firms. Competitive concerns are absent when information is shared between teams or business units of one organization, but present when knowledge crosses organizational boundaries (Bouty, 2000). Since interfirm agreements alleviate these concerns (Berends, Van Burg, & Van Raaij, 2011), I select interorganizational networks as a second level of study.

To understand how both networks influence firm innovation, I adopt a nested system approach (Harary & Batell, 1981). In this view, an actor at a higher level consists of one or more lower-level actors. Here it means that a node in the interfirm network is actually a network of individuals on itself. When two firms establish a collaboration, employees of both organizations will cooperate via joint project teams. This results in new interpersonal ties that cross organizational boundaries. Interfirm ties are thus reflected at a lower level by the creation of new interpersonal ties among (some) individuals from both firms.

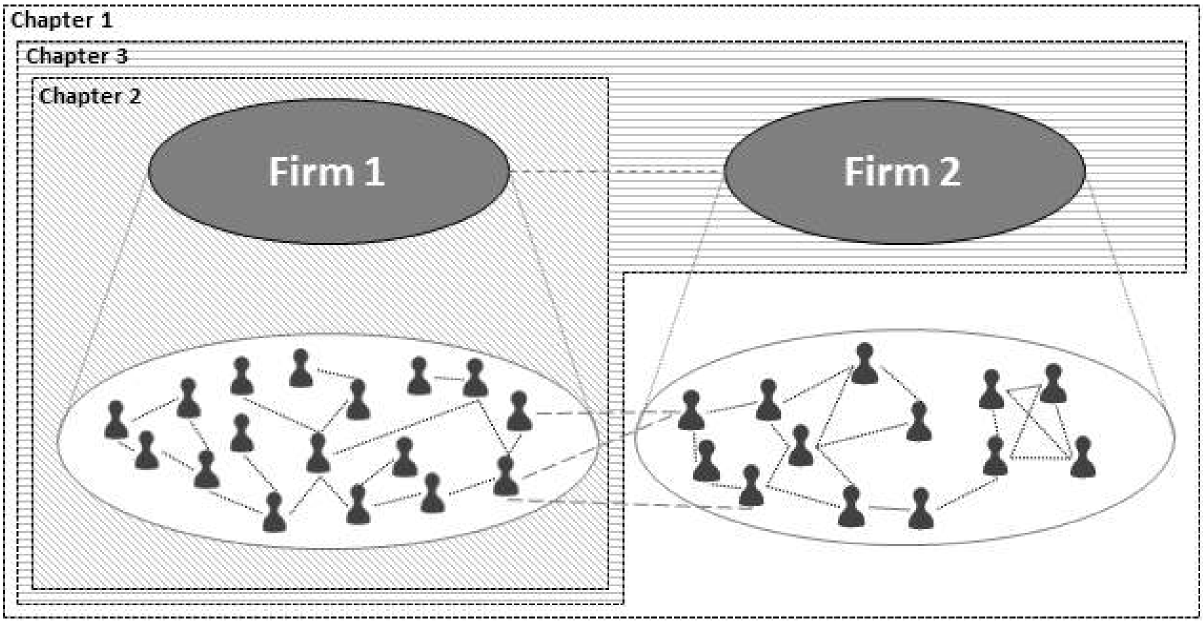


Figure 1 Dissertation structure

Figure 1 visually displays the theoretical model of my dissertation. Each chapter will deal with one part of this model, as indicated by the different boxes.

Study 1: Interorganizational Networks, Intraorganizational Networks and Innovation

The first study is motivated by a lack of integration between interorganizational and intraorganizational network literature. Most research on networks and innovation only deals with a single level of analysis and overlooks potential influences form networks at higher or lower levels (Moliterno & Mahony, 2011). Ignoring this multilevel nature of networks reduces our comprehension in two manners.

First, the literature on interorganizational networks perceives firms as individual, 'atomistic' entities. Firms may vary in their characteristics, but are considered to be internally homogeneous. This means that collaborations between any two organizations lead to similar levels of knowledge spillovers and innovation. As a consequence, it assumes that each firm is affected equally by the structure of, and its position within an organizational network. However, intraorganizational network literature has shown that firms are actually networks of individuals that all have their own characteristics. Because organizations are internally heterogeneous, the effects of interorganizational collaboration will vary by firm. To better comprehend when interfirm networks influence firm innovation, the role of individuals and their intraorganizational networks needs to be included.

Second, the literature on interorganizational networks has paid little attention to the role of individuals in this process. Most interorganizational network studies simply relate the number, structure and type of interfirm alliances directly to organizational learning and firm innovation (Van Wijk et al., 2008). However, interorganizational learning and knowledge transfer are ultimately individual-level processes that occur among employees of both partner organizations (Janowicz-Panjaitan & Noorderhaven, 2009). To understand how and when interorganizational collaboration leads to firm innovation, the role of employees and their personal networks needs to be incorporated further.

The first chapter therefore asks the question: *how do interorganizational and intraorganizational networks jointly influence firm innovation?* It aims to develop a conceptual model of interorganizational collaboration and firm innovation by integrating the intraorganizational networks. Specifically, it differentiates between microlevel processes at the level of individual employees and macrolevel processes at the level of an organization. An investigation into the relationship between interorganizational collaboration and firm innovation suggests this is two-step process. First, interfirm knowledge transfer takes place if an organization's boundary spanners, i.e. employees that are involved in interfirm projects, learn new knowledge and information via their interaction with employees from a partner firm. Second, intrafirm knowledge diffusion happens when these boundary spanners share this new knowledge and information with other colleagues via a firm's intraorganizational network.

The impact of interorganizational collaboration on firm innovation depends on the efficacy of these two processes. At the microlevel, interfirm knowledge transfer depends on the human and social capital of focal and partner firms' boundary spanners as well as the strength of their connections. Intrafirm knowledge diffusion is determined by the position of a boundary spanner in his/her intraorganizational network. At the macrolevel, interfirm knowledge transfer depends on the number and quality of boundary spanners of both firms as well as the number and strength of their connections. Intrafirm knowledge diffusion is determined by the structure of a firm's intraorganizational network.

This theoretical article primarily contributes to the literature on multilevel networks (Contractor, Wasserman, & Faust, 2006; Moliterno & Mahony, 2011). By elucidating how intraorganizational networks and interorganizational relationships jointly influence firm innovation, this study provides a foundation for further theoretical development in multilevel networks and innovation. Secondarily, it speaks to the literature on microfoundations and absorptive capacity by identifying the role of boundary spanning individuals and their personal networks for interorganizational learning and innovation.

Study 2: Intraorganizational Network Structure and Firm Innovation

Ample research has discussed the consequences of interpersonal network structure on individual creativity and innovativeness (Carpenter, Li, & Jiang, 2012; Phelps et al., 2012). However, less is known about the macrolevel effects of intrafirm network structure, i.e. the effects of the structure of an entire network on firm innovation. This is an important issue for two reasons.

First, several studies indicate that there is a micro/macro paradox between network structure at the individual and organizational level (Operti & Carnabuci, 2012). This means that network structures favoring the performance of one employee may do so at the cost of other persons in the firm and eventually decrease firm innovation. For example, Burt (1992) proposes that persons improve their performance by bridging structural holes. However, Bizzi (2013) argues that more brokers of structural holes are detrimental to employee social capital and demonstrates that more brokerage actually reduces employee performance. This is a relevant issue in management research that tries to explain firm-level innovation.

Second, existing research using macrolevel network structure has provided incomplete results. In the organizational learning literature, Fang et al. (2010) show that organizational learning and thereby firm performance improve with efficiently connected networks. However, this finding is not supported by Cowan and Jonard (2004) who find no significant effect or Lazer and Friedman (2007) who find a negative effect. There is a similar puzzling finding in the networks and innovation literature. Carnabuci and Operti (2013) confirm that intraorganizational networks are an important mechanism for knowledge sharing by showing that network connectedness increases knowledge reuse. However, Guler and Nerkar (2012) conclude network connectedness reduces firm innovation, which would imply that knowledge sharing hurts firm innovation. To understand how network structure influences firm innovation, one should identify the mechanisms that mediate this relationship.

The second chapter therefore asks: *how does intrafirm network structure influence firm innovation?* It aims to create theoretical and empirical clarity by identifying processes that mediate the structure-performance relationship. Specifically, I focus on two dominant characteristics of intraorganizational networks, namely network reach and clusters (Provan et al., 2007). Network reach refers to the degree that all employees are connected via relatively short paths and is the macrolevel equivalent of closeness centrality. I argue that network reach will facilitate knowledge transfer among employees via knowledge sharing, informal communication and joint problem-solving, but this will diminish knowledge diversity among employees. Network clusters refers to the presence of densely connected groups of employees in an organization and is the macrolevel equivalent of network closure. Clusters are effective mechanisms for developing new fields of expertise and increasing knowledge diversity, but have a dual effect on knowledge transfer among employees. Subsequently, a firm's knowledge diversity and transfer enhance firm innovative performance. However, contrary to these expectations, the empirical results indicate that both interfirm network reach and clusters reduce knowledge transfer and diversity in an organization and ultimately reduce firm innovation.

This study contributes to our understanding of networks and innovation in two ways. First, it provides a better understanding about the relationship between network structure and innovation by identifying knowledge transfer and diversity as mediating processes. Second, it provides further insights in potentially diverging micro/macro effects of network structure by examining the macrolevel effects of employee closeness centrality, or network reach, and employee ego-network closure, or network clusters, on firm innovation.

Study 3: Interorganizational Collaboration, Intraorganizational Networks and Firm Innovation

The third study relates intraorganizational networks to interorganizational collaboration and firm innovation. Interorganizational collaboration via alliances and joint ventures leads to interfirm learning and knowledge spillovers (Hamel, 1991; Lavie, 2006). The inflow of new knowledge and information via interfirm partnerships also stimulates firm innovation (Shan et al., 1994). Extant literature on interorganizational collaboration networks has shown significant effects of network size, structure, and composition on firm innovation (e.g. Ahuja, 2000a; Phelps, 2010). Despite the extensive body of literature in interorganizational collaboration, it has paid little attention to the role of intraorganizational networks. This is surprising since intraorganizational networks fulfill a different, though highly related role for firm innovation. Collaboration networks within organizations enable knowledge transfer and diffusion among employees (Brown & Duguid, 1991). These personal relationships between employees form the foundation for knowledge flows within an organization (Paruchuri, 2010). Performance of individual employees is therefore strongly influenced by the number and structure of their ties (Fleming, Mingo, et al., 2007). The number and structure of connections among employees also has a profound effect on an organization's ability to turn its knowledge and resources into innovation (Carnabuci & Operti, 2013).

Interfirm and intrafirm collaboration networks thus perform very similar roles by acting as conduits of knowledge that stimulate creativity and innovation. Few studies have examined the joint effect of interorganizational and intraorganizational networks and demonstrate that both networks influence the performance of individual employees (Lazega, Jourda, Mounier, & Stofer, 2008; Lazega, Mounier, Jourda, & Stofer, 2006; Paruchuri, 2010). However, research has not yet assessed how interorganizational and intraorganizational networks simultaneously influence organizational innovation, which is a key issue in management research. Therefore, the third chapter of this dissertation asks: *how do intraorganizational networks and interorganizational collaboration jointly influence firm innovation?*

I argue that interorganizational collaboration via alliances and joint ventures shape a firm's opportunity for knowledge absorption whereas its intraorganizational network forms its ability to absorb this knowledge and apply it in new products and processes. Cooperation with other organizations gives access to knowledge and capabilities of partner organizations (Hamel, 1991; Lavie, 2006). Initially, boundary-spanning employees learn new information and skills from a partner organization via their involvement in joint projects. Subsequently, they can share their knowledge and experience with other colleagues in their firm via its intraorganizational network. This results in a process of knowledge diffusion throughout the firm. The degree of diffusion will then depend on the number and structure of connection in a firm's intraorganizational network (Lazer & Friedman, 2007). As a result, the influence of interorganizational collaboration on firm innovation is moderated by structure of a firm's intraorganizational network.

This study makes contributions to the literature on networks and innovation, to the literature on complementarities of alliances, and to absorptive capacity research. First, by considering the joint effects of individual and organizational networks, this study reveals that firm innovation is the outcome of an interaction between inter- and intraorganizational networks. In particular, the connectedness of a firm's intraorganizational networks strengthens the positive effect of interorganizational networks on firm innovation. This study also contributes to research on alliance complementarities (Rothaermel, 2001) by examining how intrafirm networks complement interfirm alliances in pursuing innovation. Finally, this paper further unpacks the concept of absorptive capacity. A firms ability "to recognize the value of new, external information, assimilate it, and apply it" (Cohen & Levinthal, 1990: 128) is partially explained by an firm's intraorganizational network that diffuses new knowledge throughout the firm.

Setting and Data

The setting of all studies in this dissertation is the North-American medical devices industry. The medical devices industry is a fast-growing and rapidly developing industry with $300 billion annual worldwide sales and industry growth far above the general economy (Frent, 2011). Medical device firms develop and produce products for diagnostic imagining and devices in six major categories: cardiovascular, ophthalmology, neurology, orthopedics, dental, and urology. Initially this industry was dominated by innovative start-ups aiming to capitalize on a new invention, large pharmaceutical firm using their expert knowledge on medical conditions, and diversifying entrants that had identified medical applications for their technology. Over the past twenty-five years the industry has seen significant consolidation through substantial M&A and firm exits (Karim & Mitchell, 2000). Nowadays the industry is dominated by nine major corporations, accounting for 40% of the market, and many small and medium-sized companies. Industry giants include diversified corporations like Johnson & Johnson, but also focused organizations like Medtronic.

This industry is selected for three reasons. First, the medical devices sector is a technology and innovation-driven industry (Danneels, 2002). Innovation has a direct effect on firm financial performance and new product development has a strong impact on firm survival (Karim & Mitchell, 2000; Wu, 2013). Whereas the larger firms focus on incremental innovations, smaller start-ups often bring radical innovations into the industry (Chatterji, 2009). The industry also shows high levels of entrepreneurship by medical or technological experts establishing their own organization to develop and market a new product.

Second, interpersonal and interorganizational collaboration networks are important instruments for innovation in the medical devices industry (Joseph, Chatterji, & Cunningham, 2013). Medical devices are complex products requiring medical expertise (physiology, biology, life sciences) and technological knowhow (mechanical engineering, electrical engineering, materials sciences) to design, develop and produce safe and effective tools and products (Wu, 2013). New products therefor often combine various types of technological expertise and practical experience that are held by different persons. Hence, collaboration is required for successful knowledge recombination (Chatterji, 2009).

Third, collaboration and innovation are highly observable in the medical devices industry. Medical device firms rely strongly on patents to protect their intellectual property and are subject to stringent product registration requirements (De Vet & Scott, 1992). In addition, their licensing and alliance agreements are regularly discussed in industry reports and news articles. These detailed archival data provide precise records of innovation activities and outcomes.

At the start of my research I performed over thirty interviews with experts in this industry: business development directors, alliance managers, and R&D scientists. This gave detailed insights in various aspects of the innovation process, like the role of collaboration among scientists and the management of R&D alliance projects among different firms. Thereafter, I collected data on collaboration and technological innovation by individuals and firms of a sample of fifty firms from 1990 till 2005. First, patent and product data were collected from the USPTO and the Food and Drug Administration to measure firm innovative performance. Second, patent and publications data were retrieved to observe interpersonal collaboration via co-patenting and co-publication by R&D scientists. This constitutes the intraorganizational networks in my studies. Third, I scanned a larger number of newspaper articles, company reports and industry databases to obtain public announcements of licensing agreements, alliances, and joint ventures. These interorganizational collaborative activities form the ties in a firm's interorganizational network. The final panel dataset allowed for empirical testing of the earlier derived hypotheses.

CHAPTER 1: INTERORGANIZATIONAL NETWORKS, INTRAORGANIZATIONAL NETWORKS AND INNOVATION[1]

ABSTRACT

By integrating the literature on interorganizational and intraorganizational networks, we discuss the need for multilevel logic of interorganizational collaboration to explain firm innovation. We argue that processes of interfirm knowledge transfer, intrafirm knowledge diffusion and firm innovation are jointly determined by both interfirm and intrafirm networks. We develop a micro/macro framework that combines aspects of interorganizational and intraorganizational networks to explain how interfirm collaboration influences firm innovation. In particular, we identify the pivotal role of boundary spanning individuals in absorbing external knowledge as well as the major role of intraorganizational networks in diffusing new knowledge internally. Collectively, our propositions develop a multilevel network perspective that aids to our understanding of how both organizational and personal networks simultaneously influence firm innovation.

INTRODUCTION

A large body of research indicates that firm innovation is influenced by two levels of networks, namely *inter*organizational and *intra*organizational (Borgatti & Foster, 2003; Brass et al., 2004; Phelps et al., 2012). Interorganizational networks consist of organizations that are connected via contractual agreements to perform collaborative projects (e.g. alliances, joint ventures, technology licensing deals, research consortia). Intraorganizational networks consist of individuals, teams, or business units that are connected via personal relations. At both levels, creativity and innovativeness of actors are affected by the number, structure and

[1] This chapter is co-authored with Corey C. Phelps and Srikanth Paruchuri

strength of these connections (Van Wijk et al., 2008). Despite the abundant literature on both levels, it falls short in two important respects.

To begin, inter- and intraorganizational network research on innovation developed along two separate lines (Borgatti & Foster, 2003; Phelps et al., 2012). Intraorganizational network research has shown how intrafirm networks constitute important mechanisms for knowledge diffusion and learning (Borgatti & Cross, 2003; Singh, 2005). Little attention is paid to the characteristics of organizations hosting these networks or their position in interorganizational networks. Instead, firms are often considered to be closed environments. Conversely, interorganizational network research has demonstrated that such interfirm networks are a major source of new knowledge, but considers organizations to be 'atomistic entities'. That is, interorganizational network studies consider organizations as unique, indivisible entities that are internally homogeneous.

However, recent research on multilevel networks has recognized that an organization is simultaneously part of two networks: internally it is host to an intraorganizational network and externally it is part of an interorganizational network (Lazega et al., 2008; Moliterno & Mahony, 2011; Paruchuri, 2010). Harary and Batell (1981) describe this network-of-networks phenomenon as a 'nested structure' in which networks at one level constitute a node at a higher level. In such a context, the effects of networks at one particular level are contingent upon higher and lower level networks (Moliterno & Mahony, 2011). Therefore, to understand firm innovation, it is important to consider the simultaneous effects of interorganizational and intraorganizational networks.

Moreover, literature on interorganizational networks has paid little attention to the processes that explain how interfirm collaboration influences firm innovation. While it is argued that interorganizational collaboration results in interfirm knowledge transfer (e.g. Mowery, Oxley, & Silverman, 1996), the mechanisms of interfirm learning have largely remained a black box. This is surprising since there is substantial evidence that organizations benefit differently from interfirm alliances (Hamel, 1991; Khanna, Gulati, & Nohria, 1998; Rothaermel & Hess, 2007). One potential explanation for this effect is found in the origins of organizational learning, namely individuals and their personal networks (Liebeskind, Oliver, Zucker, & Brewer, 1996; Ployhart & Moliterno, 2011).

Thus, adding intraorganizational networks to the analysis of interorganizational networks can help to explain how firms learn new knowledge from their partners externally and subsequently exploit it internally. Interpersonal networks affect knowledge transfer between firms as well as diffusion of new knowledge within a firm afterwards. When studying R&D laboratories, Allen and Cohen (1969) already noted that employees who learn more external knowledge are also considered as valuable sources of information and advice by their colleagues. Similarly, Hargadon and Sutton (1997) describe how new projects benefit when employees actively share and transfer their experiences from prior interorganizational collaboration via the intrafirm network. To understand how firms benefit from interorganizational collaboration, we need to better incorporate the role of intraorganizational networks in research on interorganizational networks.

In this article, we suggest that intrafirm networks complement interfirm collaboration. We limit ourselves to dyadic interorganizational partnerships to gain a deeper comprehension of processes that explain interfirm knowledge transfer and to develop more refined propositions. In order to explain multilevel processes, we draw upon Coleman's boat model to identify the microfoundations of interorganizational learning. This model describes how actions and consequences at one level are explained by mediating processes at a lower level of analysis, or, its microfoundations. This directs our focus to the unique role of boundary spanners, i.e. employees from both organizations who collaborate on joint teams and thereby share knowledge and information (Aldrich & Herker, 1977; Tushman & Scanlan, 1981a).

Accordingly, we develop a conceptual model that incorporates both macrolevel processes at the firm level and microlevel processes at the individual level. We combine theories of social capital, in particular the heterogeneous diffusion model and the boundary spanners literature, to develop propositions about the efficacy of this process of knowledge absorption, that is, the process of acquiring and exploiting new knowledge. We suggest that this process consists of two parts, namely interorganizational knowledge transfer and intraorganizational knowledge diffusion. In the first part, we explain how knowledge transfer between firms depends on the characteristics of boundary spanners of both organizations. In the second part, we explain how diffusion and innovation depend on the characteristics of intraorganizational networks and the position of boundary spanners within this network.

CONCEPTUAL MODEL

To understand how interorganizational collaboration leads to innovation, we use Coleman's boat model (Coleman, 1994). This model helps us comprehend and analyze multilevel effects, in particular how macrolevel causes have macrolevel consequences via microlevel processes. Alliance formation and firm innovation is such a macrolevel relationship that rests on microlevel processes (Felin, Foss, Heimeriks, & Madsen, 2012). Alliances are essentially just contractual agreements among two or more organizations and it is only via their effects on individual employees that these agreements spur innovation. Knowledge spillovers and interorganizational learning are a function of formal and informal communication and cooperation among employees of two organizations (Janowicz-Panjaitan & Noorderhaven, 2008). Davis and Eisenhardt (2011) also note the importance of individual and team dynamics that go beyond alliance structure to realize innovation. Embracing this macro-micro-macro reasoning, we argue that interorganizational networks influence firm innovation via a four-step process (see Figure 2 below).

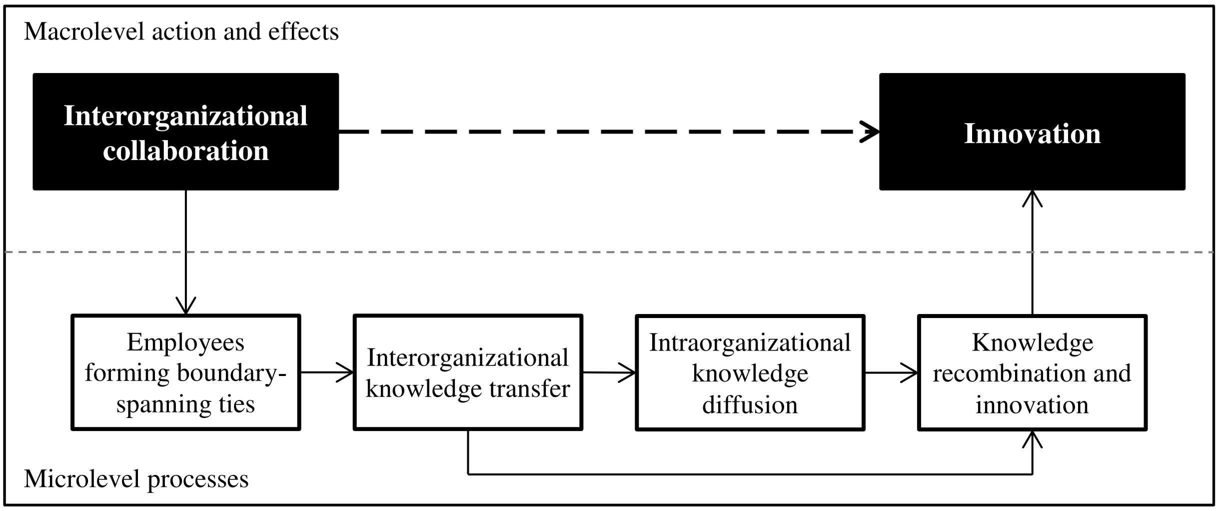


Figure 2 Coleman's boat model of interorganizational collaboration

In a multilevel network perspective, the actions by a macrolevel node influence the nodes at a microlevel. In our model, tie formation between two organizations leads to tie formation among a subset of the employees. For instance, two organizations may establish an alliance agreement at the organizational level. The implementation of such an agreement occurs at the lower level by creating joint project teams that involve employees from both organizations (Davis & Eisenhardt, 2011). However, only a subset of all employees will be involved in these joint project teams. For these employees, joint project teams lead to new interpersonal ties that cross their organizational boundaries. So, macrolevel network changes, like alliance formation, influence microlevel networks by forming boundary-crossing ties for a subset of all employees.

At the microlevel, individuals from two organizations who collaborate as part of an alliance are organizational boundary spanners (Van de Ven, 1976). These individuals have the potential to transfer knowledge across organizational boundaries (Tushman, 1977). Since their interactions with the partner organization are directed towards achieving a joint goal, they involve the frequent exchange of knowledge and information (Berends et al., 2011; Bouty, 2000). Interpersonal collaboration also involves unintended and unnecessary knowledge sharing among employees which provides additional learning benefits for the receiving organization (Lavie, 2006). But while alliances simply create an opportunity for knowledge sharing, it depends on boundary spanners to realize these benefits. Actual knowledge transfer between two boundary spanners is a function of the characteristics of each boundary spanner as well as the social relationship between them (Greve, Strang, & Tuma, 1995; Keller & Holland, 1975; Tortoriello & Krackhardt, 2010; Tushman & Scanlan, 1981b).

Afterwards, boundary spanning individuals may share their experiences from interorganizational collaboration with their colleagues within their own firm. This happens in two ways. Via communication and collaboration with colleagues, a firm's boundary spanners may pass on new information and knowhow that they obtained from the partner organization (Allen, James, & Gamlen, 2007; Allen & Cohen, 1969). In addition, colleagues may turn toward a boundary spanner to actively ask for advice and learn about new information that this boundary spanner acquired from interorganizational collaboration (Tushman & Scanlan, 1981a). The likelihood of knowledge diffusion from a boundary spanner to another employee within the same organization is again a function of their individual characteristics and the relationship between them (Greve et al., 1995; Nebus, 2006).

In the final step, we argue that intraorganizational knowledge diffusion affects firm innovation. Literature on knowledge recombination has described how individuals or teams innovate via a recombinant search process. In this process, employees aim to solve problems by combining multiple knowledge components (expertise, skills, technologies, etc.) in novel ways (Fleming & Sorenson, 2001; Fleming, 2001). New knowledge and information absorbed from a partner organization allow employees to create such combinations. To begin, boundary spanners can increase their innovative performance by applying their new knowledge and skills in other projects. In addition, other employees may become more innovative when boundary spanners share their new knowledge. At the macrolevel, this affects firm innovation in two ways. First, firm innovation increases with the degree of recombinant search and innovation by its employees (March, 1991). Second, the structure of collaboration and communication among employees influences a firm's ability to turn knowledge and resources into different types of innovation (Carnabuci & Operti, 2013; Lazer & Friedman, 2007).

As the above model has shown, adding a multilevel network perspective and microfoundational focus helps us to better understand the role of individuals in interorganizational collaborations. Primarily, it has displayed the importance of boundary spanners in realizing knowledge transfer between two organizations. Their ability to learn external knowledge and diffuse it within an organization is critical for knowledge absorption in interorganizational collaboration. Secondary, it has revealed how intrafirm networks play a central role in the relationship between interorganizational knowledge transfer and firm innovation. The ability of a firm to exploit new knowledge relies on the ability of intraorganizational networks to disperse this information to all employees.

The effect of alliance formation on organizational innovation is therefore a real macro-micro-macro process. First, alliance formation leads to boundary spanning ties among subsets of employees in both organizations. Second, these ties facilitate interorganizational knowledge transfer and interactive knowledge recombination among boundary spanners. Third, knowledge diffuses within an organization from boundary spanners to other employees. Finally, intraorganizational knowledge diffusion increases individual and collective knowledge recombination. We argue that the impact of alliance formation on organizational knowledge recombination and innovation depends on the effectiveness of each of these processes. To do so, we build upon the concept of boundary spanners as well as the heterogeneous diffusion model which we first explain and develop further.

THEORETICAL BACKGROUND AND CONCEPT DEVELOPMENT

Boundary Spanners and Knowledge Transfer

In our theorizing on interorganizational collaboration, boundary spanners are all employees involved in projects that are part of interorganizational agreements (Tushman & Scanlan, 1981a). These projects involve collaboration and communication of employees belonging to two different organizations and involve extensive knowledge sharing. Though employees also share knowledge and resources with colleagues outside their organization, it is not to the same degree as within interfirm partnerships (Berends et al., 2011; Bouty, 2000). If knowledge or resources are crucial for an organization's competitive position, employees will not share these (Bouty, 2000) but aim to formalize the relationship via a contractual agreement that permits such collaboration (Berends et al., 2011). Boundary spanners are thus in a unique position to share and transfer knowledge and resources across organizational boundaries (Tushman & Scanlan, 1981a; Tushman, 1977).

A boundary spanner bridges two otherwise unconnected groups of employees that each have their own knowledge and expertise. Therefore, boundary spanners function both as knowledge brokers and gatekeepers. On the one hand, their position as bridges allows them to take advantage of unique opportunities (Zhao & Anand, 2013). Boundary spanners can increase their individual creativity and performance by drawing upon complementary knowledge and information from two organizations (Burt, 1992). On the other hand, boundary spanners act as gatekeepers and control the inflow of new information in an organization (Allen & Cohen, 1969). Because boundaries have access to knowledge outside firm boundaries, they can turn into important sources of new information for their colleagues (Tushman & Scanlan, 1981a).

We use the heterogeneous diffusion model to explain the extent by which boundary spanners learn and share new knowledge. This model, introduced by Strang and Tuma

(1993), describes under which conditions innovations diffuse and can easily be adapted to describe how knowledge and information from one employee in an organization will reach another employee in another organization. It recognizes three factors, namely the likelihood of the source to share information (infectiousness), the probability that the recipient will learn and use this information (susceptibility), and the characteristics of their relationship (proximity).

At the source, the likelihood of a person to share information and knowledge is a function of the quality and diversity of knowledge s/he possesses or can access (Borgatti & Cross, 2003; Nahapiet & Ghoshal, 1998). A person with unique expertise and knowhow is a significant source of information for its peers. Collaboration and communication with these knowledgeable employees allows for colleagues to learn this expertise (Simonin, 1997). In addition, more colleagues will turn to this employee via the referral network within an organization (Argote & Ren, 2012). Besides possessing knowledge, social capital also shapes learning opportunities. When a partner's boundary spanner has access to unique information possessed by others, it increases opportunities for knowledge transfer (Nahapiet & Ghoshal, 1998).

At the recipient, the probability that a person receiving information will accept, remember and use it, depends on his/her ability to recognize its value and his/her opportunity to apply it (Cohen & Levinthal, 1990; Matusik & Heeley, 2005). The ability to recognize the value of new knowledge depends on how related that knowledge is to an employee's current knowhow and expertise (Cohen & Levinthal, 1990). When an employee obtains new knowledge related to his/her current or past projects, it is easier to assess the relevance and quality of this new knowledge. In this situation it is also easier to envisage how and where this new knowledge could be used. Individual absorptive capacity is therefore an important determinant for receiving, remembering and using new information (Ter Wal, Criscuolo, & Salter, 2011).

The characteristics of the relationship between source and recipient are equivalent to tie strength between boundary spanners. The likelihood of knowledge being shared between two persons increases with the strength of their relationship, i.e. the duration, intensity, intimacy and reciprocity of their relation (Granovetter, 1973). First, stronger personal ties create trust and foster reciprocity in a relationship. This stimulates employees' willingness to share knowledge (Coleman, 1988; Krackhardt, 1992). Second, stronger ties increase the mutual understanding of colleagues and improve their efficiency of communication and collaboration (Postrel, 2002). Third, stronger ties allow for the transfer of complex, tacit knowledge between individuals (Aral & Van Alstyne, 2011; Hansen, 1999). Whereas weaker ties are sufficient to pass on simple and explicit information (Granovetter, 1973), transferring tacit knowhow and expertise requires stronger interpersonal relations (Hansen, 1999).

Intraorganizational Networks and Knowledge Diffusion

The literature on social capital has shown that intraorganizational networks are important mechanisms for knowledge sharing and diffusion in an organization (Brass et al., 2004; Phelps et al., 2012). Social ties among employees act as channels for knowledge and information. First, individuals share their experiences and information with their colleagues via informal conversation and collaboration (Brown & Duguid, 1991). This uncontrolled process supports the fast diffusion of information throughout a firm. Second, employees often rely upon specialized expertise and knowhow to perform their roles. If a person lacks such expertise, s/he may turn to a colleague to learn it or ask for help (Nebus, 2006). Intraorganizational networks are an important mechanism for providing referrals, i.e. the introductions to the right colleague that possesses this knowhow (Borgatti & Cross, 2003).

Whereas the heterogeneous diffusion model explains knowledge sharing in dyadic relationships, it does not take macrolevel network structure into consideration. Macrolevel network structure refers to the pattern of ties among all employees within an organization (Wasserman & Faust, 1994) and has strong consequences for intrafirm knowledge transfer and firm knowledge recombination (Carnabuci & Operti, 2013; Guler & Nerkar, 2012; Lazer & Friedman, 2007). For the purpose of this article, we focus on one important macrolevel characteristic of network structure, namely network cohesion. Intrafirm network cohesion refers to the degree that employees are all, directly or indirectly, connected via social ties (Wasserman & Faust, 1994). In cohesive networks, all employees are (in)directly connected, whereas fragmented networks display disconnected (groups of) employees. Recent studies have shown that intrafirm network cohesion has a strong effect on firm innovation. Particularly, cohesive networks are more likely to stimulate knowledge sharing and incremental innovation (Carnabuci & Operti, 2013; Chang, Lee, & Song, 2014).

In addition to their direct effects on firm innovation, we argue that intraorganizational networks also exhibit strong joint effects with interorganizational collaboration. Interfirm networks are important means to obtain new knowledge from other organizations whereas intrafirm networks are important mechanisms to diffuse new knowledge among employees in a firm (Brown & Duguid, 1991; Paruchuri, 2010). When new information enters a firm via one person, it may spread to other colleagues via their social connections. This process occurs erratically because "knowledge is imperfectly shared over time and across people" (Hargadon & Sutton, 1997: 716). The extent of diffusion then strongly depends on the cohesiveness of intraorganizational networks. With stronger connections, shorter paths and little fragmentation, new knowledge will diffuse faster and further. Cohesive intrafirm networks are thus more effective in diffusing information obtained from interorganizational collaboration.

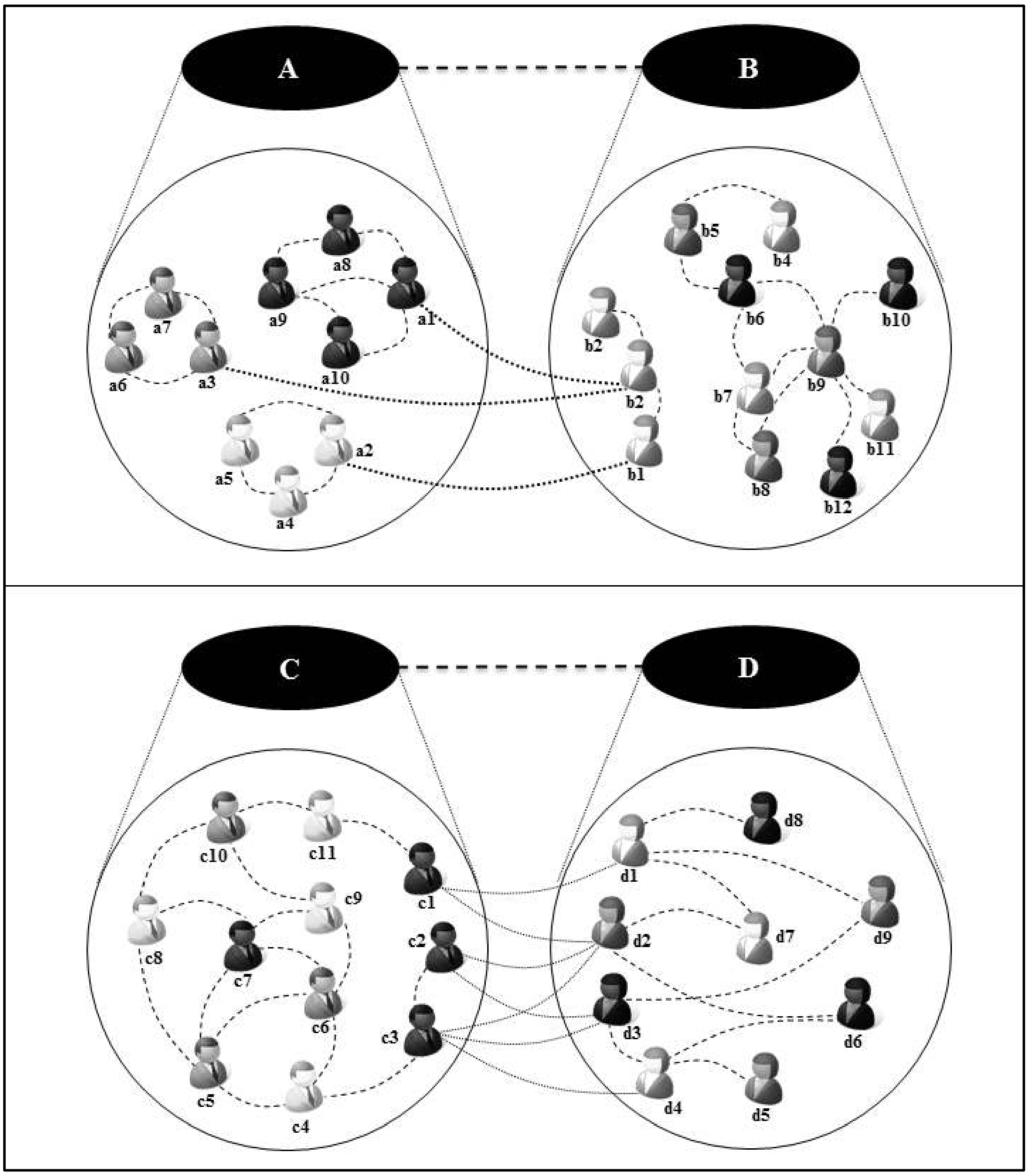


Figure 3 Two multilevel models of interorganizational collaboration

INTERORGANIZATIONAL KNOWLEDGE TRANSFER

We argue that the amount of knowledge an organization learns from its partner firm depends on the characteristics of the source and recipient boundary spanners and the connections among them. As we modeled interorganizational knowledge transfer as a multilevel process, we distinguish between microlevel and macrolevel knowledge transfer. At the microlevel, we develop propositions about the effects of boundary spanner and tie characteristics on individual learning from a partner organization. At the macrolevel, we develop propositions about the role of boundary spanners for the total amount of learning by an entire organization from a partner organization. Figure 3 above provides two models to illustrate each proposition.

Microlevel Knowledge Transfers

When an organization forms a collaborative agreement with a partner, one or more employees in the focal organization will become boundary spanners. They develop interpersonal ties with one or more employees in the partner organization and have an opportunity to learn new knowledge and information from the partner firm. The amount of knowledge a boundary spanner will learn from a partner organization is a function of the characteristics of the source (i.e. the partner's boundary spanners), the recipient (i.e. the focal boundary spanner), and their social proximity (i.e. their tie).

We argue that a partner organization's knowledge available to a boundary spanner is a combination of the human and social capital of boundary spanning employees in the partner firm. In particular, a boundary spanner will learn more new knowledge from a partner organization if s/he establishes a relationship with a more knowledgeable and more central employee in the partner (Allen & Cohen, 1969; Ployhart & Moliterno, 2011). First, interorganizational communication and collaboration may give a boundary spanner access to the knowhow and expertise of a partner firm's boundary spanner. Via observation and interaction during their joint projects, a boundary spanner can learn new skills from the partner firm (Janowicz-Panjaitan & Noorderhaven, 2008; Liebeskind et al., 1996). The opportunity to learn is then limited by the human capital of the partner's boundary spanner. For example, if a boundary spanner collaborates with a highly knowledgeable, senior employee of a partner firm (e.g. star scientist), the learning opportunities are much larger than if s/he collaborates with a junior employee of that partner firm.

Second, a boundary spanner of the focal firm may also learn from a partner firm via the social capital of a partner's boundary spanner (Kostova & Roth, 2003; Nahapiet & Ghoshal, 1998). When faced with a particular issue or looking for more information, a boundary spanner can turn to his/her partner boundary spanner. If this partner boundary spanner does not have the relevant knowledge, s/he can turn to other employees within his/her organization to ask for advice. The partner boundary spanner may then pass on this information to the focal firm or provide a referral to the right person (Berends et al., 2011). The personal network of a partner boundary spanners is thus an important source of knowledge and information. The extent to which a boundary spanner can access the partner's knowledge then depends on the social capital of the partner boundary spanner. Specifically, the opportunity to learn from the partner firm increases with the centrality of the partner's boundary spanner within his/her intrafirm network. An illustrative case is shown in Figure 3 above by comparing *a1* and *c1*: while *a1* is connected to peripheral *b2*, *c1* has a boundary-spanning tie with the more central *d1* and has indirect access to knowledge and expertise of *d7*, *d8*, and *d9*. We therefore argue that a boundary spanner's opportunity for learning is larger if s/he is connected to a more knowledgeable and more central boundary spanner in the partner organization.

P1: A boundary spanner will learn more from a partner organization when s/he is connected (a) to a boundary spanner with more human capital, and (b) to a boundary spanner that is central in the partner's intraorganizational network.

In addition to characteristics of the source, the characteristics of the focal boundary spanner also influence his/her potential to learn from a partner organization. We argue this increases with the level of a boundary spanner's human capital, in particular the motivation and ability to learn. Willingness to learn is an individual-level attitude that strongly defines an employee's motivation to engage in search and exploration (March, 1991). The 'not-invented-here' syndrome has shown that not all employees are eager to learn and adopt new practices (Katz & Allen, 1982).

In addition, employees vary in their ability to recognize the value of new knowledge and absorb it, i.e. employees vary in their individual absorptive capacity (Lane, Koka, & Pathak, 2006; Ter Wal et al., 2011). This ability is largely shaped by the boundary spanner's knowledge and experience: individuals with a broader diversity of knowledge learn new knowledge faster and see broader opportunities to employ it elsewhere (Cohen & Levinthal, 1990). Moreover, cognitive similarity allows for efficient communication between boundary spanners and enables a boundary spanner to recognize the usefulness of new knowledge and information (Aral & Van Alstyne, 2011; Cohen & Levinthal, 1990). Since mutual understanding is based on overlap in education and experience (Postrel, 2002), the likelihood of cognitive similarity increase with a boundary spanner's ability and experience. Consequently, a boundary spanner will learn more from a partner organization if s/he has more human capital, that is, a higher motivation and ability to learn.

P2: A boundary spanner will learn more from a partner organization when s/he has more human capital.

Finally, the characteristics of a relationship between two boundary spanners influence their likelihood of knowledge transfer. The quality of their personal relationship has a strong effect on the degree of communication, the extent of knowledge sharing, and their readiness to collaborate (Huang, Luo, Liu, & Yang, 2013). Their ability to develop stronger relations depends on the boundary spanners themselves as well as their environment, like the characteristics of their interorganizational relationship. The frequency, intensity and reliability of communication and collaboration between two boundary spanners are influenced by the structure and policies of interorganizational agreements (Mohr & Spekman, 1994). Structural arrangements can enable or inhibit collaboration and communication among employees. For instance, physical proximity of R&D scientists allows more intensive interactions (McKelvey, Alm, & Riccaboni, 2003). But strict policies about personal communication can seriously constrain individual employees to learn from their colleagues at a partner organization.

In interfirm collaboration, tie strength is particularly important because these interpersonal relationships cross organizational boundaries. This puts certain constraints on the level to which knowledge and resources could be shared (Berends et al., 2011; Bouty, 2000). Particularly if knowledge is proprietary, sharing it with potential competitors can harm an organization's competitive position (Lavie, 2006). Trust and reciprocity are then essential to facilitate knowledge sharing (Janowicz-Panjaitan & Noorderhaven, 2009). Therefore tie strength will have a strong effect on the quantity and quality of information that boundary spanners are willing to share.

P3: A boundary spanner will learn more from a partner organization when s/he develops a stronger relationship with a partner organization's boundary spanner.

Macrolevel Knowledge Transfer

Individual-level knowledge transfer by boundary spanners constitutes firm-level knowledge transfer in interorganizational collaboration (Janowicz-Panjaitan & Noorderhaven, 2008). Organizational-level knowledge transfer, however, is not simply the aggregate of new knowledge and information acquired by employees, because there may be substantial diversity or overlap in their newly acquired skills and knowhow. Instead, we elevate the characteristics of the source, the recipient, and their relationship to the macrolevel to understand firm-level learning.

At the source, the opportunity for an organization to acquire knowledge from its partner depends on the extent to which it can access the partner's knowledge base (Lavie, 2006). This opportunity is shaped by the human and social capital of boundary spanners in a partner organization (Janowicz-Panjaitan & Noorderhaven, 2009). If a partner organization involves more employees in alliance projects, the focal organization may be able to access more of their unique knowledge and knowhow via its own boundary spanners. This effect is stronger if a partner firm involves more senior and knowledgeable employees in their alliance, particularly when these specialists have more diverse fields of expertise. When a partner firm's alliance team consists of boundary spanners with heterogeneous expertise (e.g. organizations *A* and *D* in the figure above), the direct ties among boundary spanners will transfer more diverse knowledge and increase interfirm learning.

> *P4: An organization will learn more from a partner organization when its partner organization involves (a) more employees and (b) employees with more diverse human capital as boundary spanners.*

An individual boundary spanner's opportunity for learning is also shaped by the social capital of his/her connection to a partner organization. We argue that social capital also matters at the level of organizations. Specifically, cohesiveness of a partner's intraorganizational network changes the opportunities for the focal firm to access and learn a partner firm's knowledge. Employees in cohesive networks are generally connected to all their colleagues via relatively short paths. This stimulates knowledge sharing and transfer among them (Carnabuci & Operti, 2013; Lazer & Friedman, 2007). If a partner firm has such a cohesive intraorganizational network, the focal firm may not only learn knowledge from the partner's boundary spanners, but potentially also from non-boundary spanning employees. First, new information diffuses further and faster in cohesive networks (Fang et al., 2010). Boundary spanners are then more likely to learn new information, even when it originates from colleagues they are not directly connected to. Second, the search for information via personal referrals is more effective in cohesive networks (Singh, Hansen, & Podolny, 2010). Thus, the probability that a piece of information, possessed by a non-boundary spanning employee in the partner firm, reaches the focal firm is larger if the partner's intrafirm network is more cohesive. For example, knowledge from person *d7* (see the figure above) may still reach employees within organization *C* via boundary spanners *d1* and *d2*, but this is less likely for knowledge possessed by *b7* that is relevant to organization *A*.

Non-cohesive networks display higher levels of fragmentation, i.e. the presence of groups of employees that are not connected via social ties (Wasserman & Faust, 1994). Such fragmentation forms a barrier for knowledge and information sharing (Lawrence & Lorsch, 1967). If a partner organization has a fragmented intrafirm network, the opportunity for knowledge transfer depends on the relative position of the partner's team of boundary spanners (Kostova & Roth, 2003). When a partner firm has strong functional silos but includes one employee from each function in the alliance, the focal firm may still have an opportunity to access and learn all of its partner's knowledge. For example, organization *A* in the model above has a strong degree of fragmentation, but creates a team of boundary spanners that represents each unit with its unique expertise. Thereby organization *B* still has access to all employees of organization *A*. Alternatively, if only employees from one single group are included (like organization *B*), there is no such opportunity.

P5: An organization will learn more from a partner organization when its partner organization (a) has a more cohesive intraorganizational network, or (b) involves boundary spanners from different parts of a less cohesive network.

At the recipient side, the ability of an organization to learn from its partner during interorganizational collaboration depends on its boundary spanning employees involved in this relationship. Particularly, learning from a partner organization depends on the number of boundary spanners and their human capital (Kostova & Roth, 2003; Marrone, 2010). The degree of interaction and communication will rise if the number of boundary spanners increases (Liebeskind et al., 1996). Since each employee has an ability to recognize and absorb valuable knowledge during collaboration, the probability of learning amplifies with the number of boundary spanners (Zhao & Anand, 2013).

We claim that this effect is stronger when a firm's boundary spanners possess more diverse human capital, i.e. more diverse knowledge and expertise. This argument for absorptive capacity at the level of an organization differs slightly from the individual level. At the microlevel, individual learning increases with a boundary spanner's ability to understand and value new knowledge. In this case, a boundary spanner with broader, more generic knowledge will learn more than a specialist because s/he can assess and evaluate new information better. But at the macrolevel, organizational learning depends on their collective human capital (Ployhart & Moliterno, 2011). In this case, it is not only the human capital of boundary spanners, but also their relative diversity that is important (Dahlin, Weingart, & Hinds, 2005). Cohen and Levinthal (1990) also point out that an organization's ability to learn new knowledge is not simply the sum of individual abilities, but depends on their relative differences. For example, a team of boundary-spanning specialists will learn more than a team of boundary-spanning generalists if their fields of expertise vary. Each specialist then has an opportunity to identify and acquire knowledge relevant to his/her field during interfirm collaboration. In the illustration above, organizations *A* and *D* will learn more than their alliance partners *B* and *C* because their alliance teams comprise all types of expertise. Therefore, interfirm knowledge transfer increases with the diversity of knowledge and expertise among all boundary spanners of an organization.

P6: An organization will learn more from a partner organization when it involves more employees with more diverse human capital as boundary spanners.

Regarding the relationship, organizations can structure their collaboration differently in the number and strength of ties among boundary spanners (Tortoriello & Krackhardt, 2010; Zhao & Anand, 2013). Within an alliance, each boundary spanner from the focal organization can form one tie to a colleague in the partner firm (see *A*-*B* in the figure above) or more ties to several colleagues in the partner firm (see *C*-*D* in the figure above). Whereas fewer ties may result in less, more efficient communication and reduces interdependencies in collaboration, it also limits the opportunity for sharing information and knowledge. Therefore Zhao and Anand (2013) argue that fewer ties are sufficient in cases where knowledge is simple, but more ties among boundary spanners are needed to transfer complex knowledge between groups. Interfirm knowledge transfer will thus increase when collaborations are structured as teams with many ties.

Besides the number of connections among boundary spanners, the strength of these ties is also relevant. Stronger ties with more frequent, intense, and reliable communication allow for a richer flow of information and knowledge. Tortoriello and Krackhardt (2010) argue that strong ties are useful for boundary-crossing knowledge sharing by individuals who bridge different units. Hansen (1999) reveals that strong ties are a prerequisite to transfer complex, tacit knowledge across boundaries. Only the trust and mutual understanding present in strong ties allow for sharing and understanding such information. Tie strength among boundary spanners is affected by the structure and implementation of interorganizational agreements (Mohr & Spekman, 1994). Alliance structure shapes the extent of interaction among boundary spanners and can enable or inhibit knowledge sharing among employees. Alliance structure determines how closely boundary spanners will work together, how frequently they will interact, and to what extent they are allowed to share information (Janowicz-Panjaitan & Noorderhaven, 2009; McKelvey et al., 2003). Additionally, organizations can increase tie strength by keeping the set of boundary spanners stable over time because rotation of employees disrupts interorganizational relationships and reduces interfirm learning (Aldrich & Herker, 1977).

P7: An organization will learn more from a partner organization when its boundary spanners develop more and stronger ties with boundary spanners to the partner organization.

In summary, interorganizational knowledge transfer depends on boundary spanners both at the focal and a partner organization. At the source, the partner's number of boundary spanners and its intraorganizational network shape the opportunity to access a partner's knowledge and information. At the recipient, the focal organization's number and diversity of boundary spanners shape its ability to learn from a partner firm. Regarding the ties, the number of relationships and their average strength increase knowledge flows.

INTRAORGANIZATIONAL KNOWLEDGE DIFFUSION AND INNOVATION

Organizations initially learn via their boundary spanners. Through their interactions with employees in a partner organization, boundary spanners learn new knowledge and information that are valuable for their interfirm projects as well as other projects within their firm. This improves their creative performance and increases innovation within an organization (Subramanian, Lim, & Soh, 2013; Tushman & Scanlan, 1981a). However, boundary spanners are also an important source of information for non-boundary spanning colleagues (Tushman, 1977). We argue that interorganizational knowledge transfer is followed by a process of intraorganizational knowledge diffusion via intrafirm networks. New knowledge may be shared between boundary spanners and non-boundary spanning employees so that these non-boundary spanning employees can also learn from interorganizational collaboration. If they see opportunities to employ this knowledge, non-boundary spanning employees also become more creative. This increases overall innovation of an organization. We rely again on the heterogeneous diffusion model to make predictions about this process of knowledge diffusion at the level of individuals and organizations.

Microlevel Knowledge Diffusion

At the level of the individual, non-boundary spanning employees can learn from interorganizational collaboration via boundary spanners. The probability of diffusion depends on the characteristics of the boundary spanner sending the information, the non-boundary spanner receiving the information, and the social distance between them. The role of sender and recipient characteristics are fairly similar to these for interorganizational knowledge transfer.

Regarding the source, the opportunity for non-boundary spanners to learn from boundary spanners depends on how much information these boundary spanners absorbed from a partner firm. If a firm's boundary spanners were limited in learning new skills and expertise from a partner, then the opportunity for intraorganizational knowledge diffusion are also limited and non-boundary spanning employees will learn less. Thus, knowledge diffusion from a boundary spanner to a non-boundary spanner increases with the amount of information the former obtained from a partner firm.

At the recipient, non-boundary spanning employees are more likely to learn from boundary spanners if they have more human capital, i.e. a stronger motivation and ability to learn. The motivation to learn is largely related to their individual openness to new ideas and willingness to accept new information (Katz & Allen, 1982; March, 1991). The ability to learn is influenced by the relatedness of his/her current knowledge and expertise compared to that of the boundary spanner (Postrel, 2002). Larger similarity in field of expertise increases their mutual understanding and facilitates efficient transmission of knowledge, particularly when this is tacit and complex (Aral & Van Alstyne, 2011). Therefore, the probability of a non-boundary spanning employee learning from a partner firm increases with that employee's human capital.

Social proximity between boundary spanners and other employees shapes the opportunity to share and diffuse knowledge. Non-boundary spanning employees are more likely to learn a partner organization's knowledge if they have more, stronger and shorter connections to boundary spanning colleagues (Tortoriello & Krackhardt, 2010; Zhao & Anand, 2013). A stronger relationship between employees increases the likelihood that a boundary spanner will share his/her information. First, stronger ties create trust and reciprocity which are necessary to share valuable knowledge among employees (Coleman, 1988). Second, stronger ties improve mutual comprehension and efficiency of communication since employees will have more shared experience and expertise (Aral & Van Alstyne, 2011; Singh et al., 2010).

The likelihood of a non-boundary spanning employee to learn from a partner organization also grows with the number of boundary spanners s/he is connected to in his/her own organization. As not all boundary spanners may share their new information with their colleagues (Schilling & Fang, 2013), being connected to more boundary spanners increases the probability of learning from a partner organization. In addition, each boundary spanner may have acquired different types of knowledge and expertise. When boundary spanners acquired different knowledge from a partner organization, non-boundary spanning employees can learn more if they are connected to multiple boundary spanners in their own organization. For example, in the illustrative figure above, person *b4* is less likely to obtain new information from organization *A* than *c4* from organization *D* because of their connections to boundary spanners.

Finally, non-boundary spanning employees may rely upon indirect ties to learn from their colleagues in boundary spanning positions. If there are no direct ties, indirect ties can function as channels of knowledge and information. Shorter indirect ties result in a stronger diffusion process for new information because knowledge is shared quicker and more precisely (Freeman, 1977). Shorter indirect ties also increase the chances of finding the right expert within an organization (Jarvenpaa & Majchrzak, 2008). Non-boundary spanning employees can then effectively contact boundary spanners who acquired relevant information from the partner firm. For instance, *c5* may obtain relevant information from organization *D* if it is passed on from *c3* via *c4* or if *c4* refers *c5* directly to *c3*.

> *P8: A non-boundary spanning employee of the focal organization will learn more from a partner organization when s/he has more, stronger, and shorter ties to the focal organization's boundary spanners.*

Creativity of individuals is strongly linked to the variety of knowledge and information they possess or can access (Fleming, Mingo, et al., 2007; Fleming, 2001). So when both boundary spanning and non-boundary spanning employees learn new knowledge from another organization, it increases their potential to identify and exploit new opportunities. In summary, the likelihood for a boundary spanner to become more creative depends on his/her characteristics, the characteristics of the boundary spanner in the partner organization, and the relationships between them. For non-boundary spanning employees, more learning and increased creativity depend on their social connections to boundary spanners.

Macrolevel Knowledge Diffusion

At the level of an organization, the ability to turn newly acquired knowledge into new innovation depends on its ability to get this new knowledge from its boundary spanners to the employees who can use it. We identify three paths via which interorganizational knowledge transfer can increase innovation. First, firm innovation increases directly with the success of projects that are part of interfirm cooperation. Knowledge learned via interorganizational collaboration is controlled by boundary spanners. If this new information is relevant for their joint projects, the performance and innovativeness of these projects improve (Krishnan, Martin, & Noorderhaven, 2006). Second, boundary spanners can use their newly acquired knowledge and skills in other projects (Criscuolo, 2005). The reuse of this experience helps these projects to move quicker and enhances their performance. The third, and potentially largest, effect stems from the diffusion of newly acquired knowledge and information throughout the organization. If this information is actively shared, non-boundary spanning employees also have a chance to use it in their projects.

Knowledge diffusion from boundary spanners to other employees within an organization is strongly influenced by the structure of a firm's intraorganizational network (Allen, 1966). To start, the position of boundary spanners in their intraorganizational network affects their opportunity to share information with colleagues. If boundary spanners work in an isolated project team, knowledge is less likely to diffuse to other employees. In the illustration above, non-boundary spanning employees *b4* to *b12* in organization *B* are unlikely to receive any knowledge stemming from partner *A* because the boundary spanners in *B* are separated from the remainder of the organization. Instead, knowledge is shared more extensively if boundary spanners are well-connected and have central positions in an intraorganizational network. Another example is given in organizations *C* and *D* in the figure above where organization *C*'s boundary spanners are at the periphery of their intrafirm network while *D*'s boundary spanners are at the core. Knowledge diffusion from boundary spanners to other colleagues will thus increase with their centrality in their intraorganizational network.

P9: A focal organization will learn more from a partner organization when the focal organization's boundary spanners occupy central positions in its intraorganizational network.

Moreover, intrafirm network structure influences knowledge diffusion. First, cohesive intraorganizational networks increase the likelihood of knowledge transfer. Such networks, without disconnected groups, reduce social barriers of knowledge sharing. Shorter paths among employees also help to diffuse knowledge faster. For example, non-boundary spanning employees in organization *C* may still learn from organization *D*, but it is less likely for employees *b4* to *b12* to learn from partner organization *A* because *B*'s intrafirm network is not cohesive.

Second, knowledge disperses faster if boundary spanners belong to different parts in their intraorganizational network. Even when intrafirm networks are non-cohesive and consist of disconnected groups of employees, knowledge may still diffuse if boundary spanners belong to each of these different groups. If an interfirm project team consists of experts from each of these isolated units (like organization *A*), each boundary spanner becomes an informant for their respective unit and knowledge still spreads to all employees.

P10: An organization will learn more from a partner organization (a) when it has a more cohesive intraorganizational network, or (b) when it involves boundary spanners from different parts of their intraorganizational network.

We argue that firm innovation increases with the effectiveness of interorganizational knowledge transfer and intraorganizational knowledge diffusion. Innovation is the creation of new combinations of components, i.e. types of knowledge, skills, expertise, etc. (Fleming, 2001). Since each employee possess partially unique, non-overlapping knowledge (Kogut & Zander, 1992), each employee has the potential to identify new combinations. This potential for innovation by an employee grows with him/her receiving new knowledge and information (Fleming & Sorenson, 2001). Initially, firm innovation increases with the degree of interorganizational knowledge transfer from a partner to the focal organization. Boundary spanners can draw upon this knowledge and increase their performance. Afterwards, firm innovation rises further with the extent of intraorganizational diffusion of this new knowledge. In that case, non-boundary spanning employees can also employ it in their projects and increase their creativity.

DISCUSSION

In this chapter, we have proposed a multilevel perspective on interorganizational collaboration and firm innovation. Using a network-of-networks analogy, we conceptualized an organization as an actor embedded in an interorganizational network as well as a network of employees itself. We suggest that firm innovation is the outcome of both levels of collaboration, independently and jointly. Whereas the interorganizational network offers opportunities for obtaining new knowledge and skills, an organization's ability to learn this knowledge will depend on the employees appointed as boundary spanner. An organization's capability to share, transfer, and recombine this knowledge internally largely depends on its intraorganizational network. Our model therefore adds to three different groups of innovation management literature.

Innovation and Multilevel Networks

First, we integrate two streams of networks and innovation literature that had remained largely unconnected, namely the individual and the organizational. While both build upon the same theoretical arguments and use similar empirical methods, their intersection remained rather narrow (Phelps et al., 2012). We argue that it is necessary to combine networks at both levels to understand firm innovation.

The mechanism linking networks to innovation is the flow of knowledge and resources. This is primarily an individual activity and therefore requires a deeper assessment of the role of employees. If we were to overlook their pivotal role in interfirm knowledge transfer, we could not explain part of the variance in the effect of interfirm collaboration on innovation (Smith, Carroll, & Ashford, 1995). Alternatively, reducing a macrolevel entity entirely to its microlevel components would also be incorrect. When an interorganizational network would be reduced entirely to an interpersonal network, it would ignore the role of organizations. However, several studies have shown that organizational boundaries still help to preserve knowledge and expertise within organizations and are only shared beyond firm boundaries if organizational arrangements are present (Berends et al., 2011; Bouty, 2000). Thus, we state that multilevel theory building and testing is necessary to comprehensively understand and foresee how networks influence recombination.

Such a multilevel logic is fundamentally different from extant single-level reasoning (Klein & Kozlowski, 2000). In particular, the effects of actions at one level are contingent upon the characteristics of other levels. In our case, we identify how intraorganizational networks within firms moderate the effect of interorganizational ties on firm innovation. Whereas interorganizational networks provide a firm with an opportunity to learn new information, its ability to employ it depends on how many employees can draw upon this new information. This varies with the structure of its intrafirm network that diffuses new information among all employees.

Microfoundations of Interorganizational Learning

Second, our conceptualization of interfirm learning via alliances is a specification of the microfoundations of interorganizational learning. We apply Coleman's (1994) boat model to explain the relationship between interorganizational learning and firm innovation at the macrolevel via interpersonal learning at the microlevel. Specifically, we argue that alliances lead to interorganizational learning via a social exchange processes among boundary-spanning individuals of both organizations. Alliance agreements shape the structure and processes for interfirm collaboration, but it is the quantity and quality of employee interactions that stimulate learning. Only their personal interactions allow complex knowledge transfer across organizational boundaries (Hansen, 1999; Nonaka, 1994). This results in personal learning among boundary spanners.

Our model also points out a second microlevel process of interorganizational learning, namely intraorganizational knowledge diffusion. Individual-level network and diffusion literature pays little attention to the origin of new information, but its findings are a complement for the interorganizational network literature that visualizes organizations as 'atomistic entities'. Drawing on the heterogeneous diffusion model (Greve et al., 1995), we show that intrafirm diffusion depends on the characteristics of boundary spanners, non-boundary spanning employees, and their social ties. Initially, this explains the transfer from boundary spanners towards their direct colleagues. Ultimately, this model explains knowledge diffusion from boundary spanners throughout the entire organization.

The combination of both processes allows us to answer major questions in the alliance and innovation literature. First, we identify new factors that moderate the impact of alliances on organizational performance. In addition to an alliance's structural characteristics, the human and social capital of boundary spanners are important success factors. Second, we recognize the role of intraorganizational networks in complementing the work of boundary spanners. The effects of interfirm collaboration on firm innovation augment if boundary spanners possess central positions within cohesive intrafirm networks.

Absorptive Capacity and Recombinant Ability

Third, we contribute to the absorptive capacity and recombinant ability literatures by specifying the sources of both organizational capabilities (Cohen & Levinthal, 1990; Garud & Nayyar, 1994). With regard to absorptive capacity, our multilevel model specifies the structures and processes that support the assimilation and application of new external knowledge. First, interorganizational collaboration via alliances and joint ventures influences the level and diversity of new knowledge entering an organization. Second, intraorganizational network structure and dynamics determine diffusion and application in new products and processes. Cohen and Levinthal (1990: 132) already discussed the importance of "individuals who stand at the interface of either the firm and the external environment or at the interface between subunits within the firm" for outward-looking absorption and inward-looking transmission to colleagues. Absorptive capacity starts with the individual capabilities of boundary spanners in an organization followed by their colleagues who apply this knowledge in new products and processes.

An organization's ability to turn knowledge into innovations is grounded in its ability to share and transfer this knowledge among its employees (Garud & Nayyar, 1994; Grant, 1996). Connections among employees create an efficient system for informal knowledge sharing and referrals. The number, structure, and dynamics of such ties determine the likelihood and speed of diffusion (Fang et al., 2010; Lazer & Friedman, 2007). We argue that intraorganizational networks can complement interorganizational networks. The structure of an intrafirm network sustains the diffusion and exploitation of new knowledge obtained via interorganizational collaboration. Thereby it fulfills the second part of a firm's absorptive capacity, namely applying it for commercial purposes.

Limitation and Opportunities for Future Research

Theoretical extensions. One limitation and opportunity for further research is related to the scope of this article. The model presented here only deals with dyadic interorganizational collaboration. Reducing the model to only two organizations allowed us to be more detailed about the microlevel processes and mechanisms mediating interfirm collaboration and innovation. However, most firms are part of a larger interorganizational network and it is not only the number of interfirm relations, but also their structure that influences firm innovation (Phelps et al., 2012; Van Wijk et al., 2008). Further research on multilevel networks could address this by linking the structure of interorganizational and intraorganizational collaboration networks to firm innovation. To begin, such research could explore the multilevel nature of interorganizational network structures like closure and brokerage. In addition, further research could look at the dynamics of multilevel networks.

Moreover, we strongly simplified our model by only considering two levels of networks: individuals and organizations. While this greatly helped us in specifying structures and processes, it ignored a more complex reality of teams, departments and business units. Each of these levels creates and sustains their own boundaries that inhibit knowledge transfer. Tsai (2001), for instance, looked at formal relationships among business units of large corporations. Their structure is similar to interorganizational alliances, but their implementation is different because there are no fears for unintended knowledge spillovers. Similarly, Oh et al. (2004; 2006) explore the role of multilevel nature of networks in teams. They demonstrate that both internal and external ties affect team performance. From our current model, it is unclear how these extra layers change the mechanisms of knowledge transfer and diffusion, and eventually could affect the propositions. In addition, one could conceptualize a multilevel network model involving three different levels. Such networks are a better representation of reality, but three-level nested network will make theorizing much harder. Lastly, assuming that each level of networks consists of the same mechanisms underlying knowledge flows, one may aim to develop a meta-model of multilevel networks, similar to Moliterno and Mahoney (2011), with regard to knowledge recombination.

Further work is also needed regarding the structure versus agency debate at different levels of networks. Questions regarding structure and agency have been important in many network studies, but are particularly pertinent in multilevel network setting because of cross-level interactions. In this study, we have assumed that organizations have full agency at finding alliance partners in their interorganizational network. While this is a common assumption, Dhanaraj and Parkhe (2006) argue that hub firms reduce agency for other actors in the interorganizational network. Similarly, we have assumed that management can foster, but not force tie creation and persistence among employees, so that individuals have substantial, though not full, agency in the intraorganizational network. This may seem realistic since Sasovova et al. (2010), for instance, observe high levels of agency in their medical setting. But the degree of agency will eventually be determined by industry and setting.

Empirical testing. This study can also strengthen empirical research on networks and innovation, for instance by testing some of the proposition derived from our multilevel model. While network research has already provided us with a strong set of quantitative tools for assessing network dynamics and results, we propose two alternatives.

First, hierarchical linear modelling is very suitable for testing the effects of multilevel networks on knowledge recombination. This statistical method, also known as random coefficient models, permits researchers to simultaneously estimate the effects of network structures at different levels (Klein & Kozlowski, 2000). A first benefit is that it estimates the explanatory power of each level upon the dependent variable. A second advantage is that is relaxes the fixed intercept and slopes assumptions of traditional regressions. While fixed-effect regressions in panel data already relaxed intercept assumptions, the coefficients for network measures can now also vary among groups. Hierarchical linear modelling would allow to test how interfirm and intrafirm jointly influence innovation.

A second interesting method for empirical examination is large-scale simulations. Simulation studies are useful in environments of independent, but interdependent agents. As Coleman (1994) showed when developing his model, changes in such settings often lead to unexpected results. Secondly, simulation studies are useful to observe bottom-up effects in multilevel research (Davis, Eisenhardt, & Bingham, 2007). Current quantitative methods are applicable in testing joint-level and top-down effects, but fail in capturing and testing the effects from a lower upon a higher level. Simulations, however, allow for investigating bottom-up or emergent processes (Kozlowski et al., 2013). A third reason why simulation is especially useful for this situation is related to knowledge recombination. Over time, sophisticated algorithms have been developed that allow for personal, interpersonal and organizational learning (Fang et al., 2010; Fleming, 2001; March, 1991). A good example of such work is Kim et al. (2014) who simulate the impact of collaborative structure on the transfer of complex knowledge. Such models could easily be adapted and integrated in a multilevel networks setting.

CONCLUSION

Networks and innovation literature have gained major interest in management research (Phelps et al., 2012), and yet it has mainly revolved along two axes: interorganizational and interorganizational. Our article advances networks and innovation theory by integrating both streams of studies. We do so by combining interorganizational collaboration and intraorganizational networks into a multilevel network model for knowledge recombination and innovation. Specifically, we focus on knowledge absorption from interorganizational collaboration and identify the role of boundary spanners and intraorganizational networks in this process. Recognizing this multilevel nature of organizational networks aids to developing more sophisticated and accurate models of knowledge recombination. This article suggests new avenues for extending multilevel network theory as well as empirically assessing its validity.

CHAPTER 2: INTRAORGANIZATIONAL NETWORK STRUCTURE AND FIRM INNOVATION: THE MEDIATING PROCESSES

ABSTRACT

Extant literature assessing the effect of intrafirm network structure on firm-level innovation paid little attention to the mechanisms explaining this relationship. In this chapter, I propose to clarify this matter by investigating processes that mediate network structure and innovation. I argue that structural characteristics of an intrafirm network affect a firm's knowledge base which, in turn, influences firm innovation. In particular, I examine the impact of reach (i.e. a network being well-connected via short paths) and clusters (i.e. a network with densely connected groups) on knowledge transfer and knowledge diversity, which both stimulate firm innovation. Analyses on a longitudinal dataset of fifty firms in the medical devices industry provide interesting results. Intrafirm network reach reduces knowledge transfer and also decreases firm knowledge diversity. Clusters in an intrafirm network have a similar effect upon a firm's knowledge base. This ultimately diminishes firm innovation.

INTRODUCTION

A large section of the literature on social network has investigated how networks influence creativity and innovation (Borgatti & Foster, 2003; Phelps et al., 2012). Ties between individuals, teams, and organizations provide access to more and newer information, knowledge, and resources (Burt, 1992; Tsai & Ghoshal, 1998). This increases an actor's opportunity to identify and ability to exploit new opportunities (Fleming, 2001). The number, structure and strength of connections have a direct effect on an actor's creativity and innovativeness (Van Wijk et al., 2008). Despite the large number of articles examining the relationship between network structure and innovation, current literature falls short in three important respects.

First, the networks and innovation literature is subject to a micro/macro divide (Moliterno & Mahony, 2011). Here, *micro* denotes using an individual actor (or node) as level of analysis whereas *macro* denotes using the entire system (or network) as level of analysis (Molloy, Ployhart, & Wright, 2011). A vast majority of the existing studies are at the microlevel and investigate the influence of ego-network characteristics on actor innovativeness. For example, Fleming et al. (2007) show that closure in an inventor's collaboration network reduces its creativity while Ahuja (2000a) demonstrates that centrality in a firm's alliance network increases its innovativeness. A small number of studies have revealed that macrolevel network structure also influences actor innovativeness (Provan et al., 2007). For example, Schilling and Phelps (2007) demonstrate that the structure of industry alliance networks significantly changes firm innovativeness. But with few exceptions (Carnabuci & Operti, 2013; Guler & Nerkar, 2012), there is no literature studying the effect of macrolevel network structure and macrolevel innovativeness, i.e. the aggregate innovation of all actors in a network. This is a pertinent issue within organizational studies because firms do not aim to increase microlevel performance of individuals, but aim to maximize macrolevel performance by their entire set of employees. While current social network research has shown the effect of networks on microlevel innovation, it is yet unclear whether different network structures have a real effect on macrolevel innovation or only changes the distribution of innovation over employees.

Second, extant networks and innovation literature has hardly examined the mechanisms explaining the connection between network structure and innovation (Phelps et al., 2012). Many studies have theoretically argued about social and informational processes that mediate this relationship. For example, sparsely connected networks could give actors access to more diverse information and thereby increase actor performance (Burt, 1992). Alternatively, such an ego-network structure may result in a lack of trust and solidarity that motivates actors to exchange this information (Coleman, 1988). At the macrolevel, Guler and Nerkar (2012) argue that the social costs of creating and maintaining distant ties outweigh their informational benefits and demonstrate how clusters, i.e. groups of strongly connected actors, in an intrafirm network drive firm innovation. Carnabuci and Operti (2013) argue that connections facilitate information sharing and demonstrate that this increases knowledge reuse, particularly under conditions of knowledge diversity. While the former argue that only connections within clusters help in sharing and reusing information, the latter argue that knowledge reuse increases with the number of connections beyond clusters. A more refined explanation for this result could be gained by considering the effects on all dimensions of organization's knowledge base: while certain network structures support the creation of specific knowledge, it may simultaneously obstruct the reuse of other knowledge and vice versa. Therefore it remains unknown how global intrafirm network structure influences total firm innovation.

Third, related research on exploration and exploitation in the organizational learning literature has shown opposing results. These simulation studies have examined the impact of small-world network structures (the simultaneous presence of short paths and clusters) on firm performance. For example, Cowan and Jonard (2004) find that fewer clusters reduce knowledge diversity and firm performance. But alternative studies show a smaller impact of clusters (Lazer & Friedman, 2007). For instance, the simulation performed Fang et al. (2010) indicates that fewer clusters hardly reduces knowledge diversity or network performance. Similarly, whereas one study has found that a higher network reach reduces knowledge diversity (Fang et al., 2010), it also concludes that shorter paths decreases the network's overall performance. Cowan and Jonard (2004), on the contrary, found no substantial effects of reach on either knowledge heterogeneity or organizational performance. And finally there is evidence that higher network reacher hurts firm performance considerably (Lazer & Friedman, 2007). In short, simulation studies have delivered inconclusive findings concerning network structure, organizational knowledge base, and firm performance.

This study aims to explain the relationship between intrafirm network structure and firm innovation by analyzing the mediating processes. Drawing upon macrolevel network literature, I focus on two fundamental macrolevel network characteristics, namely network reach and network clusters (Provan et al., 2007; Watts, 1999). These network concepts are similar to network centrality and ego-network closure, which are key concepts in microlevel network research. In particular, I argue that network reach fosters knowledge transfer while network clusters assist in retaining knowledge diversity. Both knowledge transfer and diversity improve firm innovation. The model is empirically tested on a longitudinal panel of the scientific collaboration networks in fifty medical device firms. The results contradict my earlier expectations and find that networks with shorter paths actually reduce firm innovation. This effect is fully mediated by the negative effects of reach on knowledge transfer and diversity. Likewise, clusters in an intrafirm network have a negative effect on firm innovation. This effect is partially mediated by a negative effect on diversity. These results remain significant under a larger number of alternative measures and methodological specifications.

This paper primarily contributes to the literature on networks and innovation. By exploring the processes that mediate network structure and innovation, this study questions the oft-assumed mechanism explaining the relation between network structure and firm innovation (Guler & Nerkar, 2012; Uzzi & Spiro, 2005). Contrary to the common assumptions, network reach and clusters do not seem to improve firm innovation. Instead, this study reveals that reach reduces knowledge transfer among R&D scientists and that clusters do not help to keep a firm's knowledge base diverse. In addition, the results do not support the small world idea that reach combined with clusters increases creativity and innovation. Secondarily, this article sheds new light upon the role of intrafirm networks for firm recombinant ability (Carnabuci & Operti, 2013; Garud & Nayyar, 1994). In particular, it calls into question the idea that intrafirm network are effective mechanisms for knowledge transfer and recombination. Therefore this study calls for further examination of processes explaining the relationship between network structure and innovation.

THEORY AND HYPOTHESES

This article builds upon two complementary streams of research to apprehend how intrafirm network structure influences firm innovation, namely the recombinant innovation and network diffusion literatures. Recombinant innovation studies conceptualize innovation as a purposeful search process for a particular solution by combining different components (Fleming, 2001; Henderson & Clark, 1990). Components refers to knowledge, skills, abilities and other elements related to materials, technologies, and methods (Fleming, 2001; Ployhart & Moliterno, 2011). Innovation occurs when new combinations of components are created or when existing combinations are structured in a new configuration (Henderson & Clark, 1990; Schumpeter, 1939). This recombinant search process is normally performed within an organization by one R&D scientist or a team of collaborators (Fleming, 2001).

Fleming and Sorenson (2001, 2004) describe how the recombinant potential is an arithmetic function of the number and diversity of components R&D scientists have at their disposal. Not all new combinations or configurations are equally successful (Dosi, 1982). According to March (1991), R&D projects focusing on the reconfiguration of existing, known combinations will sustain existing technological trajectories and refine their current knowledge and expertise. The outcomes of such local search, or exploitation, are stable and more predictable, but seldom radical. Alternatively, R&D scientists can learn about new components and creating new combinations. Such distant search, or exploration, is more erratic and has a lower success rate, but it offers a larger opportunity for radical or break-through innovation (Fleming, 2001). March (1991) concludes that organizations with both types of employees – these that explore and these that exploit – outperform those that only look for new combinations or new configurations.

In an organization's R&D unit, scientists face cognitive limitations in their recombinant search activities (Hussler & Rondé, 2007). As a result, they are able neither to familiarize themselves with each relevant component nor examine each potential combination during their search process. Instead, they will rely on human and social factors to optimize their recombinant search efforts. Particularly, there is a tendency to reuse knowledge and expertise R&D scientists are already familiar with (Katz & Allen, 1982). In addition, they are more likely to learn related expertise instead of searching for distant, unfamiliar solutions (Cockburn & Henderson, 1998). Finally, they use their personal network of ties with colleagues to access and absorb new components more efficiently (Hussler & Rondé, 2007; Singh, 2005).

Role of Networks

Social networks in an organization form a major source of knowledge, information, and resources for employees (Ibarra, 1993; Obstfeld, 2005). Social ties among employees in an organization allow them to efficiently learn about new technologies or quickly obtain relevant resources. Past studies have therefore regularly found that employee behavior, whether performance, creativity, or mobility, is influenced by the number of his/her connections, their structure and their strength (Brass et al., 2004; Pittaway, Robertson, Munir, Denyer, & Neely, 2004). In a research and development setting, an intrafirm network consists of R&D scientist that form social ties based upon past communication and collaboration (Singh, 2005). Allen (1966) already described the importance of personal ties among scientists and technologists in R&D laboratories for sharing and transferring knowledge and information. Paruchuri (2010: 65) therefore describes such intrafirm networks as "the backbone of knowledge flows within the firm". Such a network creates and sustains knowledge transfer and diffusion among R&D laboratories.

At the microlevel, intrafirm network structure influences R&D scientist performance in two ways. First, connections among R&D scientists facilitate the transfer of new knowledge and knowhow that have entered the organization (Brown & Duguid, 1991). This information is passed on among scientists during planned and unplanned encounters. As described in ethnographic work by Orr (1996) and Latour and Woolgar (2013), this often occurs in an informal and untargeted manner such as corridor walk-ins and lunch breaks. Second, intrafirm networks influence the knowledge and resources available to R&D scientists via their social connections (Singh et al., 2010). When scientists are faced with particular issues, they will turn to their current and past colleagues for help and assistance (Orr, 1996). Both mechanisms were corroborated in exploratory interviews with R&D scientists[2]. As two scientists put it:

> *"One of my greatest sources of information is my colleague, [name], who owns more than twenty-five patents on this topic. He's one of the major experts in the field and worked in various departments." (R&D scientist #4)*

> *"I can always contact people in [another R&D laboratory]. Of course, I know a large number of people there because I spent time with them, there, and met them in person." (R&D scientist #10)*

Alternatively, most of the R&D scientists described how they rely on the knowledge and expertise of colleagues to solve issues they sometimes encounter. Their connections provide them access to knowledge and resources that improves their performance. For example:

[2] I performed over thirty semi-structured interviews with managers and scientists in the health industry to gain a deeper understanding of the antecedents of innovation. For confidentiality reasons, all quotes are paraphrased.

"I was able to define the manufacturing process for the medical device before we had even started the project by taking advantage of my colleagues and the expertise around me. People also know what my expertise and knowledge is and I'm able to make the same contributions to their projects in their departments." (R&D scientist #6)

"For every problem, the first thing people do is start talking with a colleague. The first thing we do is discuss things internally and then usually the problem can be fixed by the organization itself without turning to literature, databases, etc." (R&D scientist #12)

At a microlevel, the creativity of R&D scientists is therefore affected by his/her connections within the organization (Nerkar & Paruchuri, 2005). The number and diversity of colleagues a scientist can reach out to, is largely determined by the number and structure of network connections. For example, Fleming et al. (2007) found that the productivity of inventors increased with their number of connections, the lack of connections among their peers, and their diversity in expertise. In addition, the structure of an entire intraorganizational network and a scientist's position within network also influences his/her creativity and innovation (Ibarra, 1993).

At a macrolevel, network literature suggests that intrafirm network sustain firm innovation and performance by facilitating the flow of information and resources (Phelps et al., 2012). Social networks overcome barriers and fragmentation created by organizational structure and geographical dispersion (Chang et al., 2014; Lahiri, 2010). In terms of Lawrence and Lorsch (1967), intrafirm networks are a mechanism for knowledge integration in organizations that apply structural separation. Intraorganizational networks lead to direct communication and lateral knowledge flows in a highly efficient manner (Van Wijk & Van Den Bosch, 1998). This was clearly mentioned by R&D scientists and managers who noticed how social networks cross divisional boundaries and spatial distances:

"There are a lot of events for skill improvements that I try to participate in. That's where I get to meet people from different sides of the company and learn about what they are doing. [...] And I have established relationships with colleagues in other departments. For example, there is a senior engineer I know and when it comes to design, I can ask him who would be the best person to talk to." (R&D scientist #6)

"When I encounter a problem, first I discuss it with my peers, within my own group of engineers. If that fails, we contact our colleagues in the larger company [in geographically distant R&D labs]." (R&D scientist #15)

As a result, the structure of intrafirm networks may not only affect individual performance, but potentially also the entire organization. Assuming that firm innovation is the aggregate of successful knowledge recombination by individual employees and teams, macrolevel network structure influences firm innovation. However, Bizzi (2013) and Operti and Carnabuci (2012) have demonstrated that this relationship is not straightforward but subject to cross-level fallacies. Specifically, they demonstrate that network structures boosting performance of individual R&D scientists can reduce their joint productivity, e.g. firm innovation.

The number of ties in an intrafirm network has a dual effect on information sharing and firm innovation. Initially, each additional connection offers access to novel knowledge and resources (Paruchuri, 2010). At the macrolevel, more connections accelerate knowledge diffusion and improve the effectiveness of referrals (Carnabuci & Operti, 2013; Singh et al., 2010). However, creating and maintaining such ties requires substantial time and attention. These immaterial costs may reduce the benefits of connections (Zhou, Shin, Brass, Choi, & Zhang, 2009). In addition, the marginal benefits in information and resources decrease with each extra connection (Burt, 1992). When R&D scientists gain more ties, there is more redundancy in knowledge and resource flows. Furthermore, R&D scientist could have accessed this information or expertise via their indirect connections. In short, intrafirm network density has both positive and negative effects on knowledge transfer, diversity and firm innovation (Lazer & Friedman, 2007; Zhou et al., 2009).

Given this dual effect of the number of connections in intrafirm networks, I contend that innovation is more likely to be influenced by the structure of connections in intrafirm networks. Prior research that examined the effect of intrafirm network structure on firm innovation has not been conclusive. Therefore I aim to identify the mechanisms that mediate the relationship between network structure and innovation. With regard to network structure, I focus upon network reach and clusters. Two arguments underpin this choice. First, these macrolevel concepts that reflect important microlevel network notions, namely closeness centrality and ego-network closure (Wasserman & Faust, 1994). Second, macrolevel network literature has argued that these two network characteristics are strong determinants for performance and innovation (Provan et al., 2007; Wasserman & Faust, 1994; Watts, 1999). In the next paragraphs, I build upon knowledge transfer and recombination literature to predict how reach and clusters influence a firm's knowledge base which then affects firm innovation. A summary of the processes mediating network structure and innovation is presented in Figure 4 below.

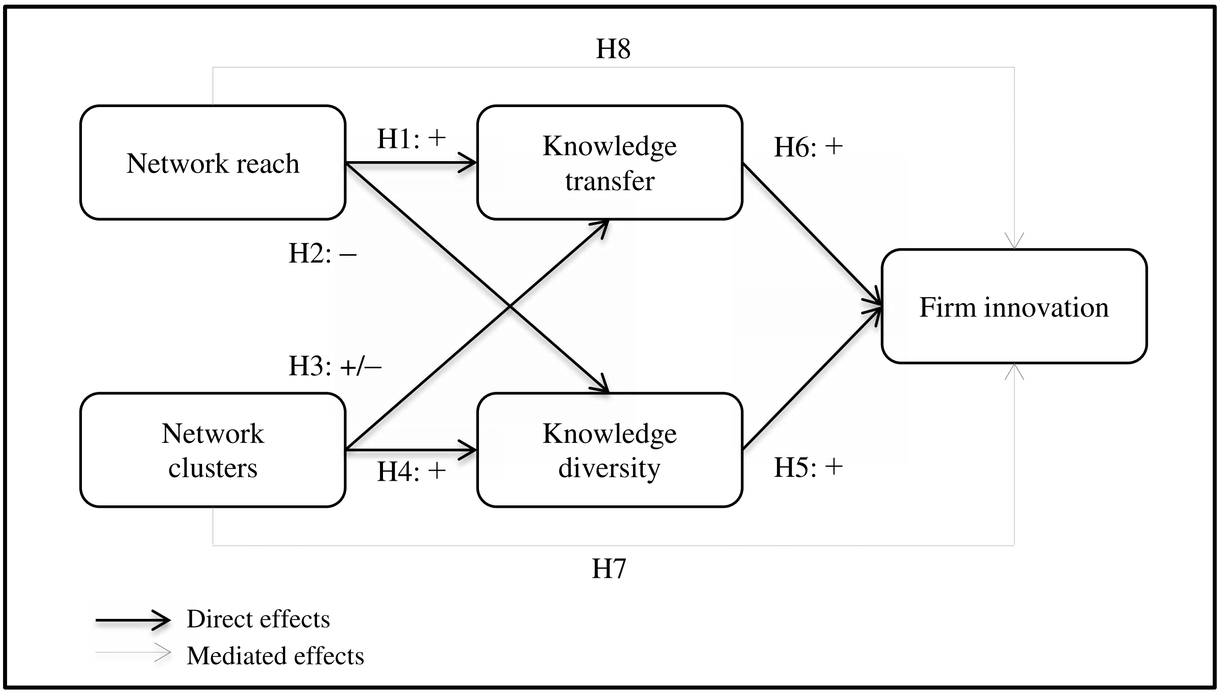


Figure 4 Theoretical model for intraorganizational network structure and firm innovation

Role of Reach

Intrafirm network reach captures two elements of network structure, namely the presence and length of ties among all R&D scientists in a firm (Wasserman & Faust, 1994). The first element gauges whether a network lacks unconnected (groups of) R&D scientists whereas the second part measures path length, i.e. the number of steps between each pair of scientists. If reach is high, each R&D scientist is connected to all colleagues via relatively short paths. In less cohesive networks, paths are much longer and there may be substantial fragmentation (e.g. unconnected components). Three illustrative examples, included in Figure 5 below, demonstrate how networks with the same number of persons and connections can still differ largely in network reach. I argue that intrafirm network reach has a dual effect on a firm's knowledge base: while it increases knowledge transfer, it reduces knowledge diversity.

Knowledge transfer refers to each instance in which one R&D scientist shares information, knowledge, and knowhow with another scientist (Argote & Ingram, 2000). Since knowledge in R&D settings is largely tacit and embodied, transfer occurs via social interaction and collaboration among employees (Kogut & Zander, 1992). Network reach increases knowledge transfer among R&D scientists for two reasons.

First, from a perspective of information diffusion, reach increases the extent, speed and reliability of knowledge transfer. Since "knowledge is imperfectly shared over time and across people" (Hargadon & Sutton, 1997: 716), the macrolevel network structure has a strong impact on knowledge dissemination. In a well-connected network, new information will spread to a larger number of R&D scientists (Freeman, 1977). The absence of fragmentation, that is, socially isolated (groups of) scientists, means there are no barriers that limit information sharing to just a subset of all employees in a cohesive intrafirm network. The shorter paths in cohesive networks also stimulate transfer because each extra step between two scientists increases the risk of knowledge not being dispersed. Since each R&D scientists could decide not to share new information, longer paths in a network reduce the likelihood of transfer. Regarding speed, communication among R&D scientists is an irregular process with substantial time intervals between receiving and passing on new knowledge. In such a case, networks with short paths increase the pace of information diffusion among scientists (Cowan & Jonard, 2004; Lazer & Friedman, 2007). Concerning reliability, each time information is transferred between employees, there is a risk of deletion, modification, or addition that can distort the value of knowledge (Freeman, 1977). Shorter paths among scientists then decrease the risks posed by alteration of information.

Second, from an active perspective of knowledge search, a higher network reach makes knowledge search via a firm's referral network more effective. R&D scientists frequently turn to their colleagues when they encounter a particular issue or are looking for a specific solution (Orr, 1996). While these direct connections may not be able to help them, they can refer them to other R&D scientists with the right expertise or skill (Jarvenpaa & Majchrzak, 2008; Singh et al., 2010). The number of peers a scientist can contact is therefore a combination of the number and structure of his/her connections. In particular, intrafirm networks lacking fragmentation and with short paths increase the likelihood of finding the right person. Two R&D scientists described this very clearly:

> *"I'm very lucky to know who the experts in my organization are. And if I don't, I ask who would know, who may have that information or maybe can refer me to whoever has that information. That's how it's done usually." (R&D scientist #3)*

> *"I think the largest challenge in an business the size of ours is to actually know who to contact when it's outside the normal day-to-day activities. But there is usually somebody you can find who knows somebody else you can get the answer from." (R&D scientist #11)*

In short, I expect that intrafirm networks with less fragmentation and shorter average path length, i.e. a higher degree of network reach, are more efficient and effective in knowledge transfer among R&D scientists.

> *H1: The higher the reach of an intrafirm network, the higher the knowledge transfer among R&D scientists.*

Organizational knowledge diversity refers to the overall variety of knowledge and beliefs held by R&D scientists (Fang et al., 2010; March, 1991). This is a combination of each R&D scientist's breadth of expertise corrected for overlap of expertise among R&D

scientists. Organizational knowledge diversity captures both breadth and depth of knowledge of all its employees. Network reach may not only increase knowledge transfer among R&D scientists, it may also engender a negative effect on knowledge diversity. Two arguments underpin this proposition.

To begin, disconnected components in a non-cohesive intrafirm network act as 'pockets' for different types of knowledge and technologies. The lack of communication and collaboration among R&D scientists from different units or laboratories reduces knowledge sharing (Carnabuci & Operti, 2013). As a result, these diverse groups of scientists will develop and refine their own technological trajectories (Dosi, 1982). This gives rise to more diverse knowledge and experience within an organization. For example, Chang et al. (2014) simulate that reduced fragmentation in Samsung's intrafirm network has a positive effect on knowledge transfer, but a non-linear effect on recombination. They argue that more cohesive networks function better as knowledge integrators, but worse as knowledge reservoirs.

In addition, networks with shorter paths lead to faster knowledge transfer and the adoption of new technologies and practices (Lazer & Friedman, 2007). Though this initially increases the performance of scientists, there is a long-term cost of discarding other, less effective technologies and practices. These seemingly inferior components may have a large potential for improvement (Fang et al., 2010; Lazer & Friedman, 2007). March (1991) has shown that such diversity is especially useful under changing environmental conditions. When environments change, previously inadequate technologies may find a new use and improve knowledge recombination (Adner & Zemsky, 2005; Christensen, 1997). Alternatively, in fragmented networks, R&D scientists face more difficulties in obtaining new knowledge. Instead, they will continue using their existing knowledge and knowhow. Repetitive use of the same knowledge components results in more minor enhancements and develops the full potential of each component (March, 1991). This process reveals alternative applications of a component and will sustain and increase organizational knowledge diversity. Therefore I pose that network reach has a negative effect on knowledge diversity.

H2: The higher the reach of an intrafirm network, the lower the knowledge diversity among R&D scientists.

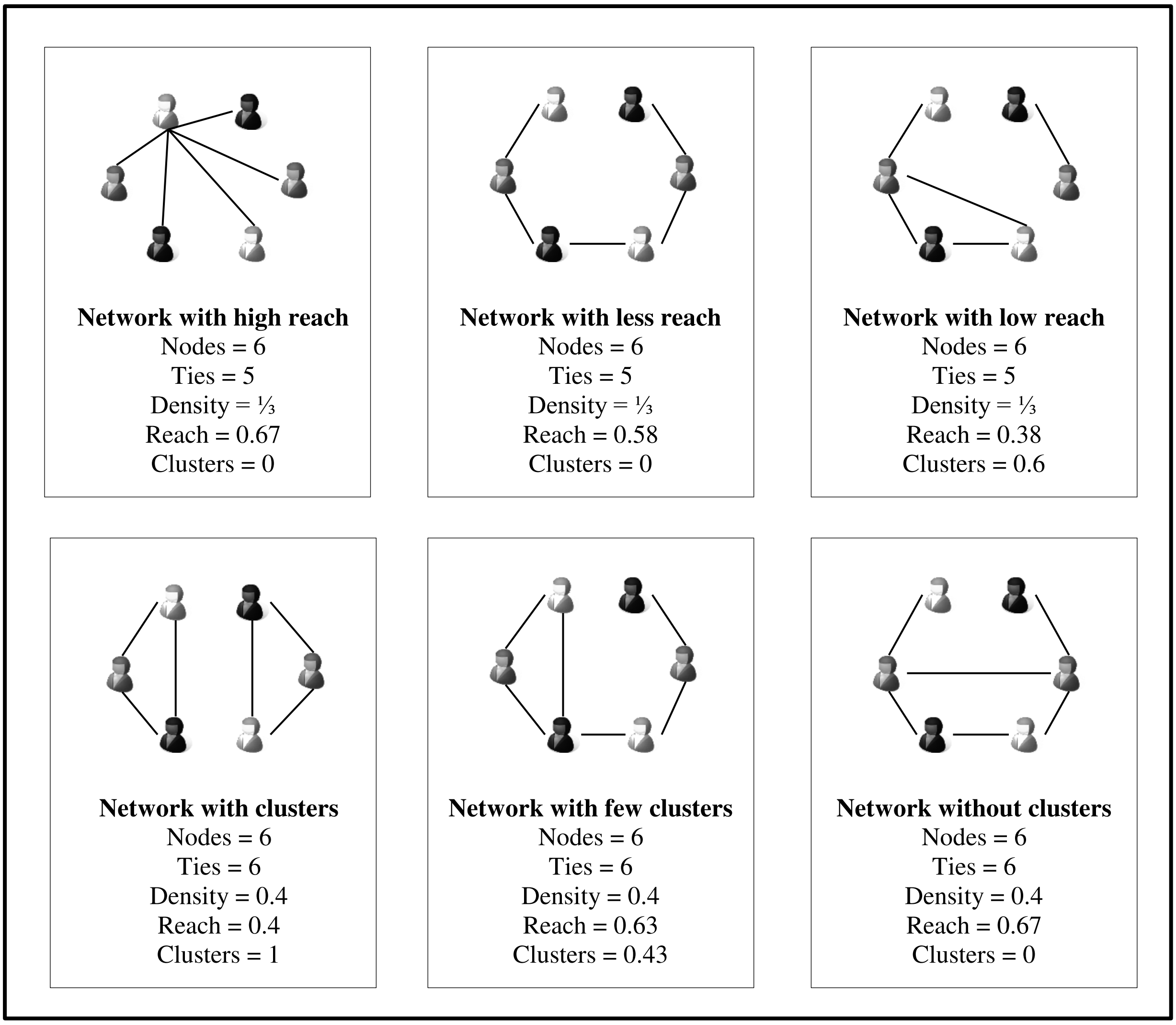


Figure 5 Reach and clusters in networks

Role of Clusters

Intrafirm social networks usually contain multiple clusters: groups of R&D scientists that are more strongly connected among themselves than with other R&D scientists (Wasserman & Faust, 1994). Network clusters tend to have a strong effect on knowledge recombination, though results have been confounding (e.g. Cowan & Jonard, 2004; Fang et al., 2010; Lazer & Friedman, 2007). I hypothesize that clusters have a twofold effect on knowledge transfer and a positive effect on knowledge diversity.

On the one hand, clusters facilitate the efficient transfer of knowledge and information among R&D scientists within a cluster. First, members of a cluster communicate and collaborate frequently or work on related projects (Brown & Duguid, 1991). Because of that, these scientists have a larger degree of shared and overlapping knowledge. This increases their mutual understanding and eases knowledge sharing among individuals (Postrel, 2002). Besides mutual understanding, the frequent interaction in clusters also indicates stronger ties among R&D scientists. These stronger ties allow for richer and more diverse information transfer among scientists, even when shared knowhow is very different from existing knowledge, when it is more complex, or when it is more tacit (Aral & Van Alstyne, 2011; Hansen, 1999). Easy access and a shared understanding of clusters are confirmed by the interviewed R&D scientists:

> *"[About solving problems.] First you ask people. I think that's an aspect that is often overlooked. But on a daily basis, for every problem, the first thing people do is start talking with a colleague." (R&D scientist #12)*

> *"First, of course, I discuss it with my peers, within my own group of engineers. Only if that fails, I contact colleagues in the larger company." (R&D scientist #15)*

Moreover, clusters create a social environment in which knowledge sharing is fostered. Because of the strong ties among scientists within a cluster, they develop higher degrees of trust and reciprocity (Uzzi, 1996). Stronger monitoring of social behavior by colleagues and joint enforcement of social norms reduces the risks of opportunistic behavior (Coleman, 1988). For example, Oldroyd et al. (2012) describe how team members jointly react in case of opportunistic knowledge hoarding by a single member. Clusters also stimulate reciprocity by allowing temporal and scope differences of exchanging and returning favors. For instance, Uzzi (Uzzi, 1996: 679) describes how entrepreneurs provide favors within the cluster without expecting reciprocity immediately or from the same partner. As a consequence of shared trust and reciprocity, R&D scientists within a cluster will share more, and more valuable, knowledge and resources.

On the other hand, clusters impede knowledge transfer among R&D scientists between clusters and lead to similarity in knowledge and expertise. As one scientist said:

> *"[When I learn], it is mainly outside the organization. In the organization, we are a small specialized group and there is not a lot I can learn from them [the colleagues]." (R&D scientist #13)*

These strongly connected groups of employees tend to develop strong professional and social norms (Brown & Duguid, 1991). Socialization processes undergone by newcomers to particular units or laboratories tend to reinforce these shared norms (Fang, Duffy, & Shaw, 2011). Such strong professional norms are often a barrier against the adoption of new practices and the acceptance of new knowledge (Fang et al., 2011; Katz & Allen, 1982). Burcharth and Fosfuri (2012) study the effect of employee socialization and the not-invented-here syndrome, that is, the tendency of groups to disregard information from outsiders. They find that stronger socialization practices in R&D settings instigate negative attitudes towards external knowledge. Intrafirm networks with strongly connected clusters may thus reduce the knowledge transfer. These opposing arguments lead to a dual hypothesis about the effect of network clusters on knowledge transfer.

> *H3a: The stronger the clusters of an intrafirm network, the higher the knowledge transfer among R&D scientists.*
> *H3b: The stronger the clusters of an intrafirm network, the lower the knowledge transfer among R&D scientists.*

While the effect of clusters on knowledge transfer is ambiguous, there is a clearer logic explaining their consequences for knowledge diversity (Cowan & Jonard, 2004). Initially, scientists within a cluster tend to develop more similar knowledge and knowhow among (Lazer & Friedman, 2007). Rapid interpersonal learning among scientists reduces diversity and differences among them (March, 1991). Stronger enforcement of social and professional norms also reduces deviant behavior and the pursuit of different R&D projects.

As a result, employees that are part of a cluster tend to become more homogenous over time, to exploit their existing knowledge and expertise, and to continue technological trajectories (Dosi, 1982; Uzzi, 1997). Since new employees undergo a socialization process via which they get acquainted with specialized knowledge and learn relevant skills, employee turnover does not immediately improve knowledge diversity (Burcharth & Fosfuri, 2012).

Whereas a single network cluster has negative effects for knowledge diversity, having multiple clusters in a firm has a positive effect upon knowledge diversity. To start, multiple professional communities are less likely to converge and become one homogenous group (Fang et al., 2010). Mutual learning within clusters strengthens the similarity of knowledge among scientists, but this reduces the likeness among R&D scientists belonging to different clusters (Cowan & Jonard, 2004). Because of the knowledge and information benefits, individual scientists face strong benefits by aligning themselves with a single cluster. In order to maintain and preserve their ties, actors adapt therefore to their direct colleagues (Lee, Lee, & Lee, 2006). Such professional conformity within a community reduces their ability to connect and learn from other groups in a firm.

In addition, network clusters foster the development of new knowledge and expertise (Brown & Duguid, 1991). As argued above, scientists with similar knowledge and expertise can easily communicate, exchange complex knowledge, and collaborate on various projects. This does not only increase knowledge sharing, but also leads to further development and refinement of this knowledge and expertise (Knorr-Cetina, 1999). Well-connected communities are wellsprings of learning and innovation and often develop unique technological trajectories (Dosi, 1982). Clusters in an intrafirm network means that groups of scientists specialize in different areas and develop skills in different directions, which increases the diversity of knowledge in an entire network. This is shown by Chang et al.

(2014), who find that the decay of clusters in a network reduces their potential as organizational knowledge reservoirs.

In short, I expect that intrafirm networks with more clusters are better in preserving heterogeneity of knowledge and may continue to increase diversity by developing new skills and expertise.

H4: The stronger the clusters of an intrafirm network, the higher the knowledge diversity among R&D scientists.

Role of Knowledge Diversity and Transfer

Firm innovation is positively influenced by knowledge diversity and knowledge transfer. Performance of each scientist depends on its motivation, opportunity, and ability in its recombinant search process. Whereas knowledge diversity creates a scientist's opportunity for successful recombination, knowledge transfer shapes their ability to access and apply diverse knowledge.

The opportunity for innovation is largely determined by the diversity of knowledge and expertise present among scientists (Fleming, 2001). Since innovation involves the recombination and reconfiguration of various components of knowledge, opportunity rises when there are more diverse components present in an organization. In an arithmetic fashion, the number of combinations increases exponentially with the degree of diversity in knowledge and expertise (Sorenson & Fleming, 2004). A firm's homogeneous knowledge base provides scientists with little opportunity for finding new combinations, but heterogeneity in knowledge and expertise increases chances for innovation (Garcia-Vega, 2006). Therefore I expect that firm innovation increases significantly with the diversity of knowledge and skills possessed by its R&D scientists.

H5: The higher the knowledge diversity among R&D scientists, the higher firm innovation.

The ability for R&D scientists to integrate diverse knowledge depends on the availability of this knowledge to all of them. This is a combination of their human and social capital (Fleming, Mingo, et al., 2007; Hansen, 1999). In firms characterized by high levels of knowledge sharing and rapid dispersion of new information, R&D scientists have access to a larger quantity and variety of knowledge possessed by their colleagues. They can build upon this larger knowledge base in their R&D projects and thereby increase their chances for success. On the contrary, if a firm is rich in knowledge held by specialists, but they are unable to share or collaborate, there is little integration and recombinant search is likely to fail. Therefore I argue that firm innovation increases further with the degree to which R&D scientists share their knowledge and expertise.

H6: The higher the knowledge transfer among R&D scientists, the higher firm innovation.

Altogether, this study proposes that knowledge base characteristics mediate the relationship between intrafirm network structure and firm innovation. Higher network reach increases the transfer of knowledge among R&D scientists in an organization because scientists are all connected in an efficient manner. The flow of knowledge improves each scientist's access to knowledge, skills and capabilities possessed by others. This increases their productivity which results in higher firm innovation. Alternatively, networks with shorter paths tend to reduce the diversity of knowledge held by R&D scientists. Faster diffusion and adoption of new practices harms the heterogeneity of technologies and skills. Therefore I expect the effect of network reach on firm innovation to be mediated by knowledge transfer and diversity.

H7: The relationship between intrafirm network reach and firm innovation is mediated by knowledge transfer and knowledge diversity.

Network clusters have a dual effect on firm innovation via knowledge transfer. Where clusters provide an organization with a transmission capacity for rich information, clusters of scientists may also obstruct the transfer of knowledge beyond their own group. Network clusters augment knowledge diversity in a firm's scientific community. This increase in heterogeneity of skills and expertise improves recombinant search by R&D scientists. Through clusters, scientists now have a larger number of knowledge components at their availability. Thus I argue that network clusters have an indirect effect on firm innovation via knowledge transfer and diversity.

H8: The relationship between intrafirm network clusters and firm innovation is mediated by knowledge transfer and knowledge diversity.

METHODOLOGY

Setting and Data Collection

The hypotheses are tested in the medical devices industry. This industry is selected for three reasons. First, this is an R&D intensive industry where firm performance and survival are strongly linked to a firm's innovative successes (Wu, 2013). Most innovation relates to new product development that incorporates novel materials and technologies, so there is a clear recombinant search process (Joseph et al., 2013). Second, innovation activities in this industry are highly observable. The medical devices industry relies heavily on patents to protect their intellectual property rights (De Vet & Scott, 1992) and the Food and Drug Administration (FDA) keeps detailed records of all devices introduced, leaving precise records of innovation efforts and outcomes. Third, knowledge and expertise in this industry are largely held by individuals, thereby making interpersonal collaboration relevant for knowledge recombination (Chatterji, 2009).

I selected the fifty largest public American medical device firms in 1990 by ranking a self-computed factor score that included their annual sales in medical devices, the number of patents they held in this field, and the number of FDA approvals (PMA and 510(k) requests). The sample was limited to the North-American market since I rely on USPTO patent data, which may introduce biases for non-US firms. Only public firms are included because details about corporate structure and operations are often not available for privately-held companies. Since the US are by far the largest market for medical devices and all major players are publicly listed (Frent, 2011), these constraints are unlikely to bias the results. The sample (included in Appendix A, p. 178) consists of three types of firms: pure-player medical device firms (like Medtronic and Stryker), diversifying pharmaceutical firms (like Eli Lilly and Wyeth) and diversifying technology firms (like GE and Kodak).

Data for each firm were obtained from a variety of sources. First, firm financial and operational data were obtained from the WRDS Compustat North America database and any missing values were obtained from Thomson One Banker. Based on SEC 10K filings and Moody's Industrial Manual, I created detailed family trees for all firms for the period 1985-2010. These are then used to obtain all USPTO patents these firms obtained by matching firm and subsidiary names to patent assignees in the NBER Patent Data Project (Hall, Jaffe, & Trajtenberg, 2001) and Harvard Patent Dataverse (Lai et al., 2011). Using an advanced USPTO technology concordance (USPTO Patent Technology Monitoring Team, 2012), non-medical device patents were excluded for further analysis. In a similar fashion, I extracted all scientific publications by medical device firms in Elsevier Scopus based on the author affiliation field.

Intrafirm Networks

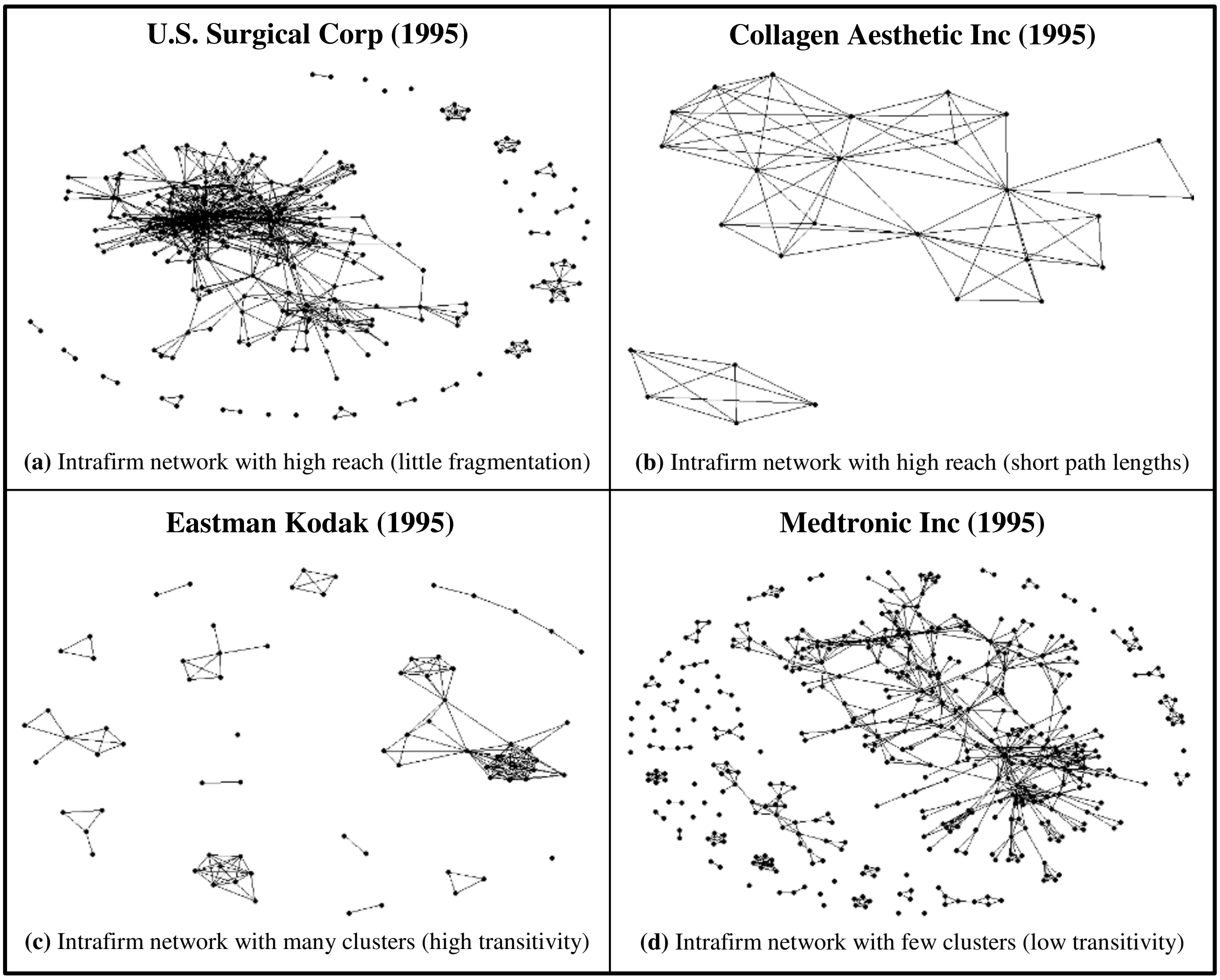
Intrafirm networks are based upon co-invention and co-authorship among R&D scientists focused on medical devices (Singh, 2005). Participation in an R&D project involves intense interaction among scientists for a longer period of time. This includes extensive information exchange and knowledge transfer among collaborating scientists. Furthermore, scientists often remain in touch with each other after a project has finished, so the exchange of information continues (Paruchuri, 2010). Several of the interviewed R&D scientists remarked this as well. For example:

> *"So, it is somewhat based on your personal relationships. Who you remain in touch with after a project. There are a few people you remain in touch with even though you did not collaborate for five years. [...] You talk with them once a month, just because you like to discuss what they are working on now." (R&D scientist #2)*

> *"I have a network of experts that I can call upon. Often because you have been working with them." (R&D scientist #8)*

Moreover, scientists learn about others' field of interest and expertise via collaboration. This creates transactive memory in an organization, that is, a mental map of who knows what (Jarvenpaa & Majchrzak, 2008). Collaborative ties are therefore strong proxies for social ties among R&D scientists.

To construct intrafirm networks, I consider medical device patents and scientific publications of the sample firms. Nodes in these intrafirm networks are all inventors mentioned on medical device patents. Since there is no simple criterion to demarcate medical device publications from non-device publications, authors are only included when they are also mentioned on a patent. In short, nodes in an intrafirm network consist of all medical device inventors in a firm and ties are all co-patenting and co-authoring instances among them. In line with the existing literature, I construct undirected, dichotomous intrafirm networks based upon co-authors and co-invention ties using five-year moving windows (e.g. Funk, 2013). Exemplary intrafirm network graphs are shown below.



(a) Intrafirm network with high reach (little fragmentation) **(b)** Intrafirm network with high reach (short path lengths) **(c)** Intrafirm network with many clusters (high transitivity) **(d)** Intrafirm network with few clusters (low transitivity)

Figure 6 Examples of intrafirm networks

Sample

Data for the fifty firms were collected from 1990 till 2005. The industry was subject to substantial merger and acquisition activity during the 1990s and several diversified firms divested their medical device activities. Therefore, the number of firms reduced from fifty at the start to seventeen at the end of the period. I further excluded firm-year observations with fewer than five R&D scientists in an intrafirm network since network characteristics are not meaningful for such small networks (e.g. Carnabuci & Operti, 2013; Funk, 2013). Finally, some knowledge characteristics cannot be measured in years with zero successful patent applications and are therefore excluded in some or all regressions. The final sample is an unbalanced panel of 50 firms with 484 firm-year observations.

Measurement

Dependent variable. *Firm innovation* is measured as a citation-weighted patent count (Hall, Jaffe, & Trajtenberg, 2000; Trajtenberg, 1990). For each firm-year, I counted the number of patents a firm successfully applied for and added the number of non-self-citations these patents received over a five-year period after their application. The choice for application year is deliberate since patents can be cited from the moment of application (before being granted) and using grant year would introduce right censoring because my observations run until 2005. A robustness check revealed that using application or grant year measures correlate at 0.986, meaning any bias is negligible.

Mediating variables. *Knowledge diversity* is measured as a Blau's index of the main technological classes of a firm's successful patent applications in a particular year. This measure (one minus a Herfindahl concentration index) combines the technological diversity, revealed by the number of technological classes of a firm's patents, with the relative spread over different classes.

Knowledge transfer is measured as the percentage of patents and citations during the focal year that is reused by other inventors, who have not cited these patents before, in the subsequent three years. Patent citations are a common proxy for measuring knowledge transfer (e.g. Singh, 2005). Despite their flaws, citations are a pretty robust indicator that is more likely to underestimate than overestimate real transfer (Roach & Cohen, 2013). I only count the reuse of knowledge by other scientists because transfer assumes passing on information between inventors and excludes re-using knowledge by the same (team of) inventor(s). A three-year window is used since knowledge search, transfer, and application processes do not occur immediately, but only when relevant opportunities arise.

Independent variables. Network *reach* is measured via intrafirm network compactness. Compactness combines two elements of network connectedness, namely the lack of fragmentation and presence of short paths (Wasserman & Faust, 1994). While fragmentation indicates the number of disconnected scientists in a network, path length indicates the average number of steps between two connected R&D scientists. It is calculated as the average inverse path length which equals zero for disconnected pairs:

$$Reach = \frac{1}{N \cdot (N-1)} \left(\sum_i^N \sum_j^N \frac{1}{path\ length_{i,j}} \right) for\ i \neq j$$

This variable is limited between 0 and 1. It is independent of the number of R&D scientists in a network and generally independent of network density.

Network *clusters* is measured via intrafirm network transitivity. Transitivity indicates the likelihood of actors *j* and *k* being connected given that both *j* and *k* are connected to *i* (Wasserman & Faust, 1994). This ratio variable gauges the potential and actual triadic closure in a network. It signifies the tendency of actors to be part of strongly connected clusters in a network and is calculated as:

$$Clusters = \frac{3 \times number\ of\ triads}{number\ of\ triples}$$

with a triad being a closed triangle (*i*, *j* and *k* all connected) and a triple being two connections to a same node (*j* and *k* both connected to *i*). This variable is limited between 0 and 1. It is independent of network size and density and more robust than alternative measures.

Control variables. Various firm and network characteristics are added to control for alternative explanations.

Firm size has diverse effects on firm innovation (Hansen, 1992). Therefore firm size is controlled for by measuring the natural log of sales (in millions) in medical devices. I specifically measure medical device sales only as some highly diversified firms earn just a fraction of their revenues in this industry.

Medical device focus indicates the relevance of a firm's medical device units among all business segments of a firm. Firms spread R&D activities disproportionally among business units (Baysinger & Hoskisson, 1989). So in order to capture the importance of medical devices, I calculate the share of a firm's medical device sales to its overall sales.

Firm performance has a positive influence on firm innovation since profitable firms have more resources and fewer constraints for R&D. Therefore return on sales (EBIT ÷ total sales) has been added.

Firm leverage reduces managerial discretion and tightens budgetary constraints, which is likely to influence R&D activities. For that reason I compute firm leverage as a debt-to-assets ratio (total debt ÷ total assets). Debt-to-assets was preferred over debt-to-equity, which provided extreme values for highly leveraged firms.

Firm slack has a two-sided effect on innovation: it increases resources available for research and development, but simultaneously reduces the need or urgency for innovation (Nohria & Gulati, 1996). Slack, measured as the current ratio (current assets ÷ current liabilities), is added to control for this effect.

Acquisitions will have a positive effect on firm innovation since firm growth leads to a larger R&D expenditure and an increased scientific workforce. A firm's acquisition intensity in a year is measured as the amount spent on acquisitions of medical device firms scaled by a firm's annual medical device sales.

Divestments of medical device units will reduce firm innovation since a firm loses human and intellectual capital. In a similar fashion to acquisitions, I compute the total value of divestments divided by the total sales in medical devices to capture this effect.

R&D scientists directly contribute to firm innovation. A larger R&D workforce increases recombinant efforts and firm productivity. The number of R&D scientists is obtained from the firm's patents using a five-year moving window. This is, of course, the same as the number of nodes observed in an intrafirm network.

R&D recruitment increases a firm's R&D workforce and leads to inflow of new knowledge (Song, Almeida, & Wu, 2003). Recruitment is observed via the number of scientist first appearing in the firm (via patents) during the focal year as a percentage of the total number of scientists.

R&D concentration relates to the geographical dispersion of a firm's R&D activities. This is an important variable since spatial proximity influences network tie formation as well as knowledge transfer (Lahiri, 2010). This is calculated as a Herfindahl concentration index based on the R&D scientists most recent address, as observed on patent applications, grouped by US state or foreign country.

R&D intensity is measured as a firm's R&D expenditures divided by its sales. It indicates the amount of resources available for R&D activities and proxies their strategic importance, which positively influences firm innovation (Cohen, Levin, & Mowery, 1987).

R&D team size influences the likelihood and quality of recombinant search efforts (Singh & Fleming, 2010). Since it also affects clusters in intrafirm networks, I add the average number of inventors on each patent as a control variable.

Network density, as a structural characteristic of intrafirm networks, influences knowledge transfer and recombination (Lazer & Friedman, 2007). Since the usual density measure is highly correlated with the number of R&D scientists, I measure network density in this study via the average degree centrality of scientists in an intrafirm network.

Network isolate ratio corrects for the number of 'lone scientists' (unconnected scientists) whose innovativeness is significantly different from connected scientists (Singh & Fleming, 2010). It is computed as a percentage of the total number of R&D scientists.

A number of control variables were initially added but eventually excluded for multicollinearity problems. First, total annual sales correlated highly with the annual sales in medical devices. Second, firm age was added since it generally reduces innovation (Hansen, 1992), but it also correlated strongly with firm size. Third, firm diversification had to be excluded since it is negatively correlated with a firm's medical device focus. Fourth, the depth and breadth of firm patent stock (Park & Park, 2006) were excluded since depth was already captured by the number of R&D scientists and breadth by firm size.

Estimation Method

The three dependent variables have two different shapes. While firm innovation is a non-negative count variable, knowledge transfer and knowledge diversity ratios are bounded between 0 and 1. Therefore I opted to use a generalized estimating equations (GEE) specification to test the hypotheses. This is a generalized linear model (GLM) relatively robust to unknown or misspecified correlation structure. In particular, a GEE specification allows defining the distribution of a regressand for each regression and corrects for non-independence caused by repeated observations over time (Hardin & Hilbe, 2003). I use Stata's xtgee command with an exchangeable correlation structure and Huber-White (robust) standard errors. An exchangeable correlation structure is applied to capture autocorrelation among repeated observations (Hardin & Hilbe, 2003: 59). Year dummies are added to capture temporal variance. Finally, to address reverse causality concerns, dependent variables are all observed at a one-year lead (t+1).

Hypotheses 7 and 8 are tested using a Sobel-Goodman mediation test with efficient standard errors (Stata's sgmediation command). This approach is preferred for several reasons. First, Baron and Kenny's (1986) method for mediation using a traditional Sobel test is generally considered over-restrictive (Shaver, 2005). This results in high type I error rates and underestimates significance. Second, the Sobel-Goodman mediation test uses a non-parametric approach. Unlike other mediation tests, it does not impose a particular distribution on any of the variables to gain meaningful results (Preacher & Hayes, 2004). This is relevant since the mediating variables are ratios while the dependent variable is a count variable. Third, it can correctly estimate mediation effects even when there are multiple mediators working in opposing directions. Fourth, it applies a bootstrapping procedure to correct for correlations in standard errors. This is useful for panel data research.

RESULTS

Table 1 below displays the descriptive statistics and correlations of variables of the final sample. It reveals there is substantial variation in firm innovation, knowledge characteristics and network structure. Unfortunately knowledge transfer and diversity could not always be calculated as they demand at least one successful patent application during prior and focal year, respectively. Because of that, the number of observations slightly varies in different regressions. Some high correlations among network control variables warn for potential multicollinearity issues. I extensively check for high VIF values of independent variables in any of the regressions (Allison, 2012a). This revealed several issues with key control variables like firm size. In cases where they exceeded 10, models were re-run leaving out on or more correlated variables. In all cases, this reduces VIF values to acceptable levels, but had no impact on the direction or significance of other regression coefficients.

Table 1 – Descriptive statistics and correlations of sample (p. 153)

Table 2 presents the regression results of network structure on knowledge transfer (models 1 to 4) and knowledge diversity (models 5 to 8). With regard to transfer, geographical concentration of R&D activities increases knowledge transfer among R&D scientists (model 1). Model 2 shows that network reach has a significant negative effect on transfer, thereby rejecting hypothesis 1. Network clusters also has a negative, though insignificant effect on knowledge transfer (model 3). So it provides no support for H3a or H3b. Knowledge diversity increases strongly with a firm's R&D intensity, the recruitment of new R&D scientists and network density (model 5). Network reach, however, has a negative impact on knowledge diversity (model 6). This supports hypothesis 2. Model 7 demonstrates that network clusters significantly decreases knowledge diversity, rejecting hypothesis 4.

Table 2 and Table 3 – Regression results for knowledge and firm innovation (p. 154)

Table 3 displays the regression results of knowledge characteristics and network structure on firm innovation. Looking at the control variables, firm innovation increases significantly with the size of a firm, its performance and its acquisition activity. R&D intensity, R&D geographical concentration, and R&D workforce also have a positive effect. Network density has no significant effect, but many isolates seem to reduce innovation. Models 2 to 4 show that both knowledge transfer and knowledge diversity increase firm innovation, thereby supporting H5 and H6.

Table 4 – Results of Sobel-Goodman mediation tests (p. 156)

Concerning hypotheses 7 and 8, regarding the mediating effects of knowledge transfer and diversity, I first checked for direct effects. Model 5 in Table 3 shows that network reach has a strong negative effect on firm innovation. This is in line with earlier results: reach has a negative effect on diversity and transfer, which both positively relate to firm innovation. The analysis for network clusters shows similar results: it negatively affects diversity as well as innovation (model 6).

Table 4 shows the results of Sobel-Goodman mediation tests of all four possible mediation effects. Even though this method incorporates the effects of control variables, it only provides coefficients and standard errors for the direct and mediated effects of focal variables. In addition, it also provides non-parametric bootstrapping estimates of confidence intervals. The first two models show that the effect of network reach on firm innovation is fully mediated. First, network reach has a negative effect on knowledge transfer, which itself has a positive effect on innovation. Second, network reach has a negative effect on knowledge diversity, which itself also has a positive effect on innovation. The next two models show that the effect of network clusters on firm innovation is partially mediated by knowledge diversity. Network clusters has a negative effect on the firm's knowledge base, which itself has a positive effect on firm innovation.

Robustness Checks

A large number of robustness checks have been carried out to confirm the above findings. To begin, I use alternative measures for each of the independent, mediating, and dependent variables. First, alternative measures are used to measure network reach and clusters. Instead of one measure for reach, I use two different components: network fragmentation (e.g. the percentage of the R&D scientists which are not (in)directly connected) and absolute path length (e.g. how many steps are there on average among all connected R&D scientists). For clusters, I use the clustering coefficient, or average ego-network density, similar to Guler and Nerkar (2012). Results, included in Table 8 (p. 160), are consistent with earlier findings. Most noticeably, the more fragmented an intrafirm network and the longer the paths, the more knowledge transfer. Other variations of reach, like the size of the largest component and the component ratio (regressions not included), provided similar significant results. The effects for clusters are slightly weaker, but still indicate a negative effect on knowledge transfer and firm innovation.

Second, I used slightly different measures for knowledge characteristics. Knowledge transfer was also measured by solely using patents (the percentage of patents applied for at [t-1] recited by others during [t0;t+2]). Knowledge diversity is also measured at the level of technological subclasses. The new measures are only moderately correlated with prior measures ($\rho>0.5$). Regressions of networks on knowledge and knowledge on innovation showed similar results (columns 1 to 3 in Table 9 on p. 161), but the negative effect from network clusters on knowledge transfer now becomes significant. One might also think that network clusters and reach may inhibit transfer and increase exploitation by the same R&D scientists. However, network reach and clusters also had negative effects on general recitation rates (the percentage of citations at [t-1] recited during [t0;t+2] by any scientist, including self-citations). In addition, I repeated the regressions of network structure on knowledge transfer and diversity by including the lags of dependent variables. While lagged variables were highly significant, network reach and clusters remained negative and significant (see columns 4 to 7 in Table 9 on p. 161). Similar stable results were obtained when the lagged variable of firm innovation was added to the regressions of network structure and knowledge characteristics on firm innovation.

Third, I also measure firm innovation by the number of new or technologically improved medical devices. Firm and subsidiary names were matched against applicant names for FDA medical device approvals in PMA and 510(k) procedures. For each firm-year, I counted the number of new or technologically improved medical devices a firm registered. Though the number of products is normally correlated with the number of patents, the new measure is slightly weaker since some firms do not commercialize their own inventions. The new products variable is lagged by two years to correct for the time gap between invention and implementation. Results are included in Table 10 (p. 162). The results are weaker than earlier results: though coefficients remain in the same direction, only network reach (negative) and knowledge diversity (positive) remain significant.

In addition to alternative measures, I use alternative estimation methods to check the significance of the results. First, the regressions in Table 3 were repeated using alternative specifications. I repeat the results with a fixed-effect negative binomial regression (Stata's xtnbreg command) and a fixed-effect Poisson quasi-maximum likelihood model (Stata's xtpoisson command). The earlier method provides stronger controls for unobserved heterogeneity via conditional firm-fixed effects, while the latter provides unconditional fixed effects without the incidental parameter problem (Wooldridge, 1999). The regressions are included in Table 11 (p. 163) and show similar significant results.

Second, the mediation check was repeated using a two-stage least squares approach as advised by Shaver (2005). I use a panel data GMM estimator (Stata's xtivreg2 plug-in) in which network reach and clusters are used as instruments for knowledge diversity and transfer. The regressions are included in Table 12 (p. 164). For knowledge transfer (model 3), the instruments are considered exogenous (Hansen J: p=0.42), but the first-stage model is only marginally significant (p=0.09). The results are still significant and provide support for a mediated relationship. For knowledge diversity (model 6), the instruments are also exogenous and this model converges correctly (first-stage model p<0.001; Hansen J: p=0.64). Results prove that diversity mediates the relationship between network structure and firm innovation. When testing each of the instruments individually, the effects of knowledge transfer and diversity seems to be driven more by network reach. The results become weaker when double mediation is tested simultaneously.

As well as alternative specifications, I also repeat the analysis on subsamples of the dataset. First, I exclude smaller networks since some network measures may be influenced by network size. Instead of using five R&D scientists as minimum network size, the analyses are repeated when networks have at least fifteen or fifty R&D scientists. Though the sample size drops considerably (by 20% and 50%, respectively), the results (see Table 13, p. 165) are very similar to the main findings above. Second, though the GEE estimation method is normally robust against outliers, I carefully check for their effect since the dependent variable firm innovation is strongly skewed. The regressions of Table 3 are repeated by (a) leaving out the 5% highest observations and (b) winsorizing the 5% highest observations. Both strategies provide results that are almost identical to the earlier findings (see Table 14, p. 166).

Finally, research on small world networks has indicated that the combination of high reach with many clusters increases performance and innovation (Fang et al., 2010; Schilling & Phelps, 2007; Uzzi & Spiro, 2005; Watts & Strogatz, 1998). Therefore I repeat all earlier analysis by including the interaction effect of mean-centered network reach and network clusters. The results, included in Table 15 (p. 167), do not provide any evidence of small world effects. While the individual effects of reach and clusters on knowledge transfer, knowledge diversity, and firm innovation remain significant, the interaction term of reach and clusters does not gain significance.

Robustness Checks at the Level of Patents and Citations

Whereas knowledge diversity is a firm-level characteristics, knowledge transfer can be measured at various levels. I use this opportunity to replicate the above results of network reach on knowledge transfer at the level of individual patents and individual citations. The detailed procedures for these robustness checks are included in Appendix C (p. 189).

At the level of the patent, I estimate the likelihood of a patent being cited by new patents from other inventors within the same organization in the subsequent three years. Such a citation indicates that an R&D scientist builds upon the work of his/her colleagues and is a proxy for knowledge transfer (Singh, 2005). The results indicate that collaborative networks among R&D scientists are a significant determinant for citing each other's patents. The findings show that knowledge transfer increases with the centrality of its inventors within an intrafirm network (similar to Paruchuri, 2010). However, if an intrafirm network has shorter paths, the likelihood of knowledge transfer reduces (see Table 16, p. 168). An extra check reveals that this effect is particularly strong for patents with central inventors (model 3). In summary, intrafirm network reach reduces the likelihood of each patent to be reused or incorporated in new inventions.

At the level of citations, I estimate the likelihood of future patents citing the focal patent. This method, adapted from Singh (2005), estimates the likelihood of a patent being cited by each patent developed by the same firm in the subsequent three years. The results (see Table 17, p. 169) indicate that social connections among R&D scientists are a significant determinant for patent citations and thus knowledge transfer. Specifically, the regression reveals that citations between two patents are more likely if inventors have had collaborative ties, but this positive effect turns negative for longer indirect ties. This negative effect occurs when the number of steps increases beyond two, that is, when there is no common acquaintance between inventors but a longer path from the existing patent to the new invention. With over 70% of all patents being connected via these longer paths, this is by far the largest group. In conclusion, compared to non-connected R&D scientists, scientists with short paths are more likely to transfer and exchange knowledge but those with longer paths are less likely.

DISCUSSION

In settings where complex, tacit knowledge is largely held by individuals, firm innovation is the product of their communication and collaboration structures. Intrafirm networks are major determinants for knowledge sharing, transfer, recombination, and ultimately innovation. However, despite an abundant academic literature on intrafirm social networks, there has been little coherence in the effects of macrolevel network structure on firm innovation. This study aimed to clarify some of these results by identifying mediating effects on knowledge diversity and transfer. Drawing upon the key concepts of macrolevel network literature, I argued that network path length and clusters would indirectly influence firm innovation via knowledge transfer and diversity. Using a longitudinal sample of the fifty largest medical device firms, this study provided results contrary to the expectations. Specifically, it revealed that reach and clusters in an intrafirm network have significant negative effects on knowledge transfer and diversity, and thereby firm innovation.

The intrafirm network structure has an unexpected negative effect on knowledge transfer. While the number of connections in a network has no significant effect on knowledge transfer or innovation, shorter paths in intrafirm networks strongly reduces it. Various robustness checks using alternative measures consistently demonstrate this negative effect. In particular, I find that both cohesion (the lack of fragmentation) and efficiency (short paths) have negative effects on knowledge transfer. At the level of individual patents, the results indicate that reach only works for very short paths. Longer paths, on the other hand, make knowledge transfer and reuse less likely compared to the absence of a connection. This finding both challenges and confirms earlier studies: while these studies argue that any tie increases knowledge sharing, some studies (e.g. Singh, 2005) also find that the effects are different within the same organization. Similarly, Guler and Nerkar (2012) also argued that distant connections often offer only limited benefits: whereas they provide novel knowledge, this information is often too distant and less relevant. This also reduces the likelihood of re-using this knowledge. In addition, distant connections indicate weak ties between R&D scientists (Granovetter, 1973). Weak ties are very useful for passing simple information, but not effective for sharing complex knowledge (Hansen, 1999). In such circumstances, shorter and stronger ties are more powerful because the willingness and ability to share increase. R&D scientists are more willing to spend time and efforts on sharing information with their closer peers. In addition, their mutual understanding increases the likelihood of success (Aral & Van Alstyne, 2011).

In line with existing research, networks with a higher reach decrease knowledge diversity. Lazer and Friedman (2007) revealed that efficient networks may share information extensively but also weed out diversity in a network. Creative deviance is reduced because strongly connected networks increase socialization among R&D scientists. This decreases the diversity of skills and expertise among R&D scientists. Instead, firms with such networks are more likely to continue along similar technological trajectories by reconfiguring existing knowledge combinations instead of pursuing new knowledge combinations (Carnabuci & Operti, 2013).

The presence of clusters in intrafirm networks has no significant effect on knowledge transfer. As argued in the hypothesis, the effect of clusters on information sharing is ambiguous: while scientists within a cluster tend to readily share information, they are less likely to obtain and use knowledge from other clusters. Fang et al. (2010) also noticed this effect in their simulation of organizational learning where learning among individuals increased with the size of the individual clusters. The citation-level robustness check confirmed this once more: knowledge transfer increases with short connections, which are more likely to occur within a cluster, but is much lower for distant connections, which span clusters.

Unexpectedly, network clusters reduce firm knowledge diversity in a network. Small world network literature has argued that clusters in a network help in maintaining knowledge heterogeneous (e.g. Cowan & Jonard, 2004; Schilling & Phelps, 2007; Uzzi & Spiro, 2005). Limited isolation of groups of R&D scientists would deliver more 'pockets of knowledge'. But the results here do not support this argument. On the contrary, it reveals that clusters tend to increase in exploitation instead of exploration. A potential explanation could be related to the effects of clusters on the knowledge diversity among R&D scientists within a cluster.

Stronger socialization processes reduces their heterogeneity (Burcharth & Fosfuri, 2012; Fang et al., 2011) and may ultimately reduce knowledge diversity in an organization.

As predicted, knowledge transfer and knowledge diversity increase firm innovation. More diverse knowledge increases the opportunities for knowledge recombination. More diverse technological resources boost the potential for knowledge exploitation (Fleming, 2001). In addition, more diverse knowledge facilitates the absorption of other knowledge (Cohen & Levinthal, 1990). This is shown in a rise in the number of new patents and new products produced by these firms. Similarly, firms that share more knowledge internally show a higher number of new patents and new products. Overall, this confirms earlier research regarding the importance of knowledge for innovation (Cohen & Levinthal, 1990; Fleming, 2001; Grant, 1996).

Intrafirm network reach has a significant negative effect on firm innovation. While the absolute number of connections among R&D scientists has no effect on firm innovation, their structure has a strong effect. Specifically, the more efficient an intrafirm network, the lower the aggregate innovation by all R&D scientists. This sheds new light on earlier findings by Guler and Nerkar (2012) who concluded that global network density reduces firm innovation. Here it is shown that it is not the number of connections per se, but their efficiency that reduces firm innovation. Mediation tests also show that this effect is fully mediated by the negative effect of network reach on knowledge transfer and diversity.

Intrafirm network clusters also have a negative effect on firm innovation. Groups of well-connected R&D scientists in a network reduce the number of new patents. This result opposes Guler and Nerkar's (2012) finding that clusters increase firm innovation. In this study, the negative effect is partially mediated by knowledge diversity. A potential explanation given by Chang et al. (2014) is that larger clusters in a network reduce the heterogeneity of knowledge held by each individual. In addition, clusters also have a direct negative effect on firm innovation that is not mediated by knowledge processes.

Contributions

The findings of this study primarily speak to the large literature on networks and innovation (Phelps et al., 2012) It assesses the mechanisms via which intrafirm network structure influences firm-level innovation. Literature on macrolevel network structures argued that cohesive network "enable the creative material in separate clusters to circulate to other clusters" (Uzzi & Spiro, 2005: 449) and network clusters "become important structures for creating and preserving the requisite variety of knowledge in the broader network that enables knowledge creation" (Schilling & Phelps, 2007: 1115). This study puts these mechanisms to a test. By shifting the level of analysis from micro (the node) to macro (the network), I can measure knowledge transfer and diversity. This is normally not possible for individual-level studies, but I am able to examine these effects by taking an organizational-level approach.

The results, however, contradict these presumed mechanisms. With regard to network reach, Carnabuci and Operti (2013: 1594) argue that a well-connected intrafirm network "increases a firm's ability to innovate through recombinant reuse". This study reveals that networks with shorter paths and less fragmentation actually reduce knowledge transfer among R&D scientists. Similarly, Fleming et al. (2007) estimate the effect of inventor networks on regional innovation and find that both less fragmentation and shorter paths increase regional innovation, but the robustness checks of this study obtained the exact opposite results. With regard to network clusters, Guler and Nerkar (2012: 546) state that "local cohesion [clusters] helps as scientists benefit from the close interaction". This is not supported by the results of my analysis that reveal that clustered networks do not increase knowledge transfer. Finally, several studies have obtained a positive small world effect for creativity and innovation (e.g. Schilling & Phelps, 2007; Uzzi & Spiro, 2005) but this effect is not corroborated by robustness checks in this study. In summary, this study questions the mechanisms that mediate the relationship between network structure and innovation.

Secondary, this study contributes to management research by bridging the micro/macro divide in social network studies (Moliterno & Mahony, 2011; Molloy et al., 2011). While the majority of the network studies considered the microlevel of individual employees and their creativity, only few network studies have taken a macrolevel view and considered aggregate innovation. This distinction is important because microlevel network structures may increase the performance of one employee at the cost of others' (Operti & Carnabuci, 2012). This study increases our understanding in various ways. First, the number of connections generally increases the number and impact of innovations for individual R&D scientists (Fleming, Mingo, et al., 2007; Paruchuri, 2010; Singh & Fleming, 2010), but not global firm innovation (Guler & Nerkar, 2012). This study's findings also support this idea since coefficients for network density remain insignificant. Second, many studies have shown that brokerage increases an individual's performance (Phelps et al., 2012) but potentially at the cost of others (Bizzi, 2013). This study contributes to the brokerage/closure debate by revealing that the macrolevel effect for a firm is still positive. Third, closeness centrality is normally positively related to an individual's creative performance (Ibarra, 1993). However, at a macrolevel it turns out that higher degrees of closeness centrality for all employees, i.e. network reach, actually have a negative influence on innovation.

CONCLUSION AND LIMITATIONS

In R&D intensive industries, firm performance is often directly linked to firm innovation. Nevertheless, innovation remains a largely serendipitous process performed by individuals or teams. This study looks how the intrafirm social network structure, which is created and sustained at the interpersonal level, influences innovative performance at the firm level. This study reinforces the idea that interpersonal connections have a major impact on knowledge sharing, diffusion and recombination within organizations. However, contrary to extant research, the results of this study suggest that high-reach networks with strong clusters are actually detrimental for firm innovation. Instead, networks with low reach and fewer clusters are able to share and transfer knowledge more effectively. Such networks also sustain higher levels of knowledge diversity and successively increase the firm's number new patents and products. Therefore this study calls for further research on the mechanisms that mediate network structure and innovation.

This study is subject to several limitations that could also give lead to new research. First, I have assumed that network nodes have large agency in tie formation, that is, R&D scientists have substantial freedom in choosing who they like to collaborate with. This was noticed in earlier research in similar R&D settings (Dahlander & McFarland, 2013; Sasovova et al., 2010) and my interviews with R&D managers have confirmed it. As one manager described the formation of R&D project teams:

> *"More often than not, it's usually political about who is chosen. Because they want to be chosen and they force their way in. That's just a very honest answer." (Manager #12)*

In addition, though managers may influence microlevel structures by composing project teams, there is little reason to assume firms actively influence macrolevel network structure. Still, new research could investigate what firm characteristics influence network structure.

Second, this study relies on archival data to measure networks, knowledge and innovation. I aimed to overcome the limitations of patent data by adding publication data and also considering the number of new products. Still, a part of all interpersonal connections, knowledge flows and creativity will not be captured by this process. In addition, I am unable to observe unsuccessful recombinant efforts: in case R&D projects do not lead to new patents or products, the processes of transfer and diversity are also unobservable. Further qualitative research could overcome these issues.

Third, the medical devices industry is a specific setting. Similar to other high-tech industries, the medical device industry is very R&D intensive. But contrary to other settings, the medical devices industry draws upon a large number of different scientific disciplines from both the medical and technical sciences. Most knowledge, skills and abilities are possessed by individual scientists and not by firms, making interpersonal collaboration even more important. The effects of social network structure on innovation may be weaker in settings with less specific and more common knowledge.

CHAPTER 3: INTERORGANIZATIONAL COLLABORATION, INTRAORGANIZATIONAL NETWORKS, AND FIRM INNOVATION

ABSTRACT

This study investigates how firm innovation is jointly influenced by two levels of collaboration. At the interorganizational level, collaboration via interfirm alliances and joint ventures is an important method for accessing external knowledge and information. At the intraorganizational level, intrafirm collaboration among R&D scientists is a significant mechanism for knowledge transfer and diffusion. Both forms of collaboration stimulate firm innovation, but little is known about their joint impact. I argue that interorganizational collaboration provides an *opportunity* for absorbing new knowledge while intraorganizational collaboration networks shape a firm's *ability* to use and exploit this information. A longitudinal study on almost fifty medical device firms over a fifteen year period shows that the positive effect of interfirm R&D alliances on firm innovation is stronger for firms with better connected intrafirm collaboration networks, whereas the presence of strongly-connected groups within a firm weakens this relationship. These results suggest that firm innovation is the outcome of a multilevel network process in which interfirm ties are complemented by intrafirm networks.

INTRODUCTION

Individual and organizational collaboration networks are a core theme in innovation research (Phelps et al., 2012). These studies are primarily guided by social network research, which meticulously examines the effects of network size, structure and strength on individual performance (Brass et al., 2004; Pittaway et al., 2004). Management researchers have intensely investigated the effects of interfirm collaboration networks on firm innovation or intrafirm social networks on individual creativity. Despite this large body of work, there is still a lack of understanding on how collaboration changes innovation.

First, traditional interorganizational network research in the field of innovation largely overlooks firms contingencies for interfirm collaboration effects. These studies control for the direct effects of firm characteristics on innovation, but they spend little attention to potential interaction effects of firm and network characteristics. However, recent research has shown that the rise in innovation after alliance formation depends upon characteristics of a firm. For example, Rothaermel and Hess (2007) reveal that the effects of alliance formation on firm innovation are contingent upon human and financial capital within a firm. Similarly, Chen (2004) demonstrates that knowledge transfer in alliances increases with firm absorptive capacity. Despite these studies on the role of a firm's human capital in interorganizational collaboration, only few studies considered the role of a firm's social capital (e.g. Holmqvist, 2003; Moreira & Markus, 2013). In particular, no studies have considered the interactive effect of interorganizational alliances and intraorganizational collaboration networks on firm innovation. This is an relevant issue since intrafirm network constitute an organization's recombinant capability (Carnabuci & Operti, 2013).

Second, innovation scholars have generally treated interfirm and intrafirm collaboration independently (Brass et al., 2004). Interorganizational network research has carefully analyzed how interfirm alliances influence interorganizational knowledge spillovers and innovation. In particular, much attention has been paid to the size, structure and composition of ego and global networks (Phelps et al., 2012). Intraorganizational network research closely looked at the impact of social network structures on employee creativity and performance, in particular the effects of size, strength and structure of their connections (Van Wijk et al., 2008). This body of work has also addressed the consequences for aggregate network performance at the level of the firm (e.g. Carnabuci & Operti, 2013; Guler & Nerkar, 2012). Though it considered how intrafirm networks help in sharing new knowledge, it generally pays little attention to where this new knowledge originates from. One potential source, interorganizational knowledge spillovers, are not considered. Overall, little attention has been paid to the joint effects of inter- and intrafirm networks. Noticeable exceptions are a some individual-level studies. Lazega et al. (Lazega et al., 2008, 2006) have shown how productivity of medical researchers is influenced by their personal networks as well as the network of their institutions. In a similar fashion, Paruchuri (2010) finds that inventor productivity is changed by both interpersonal and interfirm networks. However, to my best knowledge, no studies have yet investigated how interfirm and intrafirm collaboration jointly influence firm innovation. This is a relevant issue since collaboration structures benefiting one R&D scientist may harm the performance of their peers or the entire organization (Bizzi, 2013; Operti & Carnabuci, 2012). So network structures that benefit a single employee may not help an entire organization. Therefore, a multilevel approach could greatly contribute to research on networks and innovation by providing a more sophisticated view on knowledge sharing, transfer and recombination.

Third, research on the structure of intraorganizational collaboration network often considered firms to be isolated environments. These studies argue that organizations aim to balance knowledge diversity and knowledge sharing via their collaborative structure. Their models consists of employees learning via diffusion and recombination (Chang et al., 2014; e.g. Cowan & Jonard, 2004; Fang et al., 2010; Lazer & Friedman, 2007). In these simulations, new knowledge enters an organization via autonomous exploration or random turnover by employees (March, 1991). Despite the advances made by this line of research, it overlooks the increasingly important role of interorganizational collaboration. Interorganizational networks are a source of learning and knowledge absorption, and may be an important source of knowledge diversity (Khanna et al., 1998). Therefore, the effects of intraorganizational networks structure on firm innovation may depend on interorganizational collaboration. This could challenge the search for 'optimal' network structures and instead foster a multilevel network logic.

This study aims to address these theoretical gaps by asking how interorganizational collaboration and intraorganizational networks mutually influence firm innovation. I argue that interfirm R&D alliances provide a firm with *opportunities* to access and absorb external knowledge while their *ability* to turn it into innovation depends on their intrafirm network. In larger organizations, only a subset of all employees becomes boundary spanners via their involvement in alliance activities. This means that knowledge may cross organizational boundaries, but is not instantly available to all employees (Hargadon & Sutton, 1997). Nevertheless, R&D scientists not involved in an alliance may still receive new information via the intrafirm network that connects them to these boundary spanners. I draw upon earlier studies exploring the effects of macrolevel network structures – that is, the structure of an entire network – to identify relevant concepts (e.g. Fang et al., 2010; Lazer & Friedman, 2007; Provan et al., 2007; Watts & Strogatz, 1998). These studies highlighted the importance of network connectedness (i.e. the number of connections), clustering (i.e. the presence of strongly connected groups) and efficiency (i.e. short paths among all members). These macrolevel network concepts represent important microlevel network structures – that is, the characteristics of ego-networks of individual actors – namely actor centrality and ego-network closure (Wasserman & Faust, 1994). I expect that these intrafirm networks characteristics moderate the effect of interfirm collaboration on innovation. This proposition is tested on a longitudinal dataset of 49 North-American firms in the medical devices industry between 1990 and 2005. This is an R&D intensive setting where knowledge and expertise are mainly possessed by individuals and interpersonal collaboration is key to recombinant success. These firms collaborate externally with other organizations via R&D alliances and internally via a collaboration network including all R&D scientists. The results show that R&D alliances and intrafirm network structure jointly increase firm innovation, implying that better connected intraorganizational networks complement external R&D alliances.

This study contributes to several lines of research, including research on networks and innovation, the alliance literature, and the microfoundations of firm absorptive capacity. By demonstrating how firm innovation is jointly influenced by interfirm and intrafirm collaboration, this study illustrates the relevance for a multilevel conceptualization of innovation networks. For example, the effect of networks on innovation at one level may hinge upon a network structure at a higher or lower level. In a similar vein, this study shows how firms differ in innovation benefits they obtain from R&D alliances. Their intrafirm networks can facilitate or hamper the inflow and recombination of new information and skills obtained from interorganizational collaboration. Intraorganizational networks are an additional factor explaining how organizations gain asymmetrically from an R&D alliance. Lastly, this study identifies intrafirm networks as fundamental mechanisms for firm absorptive capacity. The origins and processes that build a firm's capability to recognize, absorb and exploit external knowledge have largely remained unexplored. This study reveals that a firm's absorptive capacity is partially determined by connectedness of a firm's intrafirm network.

THEORY AND HYPOTHESES

To understand how interorganizational collaboration and intraorganizational networks jointly influence firm innovation, I use three related literatures: recombinant innovation, boundary spanners in interfirm collaboration, and intrafirm collaboration networks. The literature on recombinant search explains innovation as a purposeful process of recombination and reconfiguration of knowledge components (i.e. technologies, materials, skills, etc.) (Fleming, 2001; Schumpeter, 1934). R&D scientists, individually or in teams, use their personal skills and expertise to find solutions for existing problems or pursue new ideas (Fleming, 2001; Sorenson & Fleming, 2004). In each occasion, R&D scientists could either build upon their existing knowledge and experience or learn about new technologies and techniques (March, 1991). Recombinant search efforts by individuals are often uncertain and have unpredictable results, but chances for success increase with the knowledge components at their availability. The more novel and diverse their experience and expertise, the larger the potential to identify new combinations or configurations. Creativity and innovativeness of R&D scientists is therefore a function of the knowledge components they possess or could access (Fleming, Mingo, et al., 2007; Singh & Fleming, 2010). Firm innovation is then the aggregate of successful recombinant search efforts by its R&D workforce.

The value of knowledge components in organizations reduces over time. Initially, organizations can continue building upon their existing knowledge by improving and refining their expertise (Dosi, 1982). However, the opportunities for reconfiguration of the same set of knowledge components are limited (Fleming & Sorenson, 2004). In addition, the magnitude of such improvements tends to decrease over time (March, 1991). Therefore organizations aim to learn new knowledge components. Since internal development of new knowledge is a costly and time-consuming endeavor, organizations also rely on interorganizational alliances and knowledge sharing agreements for organizational learning (Chesbrough, 2003).

Interorganizational Collaboration and Boundary Spanners

Interorganizational collaboration is an important source of organizational learning and firm innovation (e.g. Ahuja, 2000a; Powell, Koput, & Smith-Doerr, 1996; Shan et al., 1994). Collaboration between organizations via alliances and joint ventures is an efficient method for using complementary, non-transferable resources owned by multiple organizations (Dyer, 1997). But when it comes to innovation, the largest benefits of interfirm collaboration are related to intended and unintended knowledge spillovers between partner organizations (Inkpen, 2000; Lavie, 2006). Alliances and joint ventures function as conduits for the flow of knowledge and knowhow between partnering firms (Owen-Smith & Powell, 2004). Such knowledge spillovers, or the transfer of knowledge and knowhow between organizations, are an important source of learning and innovation because this knowledge is new to an organization. Interfirm alliances are often preferred over internal capability development because it is faster and cost-efficient (Ahuja, 2000a). The idea that interorganizational collaboration results in valuable knowledge spillovers, especially when they exceed the official purpose of the alliance, was supported during my interviews with alliance managers.[3] As two managers and one scientist explained it:

> *"When we develop new things, internally or in collaboration, there is obviously always an intent to gain new knowledge. [...] We always want to gain a solid knowledge and background." (R&D scientist #6)*
>
> *"It inevitably leads to learnings and knowledge sharing from both sides. Ultimately, the idea is that cross-company work is highly encouraged: the more information that is shared, the quicker we can get to the end goal." (Alliance manager #5)*
>
> *"For example, the engineers learned a lot of things that they wouldn't understand because they don't want to go to school again. But in this project they did learn it from the partner firm." (Alliance manager #7)*

One manager even explained how learning was an implied, but never formalized objective of interorganizational collaboration:

> *"Of course we like to learn the technology and knowledge that or partner organization owns. That is one of the unofficial objectives. [...] Our alliance with the supplier is to get their technology. Then we will modify it and take advantage of their innovations. We then bring our own product to other markets where they are not active." (Alliance manager #13)*

A large body of literature has identified factors that facilitate or hinder the effect of interorganizational collaboration on firm innovation (for a review, see Easterby-Smith, Lyles, & Tsang, 2008). First, the degree of knowledge spillovers is influenced by structural

[3] I performed over thirty semi-structured interviews with managers and scientists in the health industry to gain a deeper understanding of the antecedents of innovation. For confidentiality reasons, all quotes are paraphrased.

characteristics like scope and governance mode (Mowery et al., 1996; Oxley & Sampson, 2004). Second, the relational characteristics of alliance partners influence knowledge sharing (Tsai & Ghoshal, 1998). Especially, trust and reciprocity in interfirm relationships are important determinants for knowledge spillovers (Ahuja, 2000a; Inkpen, 2000; Uzzi, 1997). Third, certain organizational capabilities also sustain knowledge spillovers from interfirm cooperation. An organization's absorptive capacity, i.e. the ability to learn new external knowledge, increases firm innovation via R&D alliances (Chen, 2004). And firm innovation via alliances is stronger if organizations have more collaborative experience (Rothaermel & Deeds, 2006).

Less attention has been paid to the processes that lead to interorganizational knowledge spillovers. This is surprising since alliances are essentially no more than contractual agreements between two organizations (Gulati, 1995). Though these interfirm agreements are often related to firm innovation, the processes that explain this relationship occur at a lower level (Felin et al., 2012). It are individual scientists working in R&D alliances that learn new knowledge and skills from an alliance partner (Berends et al., 2011; Janowicz-Panjaitan & Noorderhaven, 2008; Oliver & Liebeskind, 1997). When an organization commences alliance activities, a number of R&D scientists of this organization will be dedicated to these joint R&D projects. Teams of employees from both organizations are actively involved in collaborative activities for a longer period of time (Davis & Eisenhardt, 2011). As such, these employees will become organizational boundary spanners (Allen, 1966; Tushman, 1977).

Communication and collaboration of boundary spanning R&D scientists leads to the exchange of knowledge and information (Tushman & Scanlan, 1981a). Boundary spanners are able to learn new knowledge and skills by forming new connections to their colleagues in a partner firm (Zhao & Anand, 2013). This interpersonal contact is particularly relevant for learning more valuable complex, tacit knowledge that could not be shared otherwise among organizations (Hansen, 1999). Therefore R&D scientists in alliances fulfill an important function by scanning, selecting and absorbing external information. As some of the interviewed managers described this process of knowledge spillovers:

> *"There are some technical skills that our scientists are learning based on the technology that the partner has and some of the technologies they use that our scientists haven't used in the past." (Alliance manager #1)*

> *"On the technical side, we learn of the polymer for pharmaceutical application which was also useful for the medical device application that we shared." (Alliance manager #3)*

Consequently, learning by boundary spanning employees, at the individual level, is crucial to learning at the organizational level. The interviewed R&D scientists mentioned frequent communication via e-mail, phone calls, conference meetings or site visits as an important source of new information. The alliance managers recognized the role of open collaboration and emphasized the importance of direct communication between boundary spanners:

> *"Well, there is a lot of unstructured communication of just people writing e-mails and picking up the phone and talking to their counterparts. There is formal communication, but there is a lot of informal and day to day communication afterwards." (Alliance manager #6)*

> *"Learning happens primarily by letting people work together. We have the experts from our suppliers sitting together with our experts and decide to work on solutions. So it's not so much we tell you what we need and then you need to execute, it's really working together." (Alliance manager #9)*

In summary, interorganizational collaboration leads to knowledge spillovers between organizations because teams of employees of both firms collaborate and exchange knowledge and information. These knowledge spillovers increase an organization's *opportunity* for knowledge recombination and innovation.

Intraorganizational Networks and Firm Innovation

Firms also rely on intraorganizational collaboration to pursue technological innovation. By integrating skills, knowledge and expertise of their employees, organizations create new or improved products and processes (Grant, 1996; Kogut & Zander, 1992). R&D

scientists in these firms, individually or in teams, use their personal skills to find solutions for existing problems or pursue new ideas (Fleming, 2001; Sorenson & Fleming, 2004). Social capital literature has shown that the productivity of scientists in R&D laboratories is not solely determined by their human capital (e.g. Borgatti & Cross, 2003; Ibarra, 1993; Tsai, 2001). Instead, a scientist's productivity is also influenced by personal connections to other scientists. Personal ties among R&D scientist lead to sharing of information in a largely informal and unorganized manner (Brown & Duguid, 1991; Gupta & Govindarajan, 2000). Personal interaction is also an important condition for the transfer of complex, tacit knowledge (Hansen, 1999; Nonaka, 1994). The stronger the connections between employees, the larger and richer the information and resources they exchange (Borgatti & Cross, 2003; Granovetter, 1973; Tsai & Ghoshal, 1998). Extant research on interpersonal networks has consistently shown that larger and more diverse connections increase an individual's performance and creativity (Van Wijk et al., 2008). Besides, the number and strength of ties, their structure is an important determinant of performance (Burt, 1992). Employees embedded in densely-connected subgroups benefit from a larger communication bandwidth, but suffer from reduced novelty and diversity in their network of peers (Aral & Van Alstyne, 2011).

In an R&D setting, interpersonal connections contribute significantly to sharing information about new technologies, materials and methods (Allen, 1966). Central actors in a network have faster access to new knowledge, resources and other components, which is critical for their recombinant search (Fleming, 2001). They are not only accumulators of information, but also hubs of knowledge: they actively collect, share and distribute information. Their role as knowledge hub in an R&D laboratory improves their individual performance, the performance of their peers and ultimately the entire organization (Grigoriou & Rothaermel, 2014).

Because interpersonal networks lead to knowledge flows at the individual level, the structure of intrafirm networks affects innovation at the organizational level (Guler & Nerkar, 2012). Structural characteristics of networks influence the likelihood, speed and extent of diffusion (Freeman, 1977). Structure also influences the diversity of knowledge among actors (Lazer & Friedman, 2007). For example, Carnabuci and Operti (2013) demonstrate that a larger fraction of connected scientists in a firm's R&D department has positive effects on innovation via knowledge recombination and that this partially depend on the heterogeneity of skills and expertise of scientists.

Network connections, network clustering and network efficiency are three network-level characteristics of intrafirm networks that have received considerable attention in social network literature (Phelps et al., 2012; Provan et al., 2007). Network connections, or density, refers to the number of connections among employees (Wasserman & Faust, 1994). At the level of individual R&D scientists, the number of connections is related to receiving more information, more diverse information and more novel information (Freeman, 1977). As a result, R&D scientist performance increases with their number of connections (Fleming, Mingo, et al., 2007; Operti & Carnabuci, 2012). At the level of an organization, intrafirm network density is related to information diffusion and knowledge transfer (Lazer & Friedman, 2007). In particular, better connected networks transfer new knowledge and information faster and to a larger part of the network.

Intraorganizational networks are also characterized by clustering, that is, the presence of strongly connected groups of employees within an organization (Wasserman & Faust, 1994). Such clusters serve to store knowledge and gain support for new initiatives. Strong clustering helps in gaining support and mobilizing resources to use it in new products and processes (Schilling & Phelps, 2007). Clustering also helps in storing diverse and different types of knowledge and expertise (Fang et al., 2010). They constitute an organization's 'pockets of knowledge' and are therefore very relevant for innovation. In addition, clustering helps to resist convergence on a unique technology or trajectory (Lee et al., 2006).

Finally, intraorganizational networks vary in their degree of efficiency (Funk, 2013). Efficiency refers to the presence of relatively short paths among employees, that is, employees are either directly connected or via few common acquaintances. In organizational learning, short paths assist in a quick transfer of knowledge and information. If information is passed on informally via a diffusion process, network path length has a direct effect on the speed by which it diffuses (Lazer & Friedman, 2007). And if a scientist is looking for a colleague with some particular expertise or experience on a topic, s/he is more likely to find the right person if path lengths are short (Singh et al., 2010).

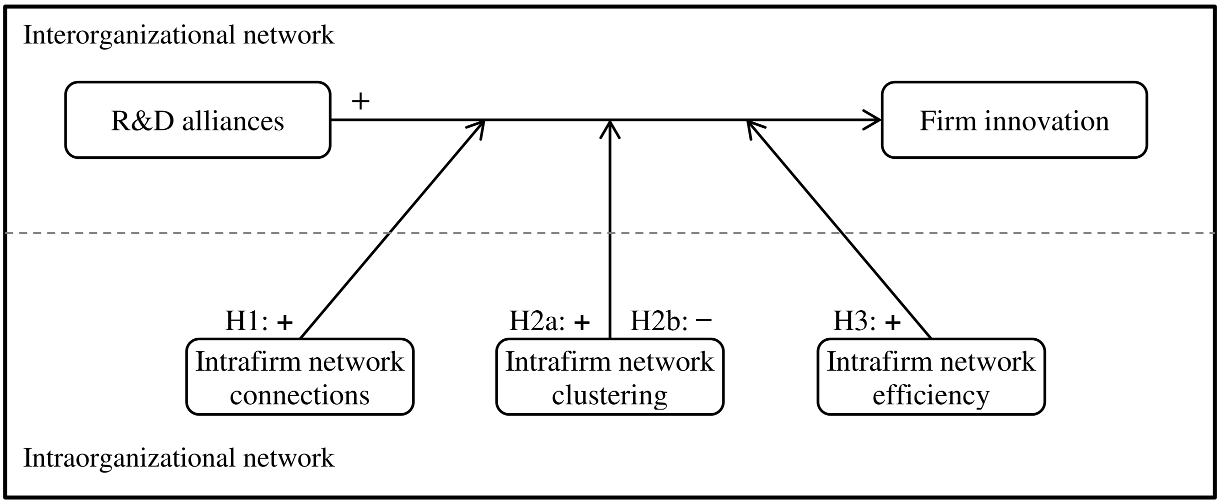


Figure 7 Theoretical framework

Hypotheses Development

The above discussion on interorganizational collaboration and intraorganizational collaboration networks has shown that both forms of collaboration lead to innovation via the efforts of individuals. Therefore I argue that both forms of collaboration are complementary means for firm innovation. R&D alliances provide an *opportunity* for absorbing novel external knowledge. Communication and collaboration among R&D scientists from cooperating organizations help in transferring complex knowledge and technologies across organizational boundaries (Janowicz-Panjaitan & Noorderhaven, 2008). A firm's *ability* to use and exploit this new information depends on the capability of its intrafirm network to diffuse knowledge and facilitate scientists in employing it. As a result, an interfirm and an intrafirm network perform different but highly complementary roles. Providing a firm enters into an R&D alliance, I argue that the magnitude of its increase in innovation is contingent upon its intrafirm network characteristics.

First, only a fraction of all scientists are involved in a firm's R&D alliances and have direct access to knowledge and resources of a partner firm. Other scientists in a firm may still learn from a partner firm's knowledge if they are (in)directly connected to one of the boundary spanners. Via conversations or collaboration on other R&D projects, they will know what is going on in an alliance. Boundary spanners may also actively share their experiences with their colleagues. The interviews confirmed that this occurs regularly:

> *"Our employees also apply these experiences in other projects that they are involved in. They have done or they've shared them with colleagues that are working on similar projects." (Alliance manager #1)*

> *"Sometimes we try to isolate alliance teams working with competitors [two competing alliance partners]. But if two people are friends and they see each other in the lunch room, then they do talk about what they do in their alliance projects." (Alliance manager #12)*

However, one R&D scientist remarked that spillovers could be exploited further if there were institutional mechanisms supporting this:

> *"[About knowledge spillovers.] I think we should do more with that then we do now. At the end of the project, we are supposed to have a sharing exercise where we look back at the project, but what typically happens is that it gets missed. The learning, by and large, does tend to stay with the individuals that were directly involved in that project." (R&D scientist #6)*

This confirms that the further sharing and circulation of new information gained by boundary spanners largely depends on their individual initiatives via their personal connections to other R&D scientists.

The larger the number of interpersonal ties in a network, the further and faster newly absorbed knowledge from a partner firm will diffuse. More connections imply that new information is passed on more frequently and more extensively. As a result, better connected networks show a fast diffusion of novel information (Lazer & Friedman, 2007). In addition, more connections also reduce the risk that information will not reach all R&D scientists of a firm. Therefore I propose that the positive effect of R&D alliances depends upon an intrafirm's network connections:

> *H1: The positive effect of R&D alliances on firm innovation is stronger for intrafirm networks with more connections.*

Second, intrafirm network clustering has a dual effect of the adoption of new information. On the one hand, a group of acquainted employees will frequently share knowledge and information. Because of their frequent communication and information sharing, there is a larger overlap in their individual knowhow. This enables the efficient transfer of tacit and complex knowledge among employees (Aral & Van Alstyne, 2011). Furthermore, clustering leads to higher levels of trust and reciprocity. The willingness to share new information is much higher in such environments since individuals are less concerned about opportunistic behavior (Coleman, 1988; Uzzi, 1997). If R&D alliances allow a firm to learn about new techniques, they will diffuse faster throughout an organization if its intrafirm network has strong clusters that efficiently share this new information. When discussing this with R&D managers, one interviewee explained how clusters helped her organization to share new information efficiently:

> *"We have therapeutic area centers. Representatives of organizational groups get together once a month to share the latest and greatest about that therapeutic area and then they are supposed to spread it to their groups." (Alliance manager #12)*

On the other hand, clustering creates strong professional norms that may resist the adoption of new practices and demotivate sharing particular knowledge (Fang et al., 2011; Katz & Allen, 1982). Strong socialization processes in a laboratory increases the not-invented-here syndrome in which employees are unwilling to learn and employ new techniques and skills developed outside an organization (Burcharth & Fosfuri, 2012). One alliance manager explained how these clusters obstruct information sharing and reduce learning from alliances:

> *"Because no matter how small the company is, there are functional silos. Due to that, it's never very easy to have a clear communication between different groups in an organization." (Alliance manager #15)*

Instead, scientists within clusters will stick to their own knowledge and expertise and potentially doubt others' findings (Latour & Woolgar, 2013). In this line of argumentation, the inflow of new information from R&D alliances will have a weaker effect on innovation if a firm's network is strongly clustered. Given these two opposing arguments about the role of clusters in adopting and diffusing information, I state the following dual hypothesis:

> *H2a: The positive effect of R&D alliances on firm innovation is stronger for intrafirm networks with stronger clustering.*

> *H2b: The positive effect of R&D alliances on firm innovation is stronger for intrafirm networks with weaker clustering.*

Third, the efficiency of intraorganizational networks will moderate the effect of R&D alliances on firm innovation. The length of paths among R&D scientists has consequences for the likelihood, speed and reliability of information transfer (Freeman, 1977). In a passive sense, information is less likely to diffuse from person A to B if A and B have no direct connections: it will then depend on common connections to pass on information. Since intermediary persons may forget, take time, or alter information (Hargadon & Sutton, 1997; Schilling & Fang, 2013), longer paths between persons reduces diffusion. In an active sense, if person A needs expertise or resources possessed by B, it can use its social capital to approach B. Person A can simply ask B for a favor if they are directly connected, but A might need to use a common intermediary for a referral if they are not directly connected. Singh et al. (2010) have shown how employees within a consulting company vary significantly in their centrality and path lengths and therefore their access to others' knowledge and expertise. With regard to alliances, one R&D manager noted that his scientists involved in alliances were approached by their colleagues for their relevant information:

> *"Even employees that themselves are not directly involved, are able to follow what is ongoing [in an R&D alliance]. And if they would need some of this technology development or problem solving for their own projects, then they are able to contact these people who can help them." (Alliance manager #13)*

This mechanism of introductions and referrals to obtain relevant information is more effective if the path between the source and recipient is shorter.

Changing from an individual to a network level, efficient networks have a positive effect on knowledge diffusion (Lazer & Friedman, 2007). I therefore argue that intrafirm networks with shorter paths are superior in diffusing new knowledge. Innovation after the inflow of knowledge from R&D alliances will be stronger if an intrafirm network is more efficient:

> *H3: The positive effect of R&D alliances on firm innovation is stronger for intrafirm networks stronger efficiency.*

METHODOLOGY

Sample Selection and Data Collection

The setting for this study is the North-American medical devices industry (SICs 3841-3851). Firms active in this industry produce a variety of devices used in the healthcare industry, ranging from syringes to pacemakers to MRI scanners. Despite their diversity, all firms have in common that their products harbor complex technological knowledge. This industry was selected for three reasons. First, it is an R&D intensive industry (Wu, 2013). The average R&D expenses count for 7% to 13% of total costs, which is well beyond average (Frent, 2011), and firm's technological innovation has an immediate effect on firm performance (Wu, 2013). Second, knowledge in this industry is mainly possessed by individuals (Chatterji, 2009). Recombinant success thus largely depends on employee search efforts, either independent or in teams (Fleming, 2001). Firm innovation is then directly related to interfirm and intrafirm collaboration among R&D scientists. Third, collaborative activities as well as innovative performance are highly observable in this industry (De Vet & Scott, 1992). Medical device firms tend to patent intensively which leaves a paper trail of their R&D activities. Moreover, interfirm R&D collaborations are quite common and publicly announced in this industry.

The initial sample consists of the fifty largest public North-American medical device firms in 1990 based on their annual medical device sales, patents and products. The sample was limited to public firms to ensure sufficient data availability. These firms were observed from 1990 till 2005, though strong M&A activity within the industry as well as divestment by diversified firms meant the final sample is unbalanced (for an overview of the period of observation for each firm, see Appendix A on p. 178).

Data were collected from 1985 till 2010 since some measures are computed over five-year windows starting before 1990 or finishing after 2005. Firm financial and operational data were obtained from the firm and segment sections of WRDS Compustat. Missing data were added from firm annual reports accessed via Thomson One Banker. Based on SEC 10K filings, I created detailed corporate trees to find all names under which a corporation is doing business. Matching these against the patent assignee fields, I obtained all medical device patents these firms were granted by the USPTO. Bibliographic details for patents were obtained from Harvard's Patent Network Dataverse (Lai et al., 2011). In a similar fashioned I obtained all publications of the fifty sample firms from the Elsevier Scopus database.

Intrafirm networks were constructed using patent and publication data. R&D scientists in the field of medical devices are observed as inventors on medical device patents of the sample firms. Collaboration ties among these scientists are observed via co-patenting and co-publication. In line with existing literature (e.g. Fleming, King, et al., 2007), I use a five-year moving window to construct unweighted, undirected networks for each firm-year. Network measures are calculated using the iGraph package in the R console.

Finally, I collected firm alliance data from three different sources. To start, I extracted relevant alliances from the SDC Platinum Alliance database and the Recombinant Capital (ReCap) dataset. While the earlier has a bias towards larger firms, the latter focuses more on biotech alliances than medical devices. In addition, I searched for any mention of interorganizational collaboration in around 1,500 annual reports and SEC 10K statements filed by the sample firms. Lastly, I searched for any announcement of alliances in the Factiva and LexisNexis databases. Using a detailed keyword search for alliances in combination with firm and subsidiary names led to over 120,000 hits. These articles were then manually scanned and, if relevant, coded. After manually eliminating all non-medical device alliances, the final sample consists of almost 2,300 unique interfirm agreements. Around 40% of these are partially or fully focused on R&D activities. Exact details regarding this procedure are included in Appendix B (p. 181).

A sample was constructed for the fifty medical device firms starting in 1990. A number of firms dropped out of the sample early because of mergers and acquisitions or by divesting their medical device units, while a part survived until the end of the observation period in 2005. This reduced the number of observations and led to an imbalanced panel. In addition, I excluded firm-year observations with fewer than five R&D scientists in their intrafirm network: network structures are not meaningful for these organizations (following Carnabuci & Operti, 2013). Lastly, because I use a fixed effects method to control for unobserved heterogeneity, each firm has to appear in the sample at least twice. The final sample therefore consists of 49 firms observed during 483 firm-years.

Measurement

Dependent variable. *Firm innovation* is measured via a citation-weighted patent count. Since medical device firms rely strongly on intellectual property rights to protect their innovations, patents are a robust proxy for innovative performance (Hall et al., 2000). These patents are weighted by their forward non-self-citations to correct for quality differences among inventions (Trajtenberg, 1990). Firm innovation in a given year is the number of patents a firm successfully applied for plus the number of citations these patents received in the next five years. This five-year window is based on application year since patents are cited from their application onwards and using grant year would introduce right censoring.

Independent and moderation variables. *R&D alliances* is the number of unique R&D alliance partners a firm is connected to in a particular year. This measure is based on the logic that interfirm collaborations give access to partner firms' knowledge base during their lifespan (Ahuja, 2000a; Lavie, 2006). This means multiple simultaneous alliances are only counted as one while multipartner alliances count for multiple. Alliances are considered from their announcement or start until their termination. If terminations were not publicly announced, I assumed a three-year duration (comparable to Schilling & Phelps, 2007) unless better approximations could be made based on announced extension or continued existence.

Intrafirm connections captures the number of ties among R&D scientists. Each connection leads to the flow of knowledge and information between scientists. It is measured as the average degree centrality of R&D scientists, that is, the number of collaborative partners over a five-year window. Network density (actual ÷ potential ties) was considered as an alternative measure, but it correlates highly with network size.

Intrafirm clustering is measured as the average ego-network density of all R&D scientists corrected for a similar density in a random network (Guler & Nerkar, 2012; Watts & Strogatz, 1998). It measures to what extent a scientist's acquaintances are also acquainted

(Burt, 1992). This indicates that a scientist is part of a strongly connected group in which collaborative partners of individuals overlap substantially. The measure is scaled for clustering caused by network size and density:

$$Intrafirm\ clustering = \frac{Actual\ CC}{Random\ CC} = \frac{(\sum_i^N[\sum_j \sum_k d_{ijk}/(.5j(j-1))])/N}{k/N}$$

with N being the number of R&D scientist and k the intrafirm network connections. The numerator computes intrafirm clustering in the observed network while the denominator calculates clustering in a random network of similar size and connections.

Intrafirm efficiency is measured as the reverse of average shortest distance among all scientist corrected for network size and connections (Watts & Strogatz, 1998). When R&D scientists are indirectly connected, their access to each other's knowledge and expertise reduces with the number of steps between them. Average shortest path length strongly influences the likelihood and speed of diffusion (Freeman, 1977). This measure is scaled to control for differences in network size and connections, and is reversed so that a higher score means a more efficient network:

$$Intrafirm\ efficiency = -\frac{Actual\ PL}{Random\ PL} = -\frac{\left(\sum_i^N\left(\sum_j^N path\ length_{ij}\right)/J\right)/N}{\ln(N)/\ln(k)}$$

with N being the number of R&D scientist and k intrafirm connections. The numerator calculates the average of all shortest paths for each scientist to all its colleagues and then averages it for the entire network. The denominator is an equal path length in an entirely random network of similar size and connections.

Control variables. Several variables at the level of the firm, the intrafirm network and interfirm collaboration are added to control for alternative explanations.

Firm size has diverse effects on firm innovation (Hansen, 1992). To control for the effects of size, the log value of a firm's sales (in millions) is added as a control variable. Since some sample firms are large and heavily diversified conglomerates, only sales in the medical devices industry are considered.

Firm medical device focus indicates the relative importance of medical device units to other business units. Baysinger and Hoskisson (1989) noted that corporations focus their R&D activities on their dominant business units and increase their R&D budgets. It is sales of medical device business units as a fraction of total firm sales.

Firm performance is measured as the firm's return on sales (EBIT ÷ total sales). It is added as a control variable since well-performing firms are financially less constrained and can invest more in riskier R&D projects.

Firm leverage is the firm's debt-to-assets ratio. Highly leveraged firms have less discretionary resources at their availability and reduce their focus on R&D activities (O'Brien, 2003).

Firm slack influences the resources available for, and strategic necessity of innovation (Nohria & Gulati, 1996). I proxy firm slack via its current ratio (current assets ÷ current liabilities) to control for this effect.

Firm technological diversity implies the diversity of technological resources a firm's R&D scientists can draw upon for knowledge recombination (Sampson, 2007). It is measured as the diversity of a firm's patent stock via one minus a Herfindahl concentration index of patents grouped by their technological main class.

Acquisitions result in the inflow of new knowledge and resources that affect firm innovation (Karim & Mitchell, 2000). To limit this effect, I calculate the amount a firm spends on acquisition of medical device firms scaled by a firm's annual sales.

Divestments, on the other hand, result in a loss of knowledge and resources which reduces innovation. To limit this effect, I calculate the amount a firm receives from sales of medical device assets scaled by a firm's annual sales.

R&D intensity is the amount spent on R&D as a percentage of total annual sales (Cohen et al., 1987). It indicates the amount of resources dedicated to perform R&D projects as well as the importance of innovation in a firm's strategic positioning.

R&D scientists constitute the firm's R&D work force. In settings where knowledge is complex and owned by individuals, the number of R&D scientists has a direct positive effect on firm innovation (Liebeskind et al., 1996). Therefore I observe the size of a firm's R&D workforce by the number of unique medical device inventors over a five-year period. This is the same as the number of nodes in an intrafirm network.

R&D recruitment is the number of new R&D scientists as a fraction of the total R&D workforce. Hiring new employees leads to the inflow of new skills and expertise (Song et al., 2003). This can influence both firm innovation and intrafirm networks, so it is controlled for via the number of scientists first observed on patents in the focal year.

R&D geographic concentration indicates the spatial proximity of R&D sites. While some firms concentrate all their R&D activities in a single location to benefit from knowledge spillovers (Alcacer & Chung, 2007), others spread their R&D activities geographically to tab into local expertise (Lahiri, 2010). I calculate geographic concentration based as a Herfindahl concentration index of all R&D scientists in a firm by US state and/or foreign country.

R&D team size is the average number of collaborators on R&D projects. The number of scientists involved in an R&D project has a significant effect on project performance (Singh & Fleming, 2010), but also influences intrafirm network connections. Therefore it is added as a control.

R&D alliance duration is the average duration of a firm's on-going R&D alliances. Age of an alliance may effect interorganizational learning in two ways. On the one hand, trust and mutual understanding are built over time (Gulati, 1995). On the other hand, the potential for learning new knowledge and skills will decrease over time.

R&D alliance strength is the average strength of ties a firm has with its R&D partners. To start, I measure individual tie strength as the number of R&D collaborations between a firm and its alliance partner scaled by the number of partners in each alliance (two divided by the number of alliance partners). Then, I computed interfirm alliance strength as the average tie strength of a firm's alliances:

$$Interfirm\ alliance\ strength = \left(\sum_i^N \sum_j 2/Partners_{ij}\right)/N$$

with *N* being the number of a firm's alliance partners and *j* being the number of collaborations of the focal firm with each partner *i*.

R&D alliance structure is the percentage of alliances that are structured as joint ventures, i.e. if it involves a newly created entity of which alliance partners are joint owners. Note that this joint ownership is different from taking a minority equity stake in a partner firm at certain milestones, which is not uncommon in the medical devices industry. Joint ventures increase the intensity of collaboration and thereby the amount of interfirm knowledge transfer (Mowery et al., 1996).

Several common control variables had to be excluded for their high correlations with other control variables. This could have caused multicollinearity issues in the regressions. Firm age normally reduces innovation (Hansen, 1992) but is omitted because it correlates highly with firm size. Firm diversification provides opportunities for knowledge spillovers (Miller, Fern, & Cardinal, 2007), but it negatively correlates with a firm's medical device focus. Firm patent stock implies the depth of technological resources a firm can draw upon, but is strongly correlated with the number of R&D scientists.

Estimation Method

The dependent variable in this study, firm innovation, is a non-negative count variable. Since such a variable is limited and often heavily skewed, linear regression could not be used. Instead, I use a negative binomial regression which is suitable for non-negative count variables and indifferent to potential overdispersion (Hilbe, 2011). Because the sample is a panel dataset, observations are not independent and unobserved heterogeneity may cause estimation biases. To choose between fixed and random effects parameters, I performed a Hausman test which is marginally significant ($\chi^2 = 41.7$; $p = 0.076$) (Hausman, Hall, & Griliches, 1984). Consequently I selected a negative binomial model with a fixed effects specification (Stata's xtnbreg command). The fixed effects in this model are conditional and do not suffer from the incidental parameter bias in unconditional fixed effects (Allison & Waterman, 2002; Allison, 2012b). To correct for potential multicollinearity, independent and moderation variables were mean-centered before interaction terms are computed. To reduce concerns about reverse causality, the dependent variable is measured at a one-year lead (t+1).

RESULTS

Table 5 below displays the descriptive statistics and correlations of the 483 observations in the final sample. The number of R&D alliance partners in a given year ranges from zero to twenty-six, but averages around four. R&D scientists in intrafirm networks have on average just over three collaborative connections, but this varies significantly in a range from almost zero to over seven. Average intrafirm clustering is almost thirty, indicating that intrafirm clustering is much higher than what would be observed in random networks. Efficiency is also higher as it would have been in an entirely random network: the mean is almost one standard deviation above the expected value in a random network. With few exceptions, correlations among independent and control variables are in an acceptable range. Any multicollinearity issue is addressed in the robustness checks further below.

Table 5 – Descriptive statistics and correlations of sample (p. 157)

Table 6 presents the results of a fixed-effects negative binomial regression and Table 7 reports the incident-rate ratios for the same analysis. Regarding the control variables, firm size and R&D intensity have a positive effect on firm innovation. Hiring new R&D scientists also increases firm innovation, but a larger R&D workforce and larger project teams reduce their productivity.

R&D alliances have a positive effect on firm innovation: each additional alliance increases firm innovation by a factor of 1.03 on average (model 1 in Table 7). For the intrafirm network, its connections have a strong positive effect on firm innovation. Clustering also have a positive, but much smaller effect and efficiency has no significant effect.

Table 6 and Table 7 – Regression results for firm innovation (p. 158)

Hypothesis 1 predicts that the effect of R&D alliances is positively moderated by intrafirm network connections. Model 2 in Table 6 provides support for this hypothesis ($\beta=0.021$; $p<0.05$). The advantages of interfirm networks hinge upon the connectedness of its intrafirm network. To see the shape and magnitude of this effect, I plot the results for additional R&D alliances for firms with low, moderate and high connectedness (i.e. at mean value and one standard deviation above/below) in panel A of **Error! Reference source not found.**. Note that these are multiplier ratios and any value above one indicates a positive effect. The plot indicates that R&D alliances have positive effect on firm innovation and this effect is much stronger for organizations with strongly connected intrafirm networks. Model 3 in Table 6 provides statistical support for H2b at the cost of H2a ($\beta=-0.000$; $p<0.001$). I argued that clusters are superior mechanisms for information sharing, but also resistant to learning outside knowledge. The evidence here indicates that the latter effect outstrips the former, though the effect size is minimal. As panel B of **Error! Reference source not found.** reveals, the direct effect of intrafirm network clustering is much stronger and interaction effects hardly change the slopes of the multiplier ratios. Hypothesis 3 predicted that the effects of alliances on innovation is positively moderated by intrafirm network efficiently, but this is not supported in model 5 of Table 6 (β=0.037; p=0.110). Panel C in **Error! Reference source not found.** demonstrates that intrafirm network efficiency has little significant direct or joint effects on firm innovation. In short, the regression results in Table 6 show that the positive relationship between R&D alliances and firm innovation is moderated by a firm's intraorganizational network. Specifically, network connections strengthen the relationship while network clustering weakens it significantly.

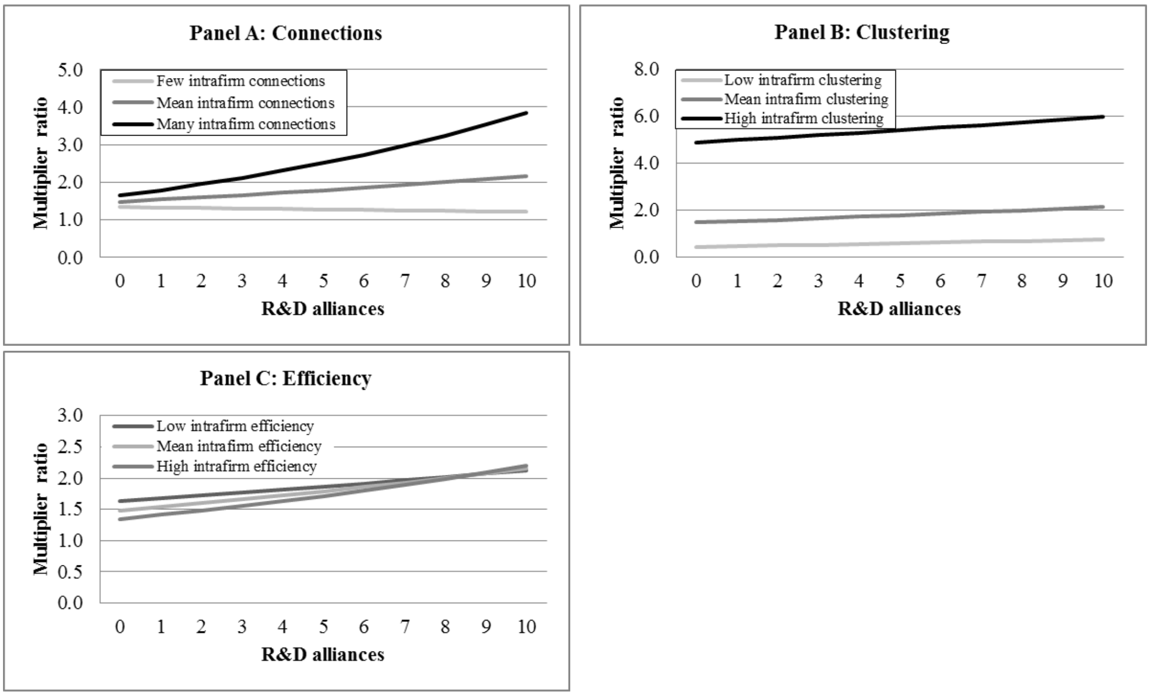


Figure 8 Effect of R&D alliances on firm innovation

Robustness Checks

Various robustness checks were performed to check the validity of these empirical results. To begin, I check for multicollinearity issues and followed the procedure described by Allison (2012a) in addressing it. Several control variables had VIF values exceeding 10, namely firm size, R&D scientists, and R&D team size. First, I rerun all regressions leaving out each of these variables individually. Second, I rerun all regressions leaving out two or more of these variables. Third, I replace the number of R&D scientists with the firm's patent stock (number of successful patent applications for medical devices in the past five years). This measure was earlier excluded for its high correlation with the number of scientists, but can now serve as a proxy with lower multicollinearity. These variations reduce the VIF for these models to acceptable values and provide similar significant results.

Then, I use alternative measures for the independent and dependent variables. First, I look for potential non-linear effects of the independent variable, R&D alliances, on firm innovation. Rothaermel and Deeds (2006) demonstrated that the effect of alliances on new product development by high-tech ventures is curvilinear. After a certain number, the positive effects of R&D alliances turn into significant negative effects. To check for such non-linear effects, I rerun all regressions (a) using the natural log value of a firm's R&D alliance partners to check for decreasing marginal returns and (b) adding the squared value to check for curvilinear effects and. The results, included in Table 18 (p. 170), are generally weaker and often less insignificant compared to earlier results. Wald χ^2 model fit did not improve by using these variables. So there is little indication for non-linear results.

Second, I use a slightly different measure for alliances. Instead of measuring the total number of R&D alliance partners a firm is currently involved with, I only count the number of new R&D alliance partners in a particular year. While the formation of an alliance leads to the inflow of new information, this effect may wear out rapidly. On average, a sample firm gains 1.25 new R&D alliance partners each year. In the new regression results (Table 19, p. 171), coefficients are substantially larger but less significant (at 10% or 5% significance levels).

Third, I use alternative measures for the moderation variables. Instead of intrafirm connections, clustering and efficiency, I use the alternative network density, transitivity and network largest component. The results (models 1 to 5 in Table 20, p. 172) are, however, not significant. I also check for potential small world effect by interacting the original clustering and efficiency measures (Fleming, King, et al., 2007; Watts & Strogatz, 1998): whereas the individual effects of connections and clustering remain, the small world factor does not reach significance (see model 8 in Table 20, p. 172).

Fourth, I use an alternative measure for firm innovation. Rather than using citation-weighted patent counts, I count the number of new or technologically improved products firm will bring to the market. Medical device firms are obliged to register all their products with the US Food and Drug Administration (FDA). This provides us with archival data on every newly developed or changed products. Contrary to pharmaceutical processes, this is a rather fast process (normally 180 days) but requires good documentation about the use and safety of a medical device at the moment of application. Accordingly, instead of citation-weighted patents at t+1, I use a firm's new products at time t+2 as dependent variable to correct for this lag between innovation and commercialization. The results (included in Table 21, p.173) are similar but much weaker when using this specification.

Afterwards, I perform several robustness checks regarding the estimation method. First, I control for the potential effect of outliers since the dependent variable is heavily skewed. The regressions testing the hypotheses are repeated by leaving out the 5% highest observations (a value of over 1500) and by winsorizing this 5% highest observations (to a value of 1500). The results (Table 22, p. 174) are virtually similar to these obtained in Table 6. Second, the regressions are re-run using a random-effects specification. As the Hausman test was marginally significant, random effects should give similarly efficient estimates. The results (models 1 to 4 in Table 23, p. 175) are comparable to a fixed-effects specification.

Third, I re-estimated the model using a Poisson quasi-maximum likelihood estimation (Stata's xtpoisson command with robust standard errors). Contrary to negative binomial regression, Poisson QMLE provides unconditional fixed effects without incidental parameter bias (Allison, 2012b; Wooldridge, 1999). The results (models 5 to 8 in Table 23, p. 175) show that the relevant coefficients are slightly smaller but equally significant.

Moreover, the effects may depend upon intrafirm network size. The main argument of this study is that R&D alliances are complemented by intrafirm networks so that R&D scientists not involved in an alliance will still have access to any shared information. Macrolevel network characteristics will influence this process of diffusion. Currently, only firm-year observations with at least five R&D scientists are used, but these networks are still relatively small. Instead, I increase the cut-offs to at least 15, 30, 50 and 100 R&D scientists. Results are generally the same as in Table 6 above (see Table 24, p. 176), but the moderation effect of intrafirm network connections becomes much stronger.

Finally, I try to control for potential endogeneity in alliance formation. Past research has shown that the formation of interfirm agreements is not a random phenomenon (Ahuja, 2000b; Gulati, 1995). Taking the number of alliances at face value can thus lead to an over- or under-estimation of true effects (Hamilton & Nickerson, 2003). In this study, intrafirm network structure may influence a firm's decision to form R&D alliances: those with efficient intrafirm networks will build larger interfirm networks. To rule out this effect, I use the number of pure commercialization/non-R&D alliances as an instrumental variable. Non-R&D alliances are a good instrument for various reasons. To begin, downstream alliances reflect a firm's willingness to collaborate with other organization which also influences their motivation to enter R&D alliances. In addition, an intrafirm R&D network is unlikely to affect non-R&D alliances. Moreover, unlike upstream alliances, downstream alliances do not lead to the knowledge spillovers that result in innovation. Rothaermal and Deeds (2004) describe how upstream alliances (those with an R&D component) fulfill a substantially different function from downstream alliances (those without an R&D component like production, distribution and marketing).

In the first-stage model, I perform a fixed-effect linear regression of non-R&D alliances on R&D alliances. A negative binomial regression would have been preferred, but such a regression cannot provide a point estimate which is required for the second estimation stage. This first-stage model is valid ($F=17.25$; $p<0.000$; $R^2=0.36$) and the instrument is highly significant ($\beta=0.162$; $p<0.000$). The predicted number of R&D alliances obtained from this model is then entered into the second model and interaction variables are calculated using this predicted value. The regression results (included in Table 25, p. 177) confirm earlier findings, but results are far more significant. So if anything, endogeneity was more likely to underestimate than overestimate the joint effects of inter- and intrafirm networks.

DISCUSSION

This study asked how interfirm and intrafirm collaboration networks jointly influence firm innovation. While collaboration networks at both levels have received ample attention in academic literature, there is little information about their combined effect. Here I argued that interorganizational collaboration provides a firm with access to new skills and knowhow for R&D alliances are conduits of knowledge and information (Owen-Smith & Powell, 2004). However, the extent to which a firm can turn this inflow of expertise into innovation will depend upon its ability to share and diffuse this to all its R&D employees, beyond the few that are involved as boundary spanners in the alliance itself. Intraorganizational collaboration networks thus complement interorganizational collaboration.

Empirical evidence from the medical devices industry provides some interesting insights in the roles of both forms of collaboration. First, the results show that R&D alliances have a strong direct effect: each additional R&D alliance increases firm innovation by a factor of 1.03 on average. Similarly, intrafirm networks also have a robust impact on firm innovation. If R&D scientists increase their number of collaborators by one, their combined innovation will generally increase by a factor 1.24. This finding supports earlier evidence on the role of network connectedness by Operti and Carnabuci (2012), but contradicts with the results of Guler and Nerkar (2012) who found a negative effect of network density on firm innovation. I also find that intrafirm clustering has a positive effect on firm innovation, supporting Guler and Nerkar's (2012) positive result for 'local density', that is, clusters. However, the results do not confirm the earlier positive finding by Funk (2013) for 'network inefficiency' (longer paths in the intrafirm network).

Second, this study shows that there are joint effects of interfirm and intrafirm collaboration. The moderation effect of intrafirm network structure on R&D alliances is especially strong for intrafirm connectedness: on average, the effect of R&D alliances is a factor 1.02 stronger if a firm's R&D scientists increase their professional connections by one. This means the rise of innovation following R&D alliances almost doubles for firms with an intrafirm density one standard deviation beyond the mean. It provides empirical support for the idea that intrafirm networks are important integration and communication mechanisms (Cohen & Levinthal, 1990; Lawrence & Lorsch, 1967). Boundary spanning R&D scientists learn new information and skills from a partner organization. If scientists in a firm are better connected, boundary spanners can share this new knowhow conveniently with their peers (Freeman, 1977; Lazer & Friedman, 2007). This increases the benefits of interorganizational collaboration.

Third, the structure of intrafirm networks has little influence on how R&D alliances influence innovation. The results indicate that strong clusters in intrafirm network have a negative moderation effect and weaken the positive impact of R&D alliances. This may be caused by the tendency of clusters to focus internally and pay less attention to external information (Burcharth & Fosfuri, 2012; Katz & Allen, 1982). If clusters also isolate themselves from their immediate environment, their over-embeddedness will lead them to ignore new practices and technologies like these stemming from R&D alliances (Uzzi, 1997). Nevertheless, even if the results are statistically valid, their economic significance is very small as displayed in **Error! Reference source not found.**. In addition, short paths could advance the speed of knowledge diffusion. Funk (2013) argues that organizations in information-rich locations increase their innovation if their intrafirm networks are less efficient, that is, have a less cohesive structure (a longer average path length). My findings do not support this finding since the interaction factor with intrafirm network efficiency is not significant. If anything, it contradicts this result since the coefficient is consistently positive.

Contributions

This study initially contributes to the literature on multilevel collaboration networks (e.g. Contractor et al., 2006; Oliver & Liebeskind, 1997; Ployhart & Moliterno, 2011; Wang, Robins, Pattison, & Lazega, 2013). Research on networks and innovation traditionally deals with a single level of networks like individuals, teams, business units, and organizations (Phelps et al., 2012), but in reality, innovation is the outcome of a multilevel process (Contractor et al., 2006). Individuals are embedded in teams, teams in business units, business units in organizations and organizations in industry networks (Harary & Batell, 1981; Moliterno & Mahony, 2011). As argued in this study, a node at a higher level, i.e. the medical device firm, is on itself networks of R&D scientists. This changes our perspective on elements as tie formation and network structure. For example, tie formation at a higher level will be reflected in new ties formed at a lower level. In my case, new R&D alliances will result in new boundary spanning ties for R&D scientists. However, tie formation at a lower level does not have to result in new ties at a higher level. For example, new ties among R&D scientists do not change an interorganizational network when both scientists are working for the same firm. Whereas this study focused on just two levels of networks, Moliterno and Mahoney (2011) provide a meta-perspective on cross-level effects in networks that applies to several possible levels.

Interfirm and intrafirm networks have a combined effect on individual creativity and firm innovation. For example, Oh et al. (2004) have shown how team creativity depends jointly on their internal collaboration and team members' external network. This study contributes to the literature on multilevel effects on innovation in a different manner. Here networks are formed at two different levels, namely by organizations and by individuals. In this setting, tie formation at each level is an independent or interdependent process and not controlled by a single entity. In a similar setting, Paruchuri (2010) investigated how the impact of an R&D scientist's invention depends on the size and structure of networks at two different levels. And Lazega et al. (2008, 2006) observed a similar joint-level effect for cancer researchers in medical research laboratories. This study looks at the same two levels of networks, but shifts the level of analysis from individuals to organizations. That is a relevant addition to multilevel network and innovation research since network studies have regularly shown that optimal network structures for individuals may not maximize firm productivity (Bizzi, 2013; Operti & Carnabuci, 2012). Specifically, my analyses have shown that intrafirm and interfirm collaboration, independently and jointly, shape firm innovation.

Though not the focus of this article, this study also speaks to the idea of cross-level and configurational effects of multilevel networks (Fiss, 2007; Gittell & Weiss, 2004). The results indicate that the effects of interfirm ties and intrafirm density on innovation reinforce each other, meaning that the two are complementary. However, for interfirm ties and intrafirm clustering, the results indicate substitution: though both have positive effects on firm innovation, their interaction is marginally negative. This contributes to the literature on complementarity of different modes of innovation (Arora & Gambardella, 1990). For example, Cassiman and Veugelers (2006) have shown that internal R&D activities supplement the acquisition of external knowledge. This study refines this conclusion by showing that the intrafirm collaboration among R&D scientists is an important supplement for interfirm R&D alliances. This also reveals the importance of multilevel networks for organizational configuration studies (Fiss, 2007). This literature has shown that the impact of strategic choices may depend on environmental characteristics, including these at a higher or lower level (Gupta, Tesluk, & Taylor, 2007). In case of multilevel networks, firms may structure their R&D activities looking for an optimal combination of interfirm and intrafirm collaboration structures.

This study secondarily contributes to the literature on complementarities of internal and external R&D activities (Cassiman & Veugelers, 2006). With regard to interorganizational collaboration, several studies have already identified factors that increase the performance of R&D alliances on firm innovation. Hoang and Rothaermel (2010) show how exploratory and exploitative R&D experience of internal R&D projects influences the results of exploration and exploitation alliances. Similarly, Rothaermel and Hess (2007) reveal that biotechnology alliances increase the performance of new ventures if accompanied by higher internal R&D expenditures, but significantly decrease with the number of non-star R&D scientists (e.g. scientists with ordinary research performance). In a more recent study (Hess & Rothaermel, 2011), they observe that the effect of R&D alliances on firm innovation decreases with the number of star scientists. This indicates that internal human capital could substitute external collaboration. This study contributes by examining the joint effects of internal social capital and external cooperation. In line with prior complementarity studies (e.g. Arora & Gambardella, 1990), I also find that internal capabilities complement external collaboration: the effect of R&D alliances on innovation is much stronger for organizations with well-connected intrafirm networks.

This study thirdly contributes to the microfoundations of firm absorptive capacity. Literature on absorptive capacity and knowledge recombination in organizations has largely examined firm-level characteristics. Thereby it overlooked the role of individuals in this process. But the microfoundations of these firm capabilities are, partially or fully, determined by individual employees (Felin et al., 2012; Ployhart & Moliterno, 2011). In their seminal article, Cohen and Levinthal (1990: 131–132) already discuss that absorptive capacity not only refers to knowledge acquisition, but also to intrafirm knowledge sharing to transfer knowledge to other units and teams. While boundary spanners and gatekeepers perform an important role in acquiring external knowhow, internal communication systems are required to transfer it to sub-units who can exploit it.

This study proposes intrafirm collaboration networks as critical knowledge integration mechanisms. Originally, Lawrence and Lorsch (1967) focused on the importance of formal integration mechanism and Cohen and Levinthal (1990) emphasized the importance of related knowledge for mutual understanding. But ethnographic studies have shown that informal communication and collaboration are much stronger antecedents for knowledge sharing and interpersonal learning (Allen et al., 2007; Brown & Duguid, 1991; Orr, 1996). This study has shown how the number and structure of interpersonal ties within an organization matter for absorbing and employing external knowledge. Contrary to formal mechanisms and routines, intrafirm networks are not organized or controlled in a top-down fashion, but stem from a bottom-up process of individuals forming and sustaining connections (Dahlander & McFarland, 2013; Sasovova et al., 2010). The results of this process complement formal activities aimed at increasing the benefits from alliances, like alliance management and alliance portfolio structuring (Prashant & Harbir, 2009; Wassmer, 2010). This study shows that the results of R&D alliances depend on other collaboration processes by R&D scientists that cannot be fully controlled by an organization.

CONCLUSIONS AND LIMITATIONS

In this era of open innovation, firms pursue technological innovation both within and beyond their organizational boundaries (Chesbrough, 2003). Adding to that literature, this article presents intrafirm social networks among R&D scientists as an important complement for a firm's external knowledge search. While interfirm collaboration via joint ventures, alliances and licensing agreements increases a firm's *opportunity* to access and absorb new knowledge, its *ability* to learn, diffuse, and employ it in innovation activities is shaped by its intrafirm network. The results of this study reveal that the positive effects of R&D alliances on innovation are significantly stronger if the community of R&D scientists within a firm is better connected.

Nonetheless, the results of this study should be interpreted bearing in mind its limitations. First, I have assumed that the number and structure of connections in intrafirm networks are not influenced or determined by firm strategy and managerial choice. Considering the strong direct and indirect effects of intraorganizational networks on firm innovation, one may expect managers would like to manipulate their intrafirm network connections and their structure. But at the microlevel, qualitative and quantitative research have shown that this is generally not the case in R&D settings: scientists have substantial autonomy in choosing their collaborators or colleagues with whom they share knowledge (Brown & Duguid, 1991; Sasovova et al., 2010). At the macrolevel, firms may spatially separate R&D activities but I explicitly control for such geographic dispersion of R&D activities.

Second, this study has taken a strict interpretation of nested networks (Harary & Batell, 1981), namely that scientists only collaborate with external scientists after R&D alliances have been formed. Some past studies have shown that boundary-spanning collaboration by R&D scientists also occurs without the presence of such agreements (Liebeskind et al., 1996; Oliver & Liebeskind, 1997). This could challenge the results because R&D alliances only capture a part of all interfirm collaboration. However, Bouty (2000) observes that scientists are less willing to share proprietary knowledge with outsiders and Berends et al. (2011) describe how informal relations among scientists are first formalized via contractual agreements between their organizations before important resources are exchanged.

Finally, this study only examined joint-level effects and did so at the expense of cross-level effects. For example, intrafirm network structure may influence a firm's motivation to enter R&D alliances. If its intrafirm network lacks the ties that result in effective knowledge sharing and innovation, a firm may tend to establish alliances to compensate for this effect. While I control for causality concerns stemming from such a cross-level effect, their presence, size and significance represent an important topic for future research.

CONCLUSION

This dissertation questions how intrafirm networks and interfirm collaboration, independent and jointly, influence firm innovation. To answer this question, I integrate the extant literature on networks and innovation, boundary spanners, and microfoundations to explore the mechanisms via which intraorganizational and interorganizational collaboration lead to new products and processes. Qualitative field data were collected by performing over thirty interviews with business development directors, R&D managers, alliance managers, and R&D scientists in the medical devices industry. These provided rich insights in the processes that lead to technological innovation. It results in a framework where firm innovation is conceptualized as a multilevel phenomenon affected by both R&D alliances externally and R&D scientist collaboration internally. Subsequently, parts of this model are empirically tested by assessing technological innovation on a panel of North-American medical device firms between 1990 and 2005. Overall, the dissertation chapters are complementary pieces in developing and testing how intrafirm and interfirm collaboration shape firm innovation.

In the first chapter, I ask how interfirm collaboration affects firm innovation. By identifying the microfoundations of knowledge transfer and employing the heterogeneous diffusion model, I develop a framework that emphasizes the importance of boundary spanning individuals and intraorganizational networks. First, boundary spanners transfer knowledge between organizations via their communication and collaboration with the partner firm. At the individual level, the efficacy of this process depends on characteristics of the source, the recipient, and the connections between them. First, the human and social capital of a boundary spanner in the source firm determine his/her ability to provide valuable knowledge. Second, the human capital of a boundary spanner at the recipient firm determines his/her ability to evaluate and learn this knowledge. Third, the strength of their relationship determines their ability to share tacit, complex knowledge. At the organizational level, the effectiveness of this process is a combination of the source organization's intrafirm network cohesion, which influences its internal social capital, the diversity of human capital of the recipient firm's boundary spanners, and the number and strength of ties among these boundary spanners. Subsequently, knowledge diffuses throughout a receiving organization via its intrafirm network. This allows all employees to use this new information and increase their creativity and innovation. At the individual level, the efficacy of this process depends on the social distance between a boundary spanner and a non-boundary spanning employee. At the organizational level, the effectiveness of diffusion rests on the centrality of boundary spanners as well as the cohesiveness of their intrafirm network. The effect of interfirm collaboration on firm innovation is thus a multilevel process involving both individuals and organizations.

In the second chapter, I ask how intrafirm network structure influences firm innovation. To resolve confounding findings by past studies, I examine the mediating processes via which network structure leads to firm innovation. I argue that the presence of high reach and strong clusters in an intrafirm network change a firm's knowledge diversity and knowledge transfer. These are the determinants for successful knowledge recombination. Shifting the level of analysis from an individual to an entire network allows for testing the intervening processes that are unobservable at the individual level. The results reveal that intrafirm network structure has a strong influence on knowledge reuse by other R&D scientists and knowledge variety within an organization. Contrary to my expectations, network reach and network clusters decrease knowledge sharing and knowledge heterogeneity, which then reduce firm innovation.

In the third chapter, I examine how interfirm collaboration and intrafirm networks jointly influence firm innovation. Interorganizational cooperation gives access to a partner's knowledge base and lead to knowledge spillovers between organizations. They provide a firm with opportunities to absorb external knowhow. Intraorganizational networks are powerful mechanisms for lateral knowledge flows and information diffusion among employees of a firm. Thereby they shape a firm's ability to share and recombine diverse knowledge into new products. Firms can augment the benefits of knowledge inflows from interfirm collaboration if its intrafirm network is more effective in diffusing it internally. The results confirm that intrafirm networks complement interfirm networks: the positive effect of R&D alliances on innovation rises with the connectedness of its intrafirm network.

Contributions

The results of this study contribute to three related streams of literature: networks and innovation, microfoundational research, and the open innovation paradigm.

Contributions to networks and innovation research. This thesis contributes firstly to the literature on multilevel networks by exploring the effects of internal and external collaborative ties on firm innovation. A large amount of literature on social network and innovation has recognized that networks and innovation are formed at different levels (Phelps et al., 2012), but most empirical studies only dealt with one level of analysis. Thereby they assumed the effects of network structure on innovation are independent of higher or lower level networks. However, multilevel research has revealed how the effects of networks at one level are contingent upon higher and lower networks (Moliterno & Mahony, 2011). This implies that there are cross-level and joint-level effects (House, Rousseau, & Thomas-Hunt, 1995; Rousseau, 1985). Therefore, one should take a multilevel network approach in order to understand how networks influence firm innovation, (Wang et al., 2013).

This thesis explores the multilevel nature of organizational networks and firm innovation by combining the individual and joint effects of interorganizational partnerships and intraorganizational collaboration networks. In the first chapter, it is exhibited how individuals and their personal ties perform a fundamental task in realizing opportunities offered by interorganizational relationships. The effectiveness of interfirm collaboration for firm innovation strongly depends on intraorganizational network characteristics as well as the social capital of boundary spanners. The third chapter provides a preliminary test of this multilevel network model by combining intrafirm collaboration networks with interfirm R&D alliances, i.e. a firm's degree centrality in the interorganizational network. Results indicate that interfirm and intrafirm networks jointly shape firm innovation. This thesis therefore poses that future research should combine networks at different levels to examine their impact on firm innovation.

Within the rich networks literature, this thesis principally added to the research on networks and innovation. The large majority of this literature has examined the effect of network size, structure and strength on the performance of an individual or organization (Phelps et al., 2012). Instead, this study employs two alternative approaches. First, one could consider the effect of network ties and structure upon an entire network instead of individual nodes. Such an approach allows to explicitly assess the processes mediating the relationship between networks and innovation. For example, the second chapter demonstrates that network structure affects knowledge transfer and diversity which then influence innovation. Such processes are much harder or impossible to measure at the level of individual nodes. Additionally, such an approach permits testing if particular network structures only lead to changes in microlevel innovation or also influence macrolevel innovation. For example, whereas Burt (1992) reveals how brokerage positions increase individual creativity, Bizzi (2013) exposes how it negatively alters the performance of those employees that are not in brokerage positions. By looking at the macrolevel results of network structure in the second chapter, it is shown that this is not a zero-sum game, but that total innovation increases with bridging positions: apparently the benefits of brokers outweigh the costs for non-brokers. Moreover, whereas closeness centrality of an employee is conventionally related to increased creativity and productivity (Ibarra, 1993), this chapter indicates firm innovation decreases when all employees would increase their closeness centrality simultaneously.

Second, this dissertation examines joint-level effects of collaboration networks at different levels. While most networks and innovations studies control for differences in nodes and their environment, few have looked at the interactions of the two. However, Rothaermel et al. (2007; 2001) observed how certain firm characteristics can complement firms' ability to manage and succeed in R&D alliances. Similar, Paruchuri (2010) and Lazega et al. (2008, 2006) have shown that the impact of patents and publications depend on scientists' positions in their intraorganizational networks in combination with their organizations' positions in the interorganizational network. Here I have shown how firm innovation is the outcome of collaboration at a higher level, i.e. the interfirm network, as well as the lower level, i.e. the intrafirm network, and their combination. The main finding of the third chapter indicates that interfirm connections and intrafirm connections have a complementary effect on firm innovation. It reveals that the impact of R&D alliances is much stronger for firms that have a strong, informal communication and collaboration system internally.

This also speaks to the innovation literature on complementarity and configurations. Whereas past studies already observed that internal and external R&D activities complement each other (e.g. Cassiman & Veugelers, 2006), the first chapter provides a detailed theoretical explanation of how this happens and the third chapter explicitly demonstrates this effect. This implies that the outcomes of collaborating at one level may hinge upon the collaboration structure at another level. For example, firms with fewer connections in their intraorganizational network may be less compelled to enter into R&D alliances since innovation advantages are only marginal and do not outweigh the costs and risks of such partnerships. This reveals that firms could structure their interfirm collaborative ties according to their intrafirm networks to optimize innovation.

Contributions to research on microfoundations. This dissertation also contributes to the growing body of literature on microfoundations in management research (Felin et al., 2012). A microfoundational approach to management research argues that research on firm's actions and consequences should examine the exact processes via which a cause leads to an effect, including processes at a lower level of analysis. Coleman (1994) provided a helpful tool for microfoundational analysis and demonstrated its use in a political setting. In the first chapter, I apply a similar approach to R&D alliances, interorganizational knowledge transfer and firm innovation. Using this approach reveals the importance of boundary spanning individuals, their boundary crossing connections and the role of intrafirm networks. It demonstrates how organizational-level effects of R&D alliances rest on many individual-level factors. The microfoundations of R&D alliances are thus individuals, and their social capital is essential for the success of interorganizational collaboration.

It also sheds new light upon the concept of firm recombinant ability (Garud & Nayyar, 1994). Organizations are essential instruments for learning, sharing and combining knowledge that results in innovation (Grant, 1996; Kogut & Zander, 1992). Extant studies have identified the role of communication channels, integration procedures, and routines as underlying mechanisms in this process (Argote, McEvily, & Reagans, 2003; Cohen & Levinthal, 1990; Lawrence & Lorsch, 1967). However, ethnographic studies noticed that a large part of information and resource sharing in organizations happens informally (Brown & Duguid, 1991; Orr, 1996). The second chapter pinpoints intrafirm networks as important mechanisms for knowledge sharing and innovation. The structure of this network emerges via a bottom-up process and has strong effects on the transfer and diversity of knowledge and expertise. Hence, a firm's recombinant ability is ultimately shaped by the structure of its intrafirm collaboration network that facilitates information sharing and transfer among its employees.

The third chapter speaks to the literature on absorptive capacity by identifying the microfoundations of a firm's ability to absorb and exploit external knowledge. In their pivotal article, Cohen and Levinthal (1990) already argued that external knowledge and expertise crossing organizational boundaries is not sufficient. Instead, organizations need procedures to transfer absorbed knowledge to the right part(s) of the organization where it can be used and developed further. Most absorptive capacity studies have simply assumed the presence of such a mechanism or taken a rough proxy for its strength, but this study aimed to open this black box. It recognizes that only a few scientists of a firm will learn new knowhow and skills during an R&D alliance. This may lead to a small increase in innovation, but a much larger potential stems from the ability of these boundary spanners to share and transfer their new knowledge to other R&D scientists. The intrafirm network, with all its informal knowledge flows, is thus as an important complement for absorbed external knowledge.

Contributions to open innovation paradigm. Likewise, this dissertation contributes to the paradigm of open innovation. In a setting and era where innovation is no longer the outcome of research and development by one organization, insights in the precise role of collaboration at multiple levels are a necessity. An open innovation approach emphasizes the importance of collaboration among various actors to spur research and development, but also reveals the risks involved in such strategies (Chesbrough, 2003). In the first chapter, I study how organizations can structure their interorganizational cooperation to influence the amount and diversity of knowledge inflows. It reveals a number of important elements in firm strategy and business policy.

To begin, learning via open innovation directly depends on boundary spanners as well as the structure and policies of R&D alliances. Dedicating more resources to R&D alliances by increasing the number of scientists will increase interfirm learning. In addition, allowing interpersonal and informal communication and collaboration, for example via colocation, leads to stronger ties among boundary spanners and results in more knowledge transfer.

Moreover, interfirm alliances and intrafirm networks should not be considered individually to understand the effects of external and internal collaboration on innovation. Combining an alliance portfolio perspective with intrafirm networks is very useful to understand how interfirm cooperation influences firm innovation. Alliance portfolio research already argues that there are complementary and substitutionary effects occurring when an organization is involved in multiple alliances (Wassmer, 2010). Furthermore, alliance research identified human capital within organizations as supplements to R&D alliances for firm innovation (Hess & Rothaermel, 2011). This thesis adds intrafirm networks as another factor that complements interorganizational collaboration. In particular, it explains how stronger intrafirm collaboration networks strengthen the positive effects of alliances on innovation. This indicates that internal and external R&D collaboration are complementary elements of an organization's innovation strategy.

Managerial Implications

This dissertation started from a practical question, namely how innovation in the medical devices industry is affected by firms' interorganizational and intraorganizational collaboration networks. Answering this practical question has resulted in three managerial implications.

First, the findings of this dissertation suggest that intrafirm networks have a strong effect on the diversity and transfer of knowledge in an organization. The findings indicate that efficiently formed intrafirm networks, i.e. these that have generally short paths among R&D scientists, reduce knowledge heterogeneity and reuse. Similarly, networks with strong clusters also become more homogeneous and reduce innovation. On average, firms are more innovative when their intrafirm network is more fragmented and less clustered. Though intrafirm network structure is mainly emergent, firms have several levers with which they influence the creation or termination of interpersonal ties. For one, organizational structure can influence the presence of ties and intrafirm network structure. Clearly defined business units, departments, and laboratories reduce opportunities for cross-departmental collaboration and the creation of new ties. Changing the current organizational structure can also be a mean to influence the formation of new ties or termination or existing connections. In addition, firms may influence intrafirm network via geographical dispersion of their R&D laboratories. Spatial dispersion of R&D activities reduces the likelihood of forming interpersonal connections and accelerates their erosion. Similarly, firms can influence intrafirm network structure during mergers and acquisitions. If newly acquired companies are fully integrated, intrafirm networks will become more cohesive and form shorter paths. Likewise, employee rotation, international assignments, and recruitment of new R&D scientists provide an opportunity to change intrafirm network structure.

Second, the findings of this thesis also indicate that the effect of interfirm collaboration strongly depends on the connectedness of its intrafirm network. In particular, the rise in innovation after forming R&D alliances is stronger for firms whose R&D scientists are better connected. This implies that managers should evaluate their firm's ability to communicate, share and diffuse knowledge internally before deciding to enter R&D alliances. Managers of firms with strongly connected intrafirm networks can enhance their innovative performance by increasing the number of interfirm agreements, but those of weakly connected intrafirm networks should reconsider the consequences of forming interorganizational alliances.

Third, the results of these studies have practical applications in the field of alliance management. If R&D alliances are used to learn about new technologies and techniques, R&D directors and alliance managers can increase learning by influencing decisions before, during, and after an alliance. During alliance formation, managers should aim to involve more central and more knowledgeable R&D scientists. These scientists are better capable to learn new knowledge from a partner firm and in a better position to share it within their organization. During the execution of an alliance contract, managers should permit free and open communication and collaboration between a firm's boundary-spanning scientists and the scientists of a partner firm. This will enable them to establish more and stronger ties which increase the flow of knowledge and information. After an alliance is terminated, managers can increase the use of newly absorbed knowledge by involving the boundary-spanning R&D scientists in related R&D projects. Also, by spreading boundary-spanning R&D scientists over multiple projects, it increases the chances that knowledge will be shared with other scientists in the firm.

Though the study was performed in the medical devices industry, the practical insights are also useful in comparable industries. These are sectors characterized by a high level of technological innovation based upon complex and largely individual knowledge, like electrical equipment, pharmaceutics, and laboratory instruments.

Limitations and Future Research

The results of this dissertation should be interpreted taking into account its limitations. First, the empirical studies in the second and third chapter are entirely based upon secondary data. Though this permitted the study to be done on a larger scale over a longer period of time, it also reduces the precision of certain measures. For example, non-successful cooperation among R&D scientists is not observed by relying on patents and publications for collaborative ties. In addition, process innovation that was not patented nor led to changes in a medical device also remains undetected. Though interviews were performed to gain qualitative insights in the industry, an in-depth study collecting first-hand data could provide further understandings of the interactions between interpersonal and interorganizational networks for knowledge diffusion and innovation.

Moreover, while the first chapter developed a comprehensive model linking interfirm collaboration and intrafirm networks at the level of organizations and individuals, the last chapter only assessed propositions at the organizational level. Limited by the absence of information on boundary spanning scientists, this study could not test suggestions about the importance of boundary spanners. Nevertheless, this remains an important issue for future research as such endeavors could provide great insights in the roles of individuals for firm innovation.

Lastly, the empirical level of this study is limited to macrolevel effects of intrafirm networks (second chapter) and the joint-level effects with interfirm ties (third chapter). In addition to joint-level effects, cross-level effects among different levels are likely to exist. For instance, while organizations create interfirm partnerships and individuals establish new collaborative ties, there is probably interdependence about between both levels of collaboration. Future research could look into these cross-level effects in multilevel innovation networks.

REFERENCES

Adner, R., & Zemsky, P. 2005. Disruptive technologies and the emergence of competition. ***The RAND Journal of Economics***, 36(2): 229–254.

Ahuja, G. 2000a. Collaboration networks, structural holes, and innovation: A longitudinal study. ***Administrative Science Quarterly***, 45(3): 425–455.

Ahuja, G. 2000b. The duality of collaboration: Inducements and opportunities in the formation of interfirm linkages. ***Strategic Management Journal***, 21(3): 317–343.

Alcacer, J., & Chung, W. 2007. Location strategies and knowledge spillovers. ***Management Science***, 53(5): 760–776.

Alcacer, J., & Gittelman, M. 2006. Patent citations as a measure of knowledge flows: The influence of examiner citations. ***The Review of Economics and Statistics***, 88(4): 774–779.

Aldrich, H., & Herker, D. 1977. Boundary spanning roles and organization structure. ***Academy of Management Review***, 2(2): 217–230.

Allen, J., James, A. D., & Gamlen, P. 2007. Formal versus informal knowledge networks in R&D: A case study using social network analysis. ***R&D Management***, 37(3): 179–196.

Allen, T. J. 1966. ***Managing the flow of scientific and technological information.*** Unpublished doctoral thesis. Cambridge: Massachusetts Institute of Technology.

Allen, T. J., & Cohen, S. I. 1969. Information flow in research and development laboratories. ***Administrative Science Quarterly***, 14(1): 12–19.

Allison, P. 2012a, September 12. When can you safely ignore multicollinearity? ***Statistical Horizons***. http://www.statisticalhorizons.com/multicollinearity.

Allison, P. 2012b, June 8. Beware of software for fixed effects negative binomial regression. ***Statistical Horizons***. http://www.statisticalhorizons.com/fe-nbreg.

Allison, P. D., & Waterman, R. P. 2002. Fixed–effects negative binomial regression models. ***Sociological Methodology***, 32(1): 247–265.

Aral, S., & Van Alstyne, M. 2011. The diversity-bandwidth trade-off. ***American Journal of Sociology***, 117(1): 90–171.

Argote, L., & Ingram, P. 2000. Knowledge transfer: A basis for competitive advantage in firms. ***Organizational Behavior and Human Decision Processes***, 82(1): 150–169.

Argote, L., McEvily, B., & Reagans, R. 2003. Managing knowledge in organizations: An integrative framework and review of emerging themes. ***Management Science***, 49(4): 571–582.

Argote, L., & Ren, Y. 2012. Transactive memory systems: A microfoundation of dynamic capabilities. ***Journal of Management Studies***, 49(8): 1375–1382.

Arora, A., & Gambardella, A. 1990. Complementarity and external linkages: The strategies of the large firms in biotechnology. ***Journal of Industrial Economics***, 38(4): 361–379.

Baron, R. M., & Kenny, D. A. 1986. The moderator–mediator variable distinction in social psychological research. ***Journal of Personality and Social Psychology***, 51(6): 1173–1182.

Baysinger, B., & Hoskisson, R. E. 1989. Diversification strategy and R&D intensity in multiproduct firms. ***Academy of Management Journal***, 32(2): 310–332.

Berends, H., Van Burg, E., & Van Raaij, E. M. 2011. Contacts and contracts: Cross-level network dynamics in the development of an aircraft material. ***Organization Science***, 22(4): 940–960.

Bizzi, L. 2013. The dark side of structural holes a multilevel investigation. ***Journal of Management***, 39(6): 1554–1578.

Borgatti, S. P., & Cross, R. 2003. A relational view of information seeking and learning in social networks. ***Management Science***, 49(4): 432–445.

Borgatti, S. P., & Foster, P. C. 2003. The network paradigm in organizational research: A review and typology. ***Journal of Management***, 29(6): 991–1013.

Bouty, I. 2000. Interpersonal and interaction influences on informal resource exchanges between R&D researchers across organizational boundaries. ***Academy of Management Journal***, 43(1): 50–65.

Brass, D. J., Galaskiewicz, J., Greve, H. R., & Tsai, W. 2004. Taking stock of networks and organizations: A multilevel perspective. ***Academy of Management Journal***, 47(6): 795–817.

Brown, J. S., & Duguid, P. 1991. Organizational learning and communities-of-practice: Toward a unified view of working, learning, and innovation. ***Organization Science***, 2(1): 40–57.

Burcharth, A. L., & Fosfuri, A. 2012. Not-invented-here: How cohesive socialization practices affect the formation of negative attitudes toward external knowledge. Presented at the DRUID Summer Conference 2012, Copenhagen (DK).

Burt, R. S. 1992. ***Structural holes: The social structure of competition***. Cambridge, MA: Harvard University Press.

Burt, R. S. 2000. The network structure of social capital. ***Research in Organizational Behavior***, 22: 345–423.

Carnabuci, G., & Operti, E. 2013. Where do firms' recombinant capabilities come from? Intraorganizational networks, knowledge, and firms' ability to innovate through technological recombination. ***Strategic Management Journal***, 34(13): 1591–1613.

Carpenter, M. A., Li, M., & Jiang, H. 2012. Social network research in organizational contexts: A systematic review of methodological issues and choices. ***Journal of Management***, 38(4): 1328–1361.

Cassiman, B., & Veugelers, R. 2006. In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition. ***Management Science***, 52(1): 68–82.

Cefis, E., & Marsili, O. 2005. A matter of life and death: Innovation and firm survival. ***Industrial and Corporate Change***, 14(6): 1167–1192.

Chang, S., Lee, J., & Song, J. 2014. Roles of giant cluster in knowledge diffusion and recombination. Presented at the Academy of Management Annual Meeting, Philadelphia, PA.

Chatterji, A. K. 2009. Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry. ***Strategic Management Journal***, 30(2): 185–206.

Chen, C.-J. 2004. The effects of knowledge attribute, alliance characteristics, and absorptive capacity on knowledge transfer performance. ***R&D Management***, 34(3): 311–321.

Chesbrough, H. W. 2003. ***Open innovation: The new imperative for creating and profiting from technology***. Boston, MA: Harvard Business School Press.

Christensen, C. M. 1997. ***The innovator's dilemma: When new technologies cause great firms to fail***. Cambridge, MA: Harvard Business Review Press.

Cockburn, I. M., & Henderson, R. M. 1998. Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery. ***The Journal of Industrial Economics***, 46(2): 157–182.

Cohen, W. M., Levin, R. C., & Mowery, D. C. 1987. ***Firm size and R&D intensity: A re-examination***. Working Paper No. 2205. http://www.nber.org/papers/w2205, National Bureau of Economic Research.

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive capacity: A new perspective on learning and innovation. ***Administrative Science Quarterly***, 35(1): 128–152.

Coleman, J. S. 1988. Social capital in the creation of human capital. ***American Journal of Sociology***, 94: S95–S120.

Coleman, J. S. 1994. ***Foundations of social theory***. Cambridge, MA: Harvard University Press.

Contractor, N. S., Wasserman, S., & Faust, K. 2006. Testing multitheoretical, multilevel hypotheses about organizational networks: An analytic framework and empirical example. ***Academy of Management Review***, 31(3): 681–703.

Cowan, R., & Jonard, N. 2004. Network structure and the diffusion of knowledge. ***Journal of Economic Dynamics and Control***, 28(8): 1557–1575.

Criscuolo, P. 2005. On the road again: Researcher mobility inside the R&D network. ***Research Policy***, 34(9): 1350–1365.

Dahlander, L., & McFarland, D. A. 2013. Ties that last tie formation and persistence in research collaborations over time. ***Administrative Science Quarterly***, 58(1): 69–110.

Dahlin, K. B., Weingart, L. R., & Hinds, P. J. 2005. Team diversity and information use. ***Academy of Management Journal***, 48(6): 1107–1123.

Danneels, E. 2002. The dynamics of product innovation and firm competences. ***Strategic Management Journal***, 23(12): 1095–1121.

Davis, J. P., & Eisenhardt, K. M. 2011. Rotating leadership and collaborative innovation recombination processes in symbiotic relationships. ***Administrative Science Quarterly***, 56(2): 159–201.

Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. 2007. Developing theory through simulation methods. ***Academy of Management Review***, 32(2): 480–499.

De Vet, J. M., & Scott, A. J. 1992. The southern Californian medical device industry: Innovation, new firm formation, and location. ***Research Policy***, 21(2): 145–161.

Dhanaraj, C., & Parkhe, A. 2006. Orchestrating innovation networks. ***Academy of Management Review***, 31(3): 659–669.

Dosi, G. 1982. Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. ***Research Policy***, 11(3): 147–162.

Dyer, J. H. 1997. Effective interim collaboration: How firms minimize transaction costs and maximise transaction value. ***Strategic Management Journal***, 18(7): 535–556.

Easterby-Smith, M., Lyles, M. A., & Tsang, E. W. 2008. Inter-organizational knowledge transfer: Current themes and future prospects. ***Journal of Management Studies***, 45(4): 677–690.

Fang, C., Lee, J., & Schilling, M. A. 2010. Balancing exploration and exploitation through structural design: The isolation of subgroups and organizational learning. ***Organization Science***, 21(3): 625–642.

Fang, R., Duffy, M. K., & Shaw, J. D. 2011. The organizational socialization process: Review and development of a social capital model. ***Journal of Management***, 37(1): 127–152.

Felin, T., Foss, N. J., Heimeriks, K. H., & Madsen, T. L. 2012. Microfoundations of routines and capabilities: Individuals, processes, and structure. ***Journal of Management Studies***, 49(8): 1351–1374.

Fiss, P. C. 2007. A set-theoretic approach to organizational configurations. ***Academy of Management Review***, 32(4): 1180–1198.

Fleming, L. 2001. Recombinant uncertainty in technological search. ***Management Science***, 47(1): 117–132.

Fleming, L., King, C., & Juda, A. I. 2007. Small worlds and regional innovation. ***Organization Science***, 18(6): 938–954.

Fleming, L., Mingo, S., & Chen, D. 2007. Collaborative brokerage, generative creativity, and creative success. ***Administrative Science Quarterly***, 52(3): 443–475.

Fleming, L., & Sorenson, O. 2001. Technology as a complex adaptive system: evidence from patent data. ***Research Policy***, 30(7): 1019–1039.

Fleming, L., & Sorenson, O. 2004. Science as a map in technological search. ***Strategic Management Journal***, 25(8-9): 909–928.

Freeman, L. C. 1977. A set of measures of centrality based on betweenness. ***Sociometry***, 40(1): 35–41.

Frent, P. 2011. ***Global Medtech companies***. No. 1XEEE2. Xerfi Global.

Funk, R. 2013. Making the most of where you are: Geography, networks, and innovation in organizations. ***Academy of Management Journal***, forthcoming.

Garcia-Vega, M. 2006. Does technological diversification promote innovation?: An empirical analysis for European firms. ***Research Policy***, 35(2): 230–246.

Garud, R., & Nayyar, P. R. 1994. Transformative capacity: Continual structuring by intertemporal technology transfer. ***Strategic Management Journal***, 15(5): 365–385.

Gittell, J. H., & Weiss, L. 2004. Coordination networks within and across organizations: A multi-level framework. ***Journal of Management Studies***, 41(1): 127–153.

Granovetter, M. 1973. The strength of weak ties. ***American Journal of Sociology***, 78(6): 1360–1380.

Grant, R. M. 1996. Toward a knowledge-based theory of the firm. ***Strategic Management Journal***, 17: 109–122.

Greve, H. R., Strang, D., & Tuma, N. B. 1995. Specification and estimation of heterogeneous diffusion models. In P. V. Marsden (Ed.), ***Sociological methodology***: 377–420. New York, NY: Blackwell Publishing.

Grigoriou, K., & Rothaermel, F. T. 2014. Structural microfoundations of innovation: The role of relational stars. ***Journal of Management***, 40(2): 586–615.

Gulati, R. 1995. Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. ***Academy of Management Journal***, 38(1): 85–112.

Guler, I., & Nerkar, A. 2012. The impact of global and local cohesion on innovation in the pharmaceutical industry. ***Strategic Management Journal***, 33(5): 535–549.

Gupta, A. K., & Govindarajan, V. 2000. Knowledge flows within multinational corporations. ***Strategic Management Journal***, 21(4): 473–496.

Gupta, A. K., Tesluk, P. E., & Taylor, M. S. 2007. Innovation at and across multiple levels of analysis. ***Organization Science***, 18(6): 885–897.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. 2000. ***Market value and patent citations: A first look***. http://www.nber.org/papers/w7741, National Bureau of Economic Research.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. 2001. ***The NBER patent citation data file: Lessons, insights and methodological tools***. http://www.nber.org/papers/w8498, National Bureau of Economic Research.

Hamel, G. 1991. Competition for competence and interpartner learning within international strategic alliances. ***Strategic Management Journal***, 12(S1): 83–103.

Hamilton, B. H., & Nickerson, J. A. 2003. Correcting for endogeneity in strategic management research. ***Strategic Organization***, 1(1): 51–78.

Hansen, J. A. 1992. Innovation, firm size, and firm age. ***Small Business Economics***, 4(1): 37–44.

Hansen, M. T. 1999. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. ***Administrative Science Quarterly***, 44(1): 82–111.

Harary, F., & Batell, M. F. 1981. What is a system? ***Social Networks***, 3(1): 29–40.

Hardin, J. W., & Hilbe, J. M. 2003. ***Generalized estimating equations***. New York, NY: Chapman & Hall/CRC.

Hargadon, A., & Sutton, R. I. 1997. Technology brokering and innovation in a product development firm. ***Administrative Science Quarterly***, 42(4): 716–749.

Hausman, J., Hall, B. H., & Griliches, Z. 1984. Econometric models for count data with an application to the patents-R&D relationship. ***Econometrica: Journal of the Econometric Society***, 52(4): 909–938.

Henderson, R. M., & Clark, K. B. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. ***Administrative Science Quarterly***, 35(1): 9–30.

Hess, A. M., & Rothaermel, F. T. 2011. When are assets complementary? Star scientists, strategic alliances, and innovation in the pharmaceutical industry. ***Strategic Management Journal***, 32(8): 895–909.

Hilbe, J. M. 2011. ***Negative binomial regression*** (2nd edition.). Cambridge (UK): Cambridge University Press.

Hitt, M. A., Beamish, P. W., Jackson, S. E., & Mathieu, J. E. 2007. Building theoretical and empirical bridges across levels: Multilevel research in management. ***Academy of Management Journal***, 50(6): 1385–1399.

Hoang, H., & Rothaermel, F. T. 2010. Leveraging internal and external experience: Exploration, exploitation, and R&D project performance. ***Strategic Management Journal***, 31(7): 734–758.

Holmqvist, M. 2003. A dynamic model of intra- and interorganizational learning. ***Organization Studies***, 24(1): 95–123.

House, R., Rousseau, D. M., & Thomas-Hunt, M. 1995. The meso paradigm: A framework for the integration of micro and macro organizational behavior. In L. L. Cummings & B. M. Staw (Eds.), ***Research in organizational behavior: An annual series of analytical essays and critical reviews***: 71–114. Greenwich, CT: JAI Press.

Huang, Y., Luo, Y., Liu, Y., & Yang, Q. 2013. An investigation of interpersonal ties in interorganizational exchanges in emerging markets: A boundary-spanning perspective. ***Journal of Management***, forthcoming.

Hussler, C., & Rondé, P. 2007. The impact of cognitive communities on the diffusion of academic knowledge: Evidence from the networks of inventors of a French university. ***Research Policy***, 36(2): 288–302.

Ibarra, H. 1993. Network centrality, power, and innovation involvement: Determinants of technical and administrative roles. ***Academy of Management Journal***, 36(3): 471–501.

Inkpen, A. C. 2000. Learning through joint ventures: A framework of knowledge acquisition. ***Journal of Management Studies***, 37(7): 1019–1044.

Janowicz-Panjaitan, M., & Noorderhaven, N. G. 2008. Formal and informal interorganizational learning within strategic alliances. ***Research Policy***, 37(8): 1337–1355.

Janowicz-Panjaitan, M., & Noorderhaven, N. G. 2009. Trust, calculation, and interorganizational learning of tacit knowledge: An organizational roles perspective. ***Organization Studies***, 30(10): 1021–1044.

Jarvenpaa, S. L., & Majchrzak, A. 2008. Knowledge collaboration among professionals protecting national security: Role of transactive memories in ego-centered knowledge networks. ***Organization Science***, 19(2): 260–276.

Joseph, J., Chatterji, A., & Cunningham, C. 2013. How do capability gaps drive reconfiguration? Evidence from U.S. medical technology industry sales force strategies. Presented at the SMS 33rd Annual International Conference, Atlanta, GA.

Karim, S., & Mitchell, W. 2000. Path-dependent and path-breaking change: Reconfiguring business resources following acquisitions in the US medical sector, 1978–1995. ***Strategic Management Journal***, 21(10-11): 1061–1081.

Katz, R., & Allen, T. J. 1982. Investigating the not invented here (NIH) syndrome: A look at the performance, tenure, and communication patterns of 50 R&D project groups. ***R&D Management***, 12(1): 7–20.

Keller, R. T., & Holland, W. E. 1975. Boundary-spanning roles in a research and development organization: An empirical investigation. ***Academy of Management Journal***, 18(2): 388–393.

Khanna, T., Gulati, R., & Nohria, N. 1998. The dynamics of learning alliances: Competition, cooperation, and relative scope. ***Strategic Management Journal***, 19(3): 193–210.

Kim, S., Zhao, Z. J., & Anand, J. 2014. Knowledge complexity and the performance of inter-unit knowledge transfer structures. Presented at the Academy of Management Annual Meeting, Philadelphia, PA.

Klein, K. J., & Kozlowski, S. W. 2000. From micro to meso: Critical steps in conceptualizing and conducting multilevel research. ***Organizational Research Methods***, 3(3): 211–236.

Knorr-Cetina, K. 1999. ***Epistemic cultures: How the sciences make knowledge***. Cambridge, MA: Harvard University Press.

Kogut, B., & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. ***Organization Science***, 3(3): 383–397.

Kostova, T., & Roth, K. 2003. Social capital in multinational corporations and a micro-macro model of its formation. ***Academy of Management Review***, 28(2): 297–317.

Kozlowski, S. W., Chao, G. T., Grand, J. A., Braun, M. T., & Kuljanin, G. 2013. Advancing multilevel research design capturing the dynamics of emergence. ***Organizational Research Methods***, 16(4): 581–615.

Krackhardt, D. 1992. The strength of strong ties: The importance of philos in organizations. In N. Nohria (Ed.), ***Networks and organizations: Structure, form, and action***: 216–239. Cambridge, MA: Harvard Business School Press.

Krishnan, R., Martin, X., & Noorderhaven, N. G. 2006. When does trust matter to alliance performance? ***Academy of Management Journal***, 49(5): 894–917.

Lahiri, N. 2010. Geographic distribution of R&D activity: How does it affect innovation quality? ***Academy of Management Journal***, 53(5): 1194–1209.

Lai, R., D'Amour, A., Yu, A., Sun, Y., Torvik, V., & Fleming, L. 2011. Disambiguation and co-authorship networks of the US Patent Inventor Database. ***Harvard Institute for Quantitative Social Science, Cambridge, MA***, 2138.

Lane, P. J., Koka, B. R., & Pathak, S. 2006. The reification of absorptive capacity: a critical review and rejuvenation of the construct. ***Academy of Management Review***, 31(4): 833–863.

Latour, B., & Woolgar, S. 2013. ***Laboratory life: The construction of scientific facts***. Princeton, NJ: Princeton University Press.

Lavie, D. 2006. The competitive advantage of interconnected firms: An extension of the resource-based view. ***Academy of Management Review***, 31(3): 638–658.

Lawrence, P. R., & Lorsch, J. W. 1967. Differentiation and integration in complex organizations. ***Administrative Science Quarterly***, 12(1): 1–47.

Lazega, E., Jourda, M.-T., Mounier, L., & Stofer, R. 2008. Catching up with big fish in the big pond? Multi-level network analysis through linked design. ***Social Networks***, 30(2): 159–176.

Lazega, E., Mounier, L., Jourda, M.-T. se, & Stofer, R. 2006. Organizational vs. personal social capital in scientists' performance: A multi-level network study of elite French cancer researchers (1996-1998). ***Scientometrics***, 67(1): 27–44.

Lazer, D., & Friedman, A. 2007. The network structure of exploration and exploitation. ***Administrative Science Quarterly***, 52(4): 667–694.

Lee, E., Lee, J., & Lee, J. 2006. Reconsideration of the winner-take-all hypothesis: Complex networks and local bias. ***Management Science***, 52(12): 1838–1848.

Liebeskind, J. P., Oliver, A. L., Zucker, L., & Brewer, M. 1996. Social networks, learning, and flexibility: Sourcing scientific knowledge in new biotechnology firms. ***Organization Science***, 7(4): 428–443.

March, J. G. 1991. Exploration and exploitation in organizational learning. ***Organization Science***, 2(1): 71–87.

Marrone, J. A. 2010. Team boundary spanning: A multilevel review of past research and proposals for the future. ***Journal of Management***, 36(4): 911–940.

Matusik, S. F., & Heeley, M. B. 2005. Absorptive capacity in the software industry: Identifying dimensions that affect knowledge and knowledge creation activities. ***Journal of Management***, 31(4): 549–572.

McGrath, R. G., Tsai, M.-H., Venkataraman, S., & MacMillan, I. C. 1996. Innovation, competitive advantage and rent: A model and test. ***Management Science***, 42(3): 389–403.

McKelvey, M., Alm, H., & Riccaboni, M. 2003. Does co-location matter for formal knowledge collaboration in the Swedish biotechnology–pharmaceutical sector? ***Research Policy***, 32(3): 483–501.

Miller, D. J., Fern, M. J., & Cardinal, L. B. 2007. The use of knowledge for technological innovation within diversified firms. ***Academy of Management Journal***, 50(2): 307–325.

Mohr, J., & Spekman, R. 1994. Characteristics of partnership success: Partnership attributes, communication behavior, and conflict resolution techniques. ***Strategic Management Journal***, 15(2): 135–152.

Moliterno, T. P., & Mahony, D. M. 2011. Network theory of organization: A multilevel approach. ***Journal of Management***, 37(2): 443–467.

Molloy, J. C., Ployhart, R. E., & Wright, P. M. 2011. The myth of “the” micro-macro divide: Bridging system-level and disciplinary divides. ***Journal of Management***, 37(2): 581–609.

Moreira, S., & Markus, A. 2013. All for one and one for all: How intrafirm networks affect the speed of knowledge recombination. Presented at the DRUID Summer Conference 2013, Barcelona (ES).

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1996. Strategic alliances and interfirm knowledge transfer. ***Strategic Management Journal***, 17: 77–91.

Nahapiet, J., & Ghoshal, S. 1998. Social capital, intellectual capital, and the organizational advantage. ***Academy of Management Review***, 23(2): 242–266.

Nebus, J. 2006. Building collegial information networks: A theory of advice network generation. ***Academy of Management Review***, 31(3): 615–637.

Nerkar, A., & Paruchuri, S. 2005. Evolution of R&D capabilities: The role of knowledge networks within a firm. ***Management Science***, 51(5): 771–785.

Nohria, N., & Gulati, R. 1996. Is slack good or bad for innovation? ***Academy of Management Journal***, 39(5): 1245–1264.

Nonaka, I. 1994. A dynamic theory of organizational knowledge creation. ***Organization Science***, 5(1): 14–37.

O’Brien, J. P. 2003. The capital structure implications of pursuing a strategy of innovation. ***Strategic Management Journal***, 24(5): 415–431.

Obstfeld, D. 2005. Social networks, the tertius iungens orientation, and involvement in innovation. ***Administrative Science Quarterly***, 50(1): 100–130.

Oh, H., Chung, M.-H., & Labianca, G. 2004. Group social capital and group effectiveness: The role of informal socializing ties. ***Academy of Management Journal***, 47(6): 860–875.

Oh, H., Labianca, G., & Chung, M.-H. 2006. A multilevel model of group social capital. ***Academy of Management Review***, 31(3): 569–582.

Oldroyd, J., Evans, J., & Hendron, M. 2012. Withholding the ace: The performance effects on knowledge hoarding. Presented at the SMS 32nd Annual International Conference, Prague (CZ).

Oliver, A. L., & Liebeskind, J. P. 1997. Three levels of networking for sourcing intellectual capital in biotechnology: Implications for studying interorganizational networks. ***International Studies of Management & Organization***, 27(4): 76–103.

Operti, E., & Carnabuci, G. 2012. Good for one, bad for most? Intrafirm networks and innovation at the inventor and firm level. Presented at the Academy of Management Annual Meeting, Boston, MA.

Orr, J. E. 1996. ***Talking about machines: An ethnography of a modern job***. Ithaca, NY: Cornell University Press.

Owen-Smith, J., & Powell, W. W. 2004. Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. ***Organization Science***, 15(1): 5–21.
Oxley, J. E., & Sampson, R. C. 2004. The scope and governance of international R&D alliances. ***Strategic Management Journal***, 25(8-9): 723–749.
Park, G., & Park, Y. 2006. On the measurement of patent stock as knowledge indicators. ***Technological Forecasting and Social Change***, 73(7): 793–812.
Paruchuri, S. 2010. Intraorganizational networks, interorganizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. ***Organization Science***, 21(1): 63–80.
Payne, G. T., Moore, C. B., Griffis, S. E., & Autry, C. W. 2011. Multilevel challenges and opportunities in social capital research. ***Journal of Management***, 37(2): 491–520.
Phelps, C. C. 2010. A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. ***Academy of Management Journal***, 53(4): 890–913.
Phelps, C., Heidl, R., & Wadhwa, A. 2012. Knowledge, networks, and knowledge networks a review and research agenda. ***Journal of Management***, 38(4): 1115–1166.
Pittaway, L., Robertson, M., Munir, K., Denyer, D., & Neely, A. 2004. Networking and innovation: A systematic review of the evidence. ***International Journal of Management Reviews***, 5(3-4): 137–168.
Ployhart, R. E., & Moliterno, T. P. 2011. Emergence of the human capital resource: A multilevel model. ***Academy of Management Review***, 36(1): 127–150.
Postrel, S. 2002. Islands of shared knowledge: Specialization and mutual understanding in problem-solving teams. ***Organization Science***, 13(3): 303–320.
Powell, W. W., Koput, K. W., & Smith-Doerr, L. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. ***Administrative Science Quarterly***, 41(1): 116–145.
Prashant, K., & Harbir, S. 2009. Managing strategic alliances: What do we know now, and where do we go from here? ***Academy of Management Perspectives***, 23(3): 45–62.
Preacher, K. J., & Hayes, A. F. 2004. SPSS and SAS procedures for estimating indirect effects in simple mediation models. ***Behavior Research Methods, Instruments, & Computers***, 36(4): 717–731.
Provan, K. G., Fish, A., & Sydow, J. 2007. Interorganizational networks at the network level: A review of the empirical literature on whole networks. ***Journal of Management***, 33(3): 479–516.
Roach, M., & Cohen, W. M. 2013. Lens or prism? Patent citations as a measure of knowledge flows from public research. ***Management Science***, 59(2): 504–525.
Roberts, P. W. 1999. Product innovation, product-market competition and persistent profitability in the US pharmaceutical industry. ***Strategic Management Journal***, 20(7): 655–670.
Rosenkopf, L., & Nerkar, A. 2001. Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. ***Strategic Management Journal***, 22(4): 287–306.
Rothaermel, F. T. 2001. Complementary assets, strategic alliances, and the incumbent's advantage: An empirical study of industry and firm effects in the biopharmaceutical industry. ***Research Policy***, 30(8): 1235–1251.
Rothaermel, F. T., & Deeds, D. L. 2004. Exploration and exploitation alliances in biotechnology: A system of new product development. ***Strategic Management Journal***, 25(3): 201–221.
Rothaermel, F. T., & Deeds, D. L. 2006. Alliance type, alliance experience and alliance management capability in high-technology ventures. ***Journal of Business Venturing***, 21(4): 429–460.
Rothaermel, F. T., & Hess, A. M. 2007. Building dynamic capabilities: Innovation driven by individual-, firm-, and network-level effects. ***Organization Science***, 18(6): 898–921.
Rousseau, D. M. 1985. Issues of level in organizational research: Multi-level and cross-level perspectives. In L. L. Cummings & B. M. Staw (Eds.), ***Research in organizational behavior: An annual series of analytical essays and critical reviews***: 1–37. Greenwich, CT: JAI Press.
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(2): 364–386.
Sasovova, Z., Mehra, A., Borgatti, S. P., & Schippers, M. C. 2010. Network churn: The effects of self-monitoring personality on brokerage dynamics. ***Administrative Science Quarterly***, 55(4): 639–670.
Schilling, M. A. 2009. Understanding the alliance data. ***Strategic Management Journal***, 30(3): 233–260.

Schilling, M. A., & Fang, C. 2013. When hubs forget, lie, and play favorites: Interpersonal network structure, information distortion, and organizational learning. ***Strategic Management Journal***, forthcoming.

Schilling, M. A., & Phelps, C. C. 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. ***Management Science***, 53(7): 1113–1126.

Schumpeter, J. A. 1934. ***The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle***. Cambridge, MA: Harvard University Press.

Schumpeter, J. A. 1939. ***Business cycles***. New York, NY: McGraw-Hill.

Schumpeter, J. A. 1942. ***Socialism and democracy***. New York, NY: Harper.

Shan, W., Walker, G., & Kogut, B. 1994. Interfirm cooperation and startup innovation in the biotechnology industry. ***Strategic Management Journal***, 15(5): 387–394.

Shaver, J. M. 2005. Testing for mediating variables in management research: Concerns, implications, and alternative strategies. ***Journal of Management***, 31(3): 330–353.

Simonin, B. L. 1997. The importance of collaborative know-how: An empirical test of the learning organization. ***Academy of Management Journal***, 40(5): 1150–1174.

Singh, J. 2005. Collaborative networks as determinants of knowledge diffusion patterns. ***Management Science***, 51(5): 756–770.

Singh, J., & Fleming, L. 2010. Lone inventors as sources of breakthroughs: Myth or reality? ***Management Science***, 56(1): 41–56.

Singh, J., Hansen, M. T., & Podolny, J. M. 2010. The world is not small for everyone: Inequity in searching for knowledge in organizations. ***Management Science***, 56(9): 1415–1438.

Smith, K. G., Carroll, S. J., & Ashford, S. J. 1995. Intra- and interorganizational cooperation: Toward a research agenda. ***Academy of Management Journal***, 38(1): 7–23.

Song, J., Almeida, P., & Wu, G. 2003. Learning-by-hiring: When is mobility more likely to facilitate interfirm knowledge transfer? ***Management Science***, 49(4): 351–365.

Sorenson, O., & Fleming, L. 2004. Science and the diffusion of knowledge. ***Research Policy***, 33(10): 1615–1634.

Strang, D., & Tuma, N. B. 1993. Spatial and temporal heterogeneity in diffusion. ***American Journal of Sociology***, 99(3): 614–639.

Subramanian, A. M., Lim, K., & Soh, P.-H. 2013. When birds of a feather don't flock together: Different scientists and the roles they play in biotech R&D alliances. ***Research Policy***, 42(3): 595–612.

Swan, J., Newell, S., Scarbrough, H., & Hislop, D. 1999. Knowledge management and innovation: Networks and networking. ***Journal of Knowledge Management***, 3(4): 262–275.

Ter Wal, A., Criscuolo, P., & Salter, A. 2011. Absorptive capacity at the individual level: An ambidexterity approach to external engagement. Presented at the DRUID Summer Conference 2011, Copenhagen (DK).

Tomz, M., King, G., & Zeng, L. 2003. ReLogit: Rare events logistic regression. ***Journal of Statistical Software***, 08(i02): 137–163.

Tortoriello, M., & Krackhardt, D. 2010. Activating cross-boundary knowledge: The role of Simmelian ties in the generation of innovations. ***Academy of Management Journal***, 53(1): 167–181.

Trajtenberg, M. 1990. A penny for your quotes: Patent citations and the value of innovations. ***RAND Journal of Economics***, 21(1): 172–187.

Tsai, W. 2001. Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. ***Academy of Management Journal***, 44(5): 996–1004.

Tsai, W., & Ghoshal, S. 1998. Social capital and value creation: The role of intrafirm networks. ***Academy of Management Journal***, 41(4): 464–476.

Tushman, M. L. 1977. Special boundary roles in the innovation process. ***Administrative Science Quarterly***, 22(4): 587–605.

Tushman, M. L., & Scanlan, T. J. 1981a. Boundary spanning individuals: Their role in information transfer and their antecedents. ***Academy of Management Journal***, 24(2): 289–305.

Tushman, M. L., & Scanlan, T. J. 1981b. Characteristics and external orientations of boundary spanning individuals. ***Academy of Management Journal***, 24(1): 83–98.

USPTO Patent Technology Monitoring Team. 2012. ***Medical devices: All classified utility patents (OR/XR)***. http://www.uspto.gov/web/offices/ac/ido/oeip/taf/meddev.htm, April 26, 2013.

Uzzi, B. 1996. The sources and consequences of embeddedness for the economic performance of organizations: The network effect. ***American Sociological Review***, 61(4): 674–698.

Uzzi, B. 1997. Social structure and competition in interfirm networks: The paradox of embeddedness. ***Administrative Science Quarterly***, 42(1): 35–67.

Uzzi, B., & Spiro, J. 2005. Collaboration and creativity: The small world problem. ***American Journal of Sociology***, 111(2): 447–504.

Van de Ven, A. H. 1976. On the nature, formation, and maintenance of relations among organizations. ***Academy of Management Review***, 1(4): 24–36.

Van Wijk, R. A., & Van Den Bosch, F. A. J. 1998. Knowledge characteristics of internal network-based forms of organizing. ***Academy of Management Proceedings***, 1998(1): B1–B7.

Van Wijk, R., Jansen, J. J., & Lyles, M. A. 2008. Inter- and intra-organizational knowledge transfer: A meta-analytic review and assessment of its antecedents and consequences. ***Journal of Management Studies***, 45(4): 830–853.

Wang, P., Robins, G., Pattison, P., & Lazega, E. 2013. Exponential random graph models for multilevel networks. ***Social Networks***, 35(1): 96–115.

Wasserman, S., & Faust, K. 1994. ***Social network analysis: Methods and applications.*** Cambridge (UK): Cambridge University Press.

Wassmer, U. 2010. Alliance portfolios: A review and research agenda. ***Journal of Management***, 36(1): 141–171.

Watts, D. J. 1999. ***Small worlds: The dynamics of networks between order and randomness***. Princeton, NJ: Princeton University Press.

Watts, D. J., & Strogatz, S. H. 1998. Collective dynamics of “small-world”networks. ***Nature***, 393(6684): 440–442.

Wooldridge, J. M. 1999. Distribution-free estimation of some nonlinear panel data models. ***Journal of Econometrics***, 90(1): 77–97.

Wu, B. 2013. Opportunity costs, industry dynamics, and corporate diversification: Evidence from the cardiovascular medical device industry, 1976–2004. ***Strategic Management Journal***, 34(11): 1265–1287.

Zhao, Z. J., & Anand, J. 2013. Beyond boundary spanners: The “collective bridge” as an efficient interunit structure for transferring collective knowledge. ***Strategic Management Journal***, 34(13): 1513–1530.

Zhou, J., Shin, S. J., Brass, D. J., Choi, J., & Zhang, Z.-X. 2009. Social networks, personal values, and creativity: Evidence for curvilinear and interaction effects. ***Journal of Applied Psychology***, 94(6): 1544–1552.

TABLES

Table 1 Sample descriptive statistics and correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Firm innovation	1.000																		
2. Diversity	0.364	1.000																	
3. Transfer	0.486	0.332	1.000																
4. Reach	-0.264	-0.487	-0.266	1.000															
5. Clusters	-0.346	-0.315	-0.425	0.124	1.000														
6. Firm size	0.385	0.415	0.272	-0.655	-0.127	1.000													
7. Medical device focus	-0.013	-0.048	0.134	0.248	-0.123	-0.278	1.000												
8. Firm performance	0.255	0.277	0.318	-0.333	-0.091	0.454	-0.134	1.000											
9. Firm leverage	-0.092	-0.010	-0.081	-0.124	0.167	0.161	-0.093	-0.031	1.000										
10. R&D intensity	0.115	0.063	0.022	0.128	-0.156	-0.153	0.104	-0.481	-0.318	1.000									
11. Firm slack	-0.128	-0.062	-0.041	0.372	-0.060	-0.473	0.311	-0.046	-0.278	0.092	1.000								
12. Acquisitions	0.230	0.033	0.099	-0.040	-0.030	0.025	0.008	0.071	0.114	0.018	-0.018	1.000							
13. Divestments	-0.041	-0.016	-0.065	-0.021	0.111	-0.041	-0.009	-0.024	-0.001	-0.023	-0.033	-0.010	1.000						
14. R&D concentration	-0.277	-0.342	-0.035	0.697	0.001	-0.593	0.252	-0.253	-0.258	0.200	0.357	-0.089	-0.026	1.000					
15. R&D recruitment	0.052	-0.026	0.147	-0.057	0.041	0.037	0.006	0.101	0.021	-0.018	-0.001	0.126	-0.068	0.035	1.000				
16. R&D scientists	0.759	0.388	0.420	-0.335	-0.322	0.536	-0.153	0.285	-0.021	0.053	-0.202	0.108	-0.035	-0.403	-0.038	1.000			
17. Network density	0.263	0.129	0.132	0.141	-0.076	0.251	-0.125	0.081	0.062	0.197	-0.192	0.056	-0.013	-0.023	-0.093	0.377	1.000		
18. Network isolate ratio	-0.086	-0.039	-0.029	-0.285	0.067	0.016	0.027	0.010	0.053	-0.151	0.059	-0.002	0.010	-0.164	0.079	-0.151	-0.573	1.000	
19. R&D team size	-0.022	-0.092	-0.146	0.369	0.228	0.023	-0.047	-0.012	0.019	0.173	-0.108	0.003	0.010	0.163	-0.060	0.054	0.743	-0.554	1.000
N	484	441	445	484	484	484	484	484	484	484	484	484	484	484	484	484	484	484	484
Mean	279.4	0.429	0.147	0.183	0.683	6.333	0.778	0.135	0.126	0.081	2.825	0.047	0.029	0.408	0.191	134.2	3.307	0.095	2.529
St.Dev.	593.6	0.278	0.153	0.177	0.178	1.972	0.338	0.157	0.126	0.063	2.46	0.186	0.225	0.264	0.159	230	1.36	0.086	0.777
Min	0	0	0	0.017	0	0	0	-0.928	0	0.004	0.824	0	0	0.086	0	5	0.333	0	1.357
Max	4825	0.815	0.935	1	1	9.734	1	0.52	0.817	0.593	27.1	1.952	3.695	1	0.857	1628	7.217	0.667	7

Correlations exceeding |0.09| are generally significant at the 5%-level

Correlations exceeding |0.12| are generally significant at the 1%-level

Table 2 GEE regressions predicting knowledge transfer and diversity

	(Model 1) Transfer	(Model 2) Transfer	(Model 3) Transfer	(Model 4) Transfer	(Model 5) Diversity	(Model 6) Diversity	(Model 7) Diversity	(Model 8) Diversity
Firm size	0.188*	0.070	0.202**	0.073	0.235**	0.147+	0.242**	0.152+
	(0.076)	(0.100)	(0.074)	(0.102)	(0.087)	(0.089)	(0.088)	(0.089)
Medical device focus	0.322	0.447	0.308	0.398	-0.330	-0.239	-0.382	-0.298
	(0.427)	(0.382)	(0.385)	(0.334)	(0.340)	(0.314)	(0.338)	(0.313)
Firm performance	2.130*	2.240*	2.240*	2.331**	0.545	0.253	0.472	0.158
	(0.952)	(0.892)	(0.905)	(0.787)	(0.641)	(0.646)	(0.630)	(0.647)
Firm leverage	0.953	0.863	0.939	0.658	-0.161	-0.178	-0.136	-0.180
	(0.661)	(0.690)	(0.703)	(0.771)	(0.465)	(0.436)	(0.459)	(0.428)
R&D intensity	2.632*	1.332	2.409*	0.767	4.156***	3.425**	3.926**	3.154**
	(1.252)	(1.356)	(1.215)	(1.290)	(1.183)	(1.167)	(1.201)	(1.207)
Firm slack	-0.058	-0.010	-0.046	0.006	0.032	0.053+	0.039	0.062+
	(0.070)	(0.046)	(0.058)	(0.033)	(0.027)	(0.031)	(0.031)	(0.036)
Acquisitions	0.313	0.277	0.328	0.292	0.122	0.115	0.137	0.129
	(0.258)	(0.244)	(0.255)	(0.236)	(0.123)	(0.114)	(0.125)	(0.116)
Divestments	0.019	-0.052	0.057	-0.007	-0.790	-0.773+	-0.814	-0.797+
	(0.202)	(0.183)	(0.222)	(0.215)	(0.489)	(0.430)	(0.542)	(0.475)
R&D concentration	1.488**	2.591***	1.547**	2.624***	-0.007	0.585	0.026	0.621
	(0.558)	(0.639)	(0.570)	(0.626)	(0.443)	(0.484)	(0.444)	(0.492)
R&D recruitment	0.403	0.536	0.465	0.706	0.572*	0.513+	0.595*	0.536*
	(0.524)	(0.599)	(0.553)	(0.675)	(0.243)	(0.271)	(0.242)	(0.270)
R&D scientists	0.000	0.000	0.000	0.000	0.001	0.001*	0.001	0.001+
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network density	0.031	0.181+	0.019	0.168+	0.140*	0.200**	0.122+	0.181*
	(0.084)	(0.102)	(0.080)	(0.087)	(0.069)	(0.076)	(0.069)	(0.077)
Network isolate ratio	0.573	-0.010	0.974	0.445	-0.260	-0.521	0.025	-0.185
	(1.206)	(1.243)	(1.285)	(1.476)	(1.083)	(1.198)	(1.123)	(1.259)
R&D team size	-0.465*	-0.429+	-0.359*	-0.248	-0.238*	-0.176+	-0.145	-0.068
	(0.204)	(0.221)	(0.182)	(0.232)	(0.096)	(0.095)	(0.099)	(0.104)
Reach		-5.434**		-5.843**		-2.857**		-2.939**
		(1.905)		(2.015)		(1.001)		(1.010)
Clusters			-0.919	-1.326			-0.782*	-0.866*
			(0.619)	(0.808)			(0.351)	(0.367)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-3.963***	-3.438***	-3.671***	-2.831**	-2.014**	-1.531*	-1.631*	-1.083
	(0.854)	(0.905)	(0.968)	(1.088)	(0.731)	(0.735)	(0.710)	(0.711)
Observations	441	441	441	441	431	431	431	431
Number of firms	50	50	50	50	49	49	49	49

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 3 GEE regressions predicting firm innovation

	(Model 1) Firm innov.	(Model 2) Firm innov.	(Model 3) Firm innov.	(Model 4) Firm innov.	(Model 5) Firm innov.	(Model 6) Firm innov.	(Model 7) Firm innov.
Firm size	0.524***	0.494***	0.433***	0.416***	0.355***	0.450***	0.347***
	(0.076)	(0.077)	(0.065)	(0.066)	(0.065)	(0.059)	(0.057)
Medical device focus	0.280	0.248	0.130	0.087	0.125	-0.083	0.010
	(0.301)	(0.295)	(0.271)	(0.267)	(0.249)	(0.248)	(0.224)
Firm performance	1.699*	1.493*	1.122*	0.884+	1.396+	1.655**	1.477*
	(0.729)	(0.662)	(0.532)	(0.476)	(0.724)	(0.561)	(0.639)
Firm leverage	0.399	0.291	-0.095	-0.186	0.346	0.533	0.506
	(0.517)	(0.573)	(0.417)	(0.425)	(0.442)	(0.479)	(0.496)
R&D intensity	4.008*	3.492*	4.038*	3.515*	3.975*	4.200**	3.885**
	(1.813)	(1.684)	(1.688)	(1.534)	(1.816)	(1.481)	(1.490)
Firm slack	-0.028	-0.034	-0.002	-0.006	-0.021	-0.025	-0.002
	(0.035)	(0.036)	(0.023)	(0.024)	(0.021)	(0.020)	(0.016)
Acquisitions	0.229+	0.263+	0.236	0.273	0.277*	0.194+	0.296+
	(0.136)	(0.154)	(0.156)	(0.173)	(0.134)	(0.118)	(0.153)
Divestments	-0.261	-0.234	-0.217	-0.187	-0.320+	-0.213	-0.220
	(0.256)	(0.272)	(0.348)	(0.354)	(0.190)	(0.241)	(0.220)
R&D concentration	0.883*	1.038*	0.004	0.199	0.920**	0.391	0.932**
	(0.438)	(0.445)	(0.361)	(0.378)	(0.332)	(0.343)	(0.346)
R&D recruitment	0.167	0.028	0.284	0.147	-0.147	0.084	-0.109
	(0.345)	(0.347)	(0.389)	(0.383)	(0.279)	(0.272)	(0.295)
R&D scientists	0.001**	0.002**	0.002***	0.002***	0.002***	0.001**	0.002***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network density	0.110	0.100	0.104	0.090	0.161+	0.026	0.096
	(0.106)	(0.112)	(0.099)	(0.105)	(0.085)	(0.091)	(0.079)
Network isolate ratio	-2.151+	-2.297+	-2.211+	-2.222+	-1.102	-0.831	-0.761
	(1.199)	(1.196)	(1.168)	(1.142)	(0.728)	(0.823)	(0.763)
R&D team size	-0.577**	-0.558**	-0.342+	-0.316	-0.328+	-0.337+	-0.159
	(0.185)	(0.200)	(0.198)	(0.212)	(0.188)	(0.185)	(0.167)
Knowledge diversity		0.660*		0.563*			
		(0.289)		(0.274)			
Knowledge transfer			3.516***	3.474***			
			(0.319)	(0.326)			
Reach					-2.881***		-2.897***
					(0.720)		(0.701)
Clusters						-1.379***	-1.422***
						(0.392)	(0.361)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	1.675*	1.600*	1.833**	1.710**	2.534***	3.083***	3.341***
	(0.669)	(0.716)	(0.571)	(0.599)	(0.450)	(0.604)	(0.538)
Observations	415	415	412	412	484	484	484
Number of firms	48	48	48	48	50	50	50

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 4 Sobel-Goodman mediation tests

Independent → mediating → dependent Independent → dependent	Beta coeff.	Bootstr. St.Dev.	z	P>|z|	Bootstr. 95%L	Bootstr. 95%U
Reach → transfer → firm innovation	-225.330	78.718	-2.860	0.004	-403.574	-93.650
Reach → firm innovation	258.001	126.687	2.040	0.042	2.846	499.012
Reach → diversity → firm innovation	-163.733	56.639	-2.890	0.004	-285.662	-60.151
Reach → firm innovation	19.295	154.621	0.120	0.901	-281.428	316.540
Clusters → transfer → firm innovation	-113.735	63.344	-1.800	0.073	-266.095	-22.916
Clusters → firm innovation	-184.526	99.290	-1.860	0.063	-361.533	31.272
Clusters → diversity → firm innovation	-40.703	19.621	-2.070	0.038	-84.157	-9.500
Clusters → firm innovation	-259.795	104.894	-2.480	0.013	-461.111	-44.039

Bootstrapping coefficients and 95%-confidence intervals based on 5,000 iterations
Mediation tests includes the same control variables as the earlier regressions

Table 5 Sample descriptive statistics and correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. Firm innovation	1.000																				
2. R&D alliances	0.624	1.000																			
3. Intrafirm connections	0.228	0.390	1.000																		
4. Intrafirm clustering	0.665	0.720	0.239	1.000																	
5. Intrafirm efficiency	-0.368	-0.539	-0.785	-0.436	1.000																
6. Firm size	0.368	0.431	0.248	0.611	-0.254	1.000															
7. Medical device focus	-0.005	-0.191	-0.123	-0.192	0.080	-0.277	1.000														
8. Firm performance	0.255	0.229	0.080	0.303	-0.107	0.454	-0.133	1.000													
9. Firm leverage	-0.097	-0.038	0.060	-0.017	0.059	0.159	-0.092	-0.032	1.000												
10. Firm slack	-0.120	-0.163	-0.191	-0.248	0.101	-0.472	0.310	-0.046	-0.278	1.000											
11. Firm tech. diversity	0.247	0.182	-0.038	0.306	-0.008	0.265	-0.008	0.173	-0.024	-0.020	1.000										
12. Acquisitions	0.256	0.133	0.056	0.097	-0.053	0.024	0.008	0.070	0.113	-0.017	-0.007	1.000									
13. Divestments	-0.048	-0.002	-0.013	-0.037	0.065	-0.042	-0.009	-0.024	-0.001	-0.033	-0.001	-0.010	1.000								
14. R&D intensity	0.116	0.091	0.198	0.024	-0.216	-0.153	0.103	-0.480	-0.318	0.092	0.079	0.018	-0.023	1.000							
15. R&D scientists	0.655	0.742	0.376	0.951	-0.550	0.536	-0.153	0.284	-0.022	-0.202	0.271	0.108	-0.036	0.053	1.000						
16. R&D recruitment	0.067	-0.035	-0.084	-0.018	0.094	0.053	0.001	0.107	0.027	-0.006	-0.038	0.130	-0.068	-0.021	-0.034	1.000					
17. R&D geographic conc.	-0.250	-0.305	-0.019	-0.499	-0.038	-0.591	0.251	-0.252	-0.257	0.356	-0.349	-0.089	-0.026	0.199	-0.402	0.025	1.000				
18. R&D team size	-0.038	0.106	0.743	-0.041	-0.460	0.022	-0.046	-0.012	0.018	-0.108	-0.190	0.002	0.010	0.174	0.053	-0.058	0.164	1.000			
19. R&D alliance duration	0.000	0.242	0.079	0.053	-0.191	-0.050	-0.004	0.019	-0.061	0.153	-0.191	0.039	-0.052	0.001	0.048	-0.071	0.102	0.022	1.000		
20. R&D alliance strength	0.159	0.388	0.144	0.243	-0.191	0.355	-0.070	0.115	-0.009	-0.117	0.091	0.022	-0.071	0.097	0.199	0.014	-0.209	-0.062	0.476	1.000	
21. R&D alliance structure	0.001	-0.029	-0.077	-0.027	0.102	0.117	-0.076	0.033	0.089	-0.073	-0.174	-0.050	-0.049	-0.076	-0.048	0.138	-0.035	-0.103	0.074	0.162	1.000
N	483	483	483	483	483	483	483	483	483	483	483	483	483	483	483	483	483	483	483	483	483
Mean	289.2	4.095	3.311	29.23	-0.645	6.339	0.778	0.135	0.126	2.822	0.511	0.047	0.029	0.081	134.4	0.190	0.408	2.530	2.061	0.854	0.080
St.Dev.	598.9	4.211	1.359	38.63	0.336	1.969	0.338	0.157	0.126	2.461	0.246	0.186	0.225	0.063	230.2	0.156	0.264	0.778	1.756	0.382	0.200
Min	0	0	0.333	0	-1.946	0	0	-0.928	0	0.824	0	0	0	0.004	5	0	0.086	1.357	0	0	0
Max	4825	26	7.217	246.1	-0.037	9.734	1	0.520	0.817	27.10	0.811	1.952	3.695	0.593	1628	0.857	1	7	10.05	2	1

Correlations exceeding |0.090| are significant at the 5% level
Correlations exceeding |0.117| are significant at the 1% level

Table 6 Fixed-effect negative binomial regressions predicting firm innovation

	(Model 1) Innovation	(Model 2) Innovation	(Model 3) Innovation	(Model 4) Innovation	(Model 5) Innovation	(Model 6) Innovation	(Model 7) Innovation	(Model 8) Innovation
Firm size	0.290***	0.230***	0.233***	0.207***	0.230***	0.211***	0.240***	0.220***
	(0.052)	(0.053)	(0.053)	(0.052)	(0.053)	(0.052)	(0.053)	(0.053)
Medical device focus	-0.646***	-0.283	-0.319	-0.259	-0.304	-0.302	-0.386+	-0.344
	(0.194)	(0.212)	(0.214)	(0.212)	(0.211)	(0.214)	(0.213)	(0.216)
Firm performance	0.479	0.822	0.882+	0.789	0.751	0.844+	0.754	0.775
	(0.494)	(0.510)	(0.515)	(0.493)	(0.509)	(0.496)	(0.513)	(0.499)
Firm leverage	-0.051	0.126	-0.044	-0.047	0.127	-0.301	-0.193	-0.365
	(0.381)	(0.380)	(0.392)	(0.384)	(0.381)	(0.398)	(0.401)	(0.404)
Firm slack	-0.012	-0.010	-0.014	-0.003	-0.004	-0.008	-0.003	-0.003
	(0.024)	(0.024)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Firm tech. diversity	-0.433	-0.264	-0.228	-0.209	-0.287	-0.191	-0.264	-0.207
	(0.293)	(0.297)	(0.297)	(0.291)	(0.297)	(0.289)	(0.295)	(0.289)
Acquisitions	0.196	0.143	0.128	0.119	0.159	0.094	0.147	0.105
	(0.121)	(0.117)	(0.115)	(0.107)	(0.118)	(0.105)	(0.115)	(0.106)
Divestments	-0.544*	-0.505*	-0.516*	-0.571*	-0.516*	-0.578*	-0.540*	-0.582*
	(0.252)	(0.245)	(0.244)	(0.239)	(0.244)	(0.237)	(0.241)	(0.237)
R&D intensity	2.886**	2.919**	3.081**	2.712**	2.757**	2.891**	2.828**	2.776**
	(0.989)	(1.006)	(0.998)	(0.971)	(1.013)	(0.955)	(0.995)	(0.960)
R&D scientists	0.001***	-0.001**	-0.003***	-0.001+	-0.001*	-0.002***	-0.003***	-0.003***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D recruitment	0.593*	0.577*	0.610*	0.576*	0.593*	0.619*	0.676**	0.650**
	(0.237)	(0.248)	(0.246)	(0.248)	(0.250)	(0.246)	(0.248)	(0.247)
R&D geographic conc.	-0.529	-0.416	-0.422	-0.261	-0.440	-0.271	-0.499	-0.325
	(0.325)	(0.323)	(0.321)	(0.326)	(0.324)	(0.322)	(0.320)	(0.324)
R&D team size	-0.260***	-0.490***	-0.472***	-0.449***	-0.470***	-0.429***	-0.418***	-0.410***
	(0.076)	(0.118)	(0.119)	(0.115)	(0.119)	(0.115)	(0.120)	(0.117)
R&D alliance duration	-0.045	-0.052	-0.054+	-0.043	-0.048	-0.044	-0.044	-0.037
	(0.033)	(0.033)	(0.032)	(0.034)	(0.033)	(0.033)	(0.032)	(0.033)
R&D alliance strength	0.107	0.091	0.101	-0.044	0.032	-0.041	-0.020	-0.092
	(0.140)	(0.140)	(0.137)	(0.145)	(0.147)	(0.140)	(0.143)	(0.145)
R&D alliance structure	0.289	0.283	0.302	0.342+	0.314+	0.367+	0.376*	0.396*
	(0.189)	(0.188)	(0.189)	(0.190)	(0.190)	(0.190)	(0.190)	(0.191)
R&D alliances	0.027*	0.010	-0.003	0.047***	0.023	0.033*	0.014	0.038*
	(0.012)	(0.012)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.015)
Intrafirm connections		0.257***	0.276***	0.230**	0.222**	0.245***	0.213**	0.218**
		(0.073)	(0.073)	(0.072)	(0.077)	(0.071)	(0.077)	(0.074)
Intrafirm clustering		0.017***	0.023***	0.020***	0.016***	0.028***	0.026***	0.029***
		(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Intrafirm efficiency		0.072	0.018	0.096	-0.049	0.012	-0.293	-0.151
		(0.176)	(0.174)	(0.167)	(0.190)	(0.164)	(0.200)	(0.207)
R&D alliances x Intrafirm connect.			0.021*			0.027**	0.038**	0.035**
			(0.011)			(0.010)	(0.012)	(0.011)
R&D alliances x Intrafirm clustering				-0.000***		-0.001***		-0.000***
				(0.000)		(0.000)		(0.000)
R&D alliances x Intrafirm efficiency					0.037		0.077**	0.033
					(0.023)		(0.026)	(0.027)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-0.461	0.466	0.477	0.654	0.530	0.713	0.621	0.761
	(0.459)	(0.528)	(0.527)	(0.515)	(0.527)	(0.514)	(0.525)	(0.515)
Observations	483	483	483	483	483	483	483	483
Number of firms	49	49	49	49	49	49	49	49

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 7 Incident-rate ratios of negative binomial regressions predicting firm innovation

	(Model 1) Innovation	(Model 2) Innovation	(Model 3) Innovation	(Model 4) Innovation	(Model 5) Innovation	(Model 6) Innovation	(Model 7) Innovation	(Model 8) Innovation
Firm size	1.336***	1.259***	1.263***	1.230***	1.259***	1.235***	1.272***	1.246***
	(0.069)	(0.067)	(0.067)	(0.065)	(0.067)	(0.065)	(0.068)	(0.066)
Medical device focus	0.524***	0.753	0.727	0.772	0.738	0.739	0.679+	0.709
	(0.102)	(0.160)	(0.155)	(0.163)	(0.156)	(0.158)	(0.144)	(0.153)
Firm performance	1.614	2.274	2.415+	2.200	2.119	2.326+	2.126	2.171
	(0.798)	(1.160)	(1.243)	(1.086)	(1.079)	(1.153)	(1.090)	(1.082)
Firm leverage	0.951	1.134	0.957	0.954	1.136	0.740	0.825	0.694
	(0.363)	(0.431)	(0.375)	(0.366)	(0.433)	(0.294)	(0.330)	(0.281)
Firm slack	0.988	0.990	0.986	0.997	0.996	0.992	0.997	0.997
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Firm tech. diversity	0.649	0.768	0.796	0.811	0.750	0.826	0.768	0.813
	(0.190)	(0.228)	(0.236)	(0.236)	(0.223)	(0.239)	(0.226)	(0.235)
Acquisitions	1.216	1.154	1.136	1.126	1.172	1.099	1.159	1.111
	(0.148)	(0.135)	(0.131)	(0.121)	(0.138)	(0.115)	(0.134)	(0.117)
Divestments	0.581*	0.603*	0.597*	0.565*	0.597*	0.561*	0.583*	0.559*
	(0.146)	(0.148)	(0.146)	(0.135)	(0.146)	(0.133)	(0.141)	(0.132)
R&D intensity	17.930**	18.523**	21.772**	15.064**	15.756**	18.005**	16.909**	16.062**
	(17.725)	(18.634)	(21.730)	(14.620)	(15.954)	(17.186)	(16.820)	(15.423)
R&D scientists	1.001***	0.999**	0.997***	0.999+	0.999*	0.998***	0.997***	0.997***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D recruitment	1.809*	1.780*	1.840*	1.779*	1.809*	1.857*	1.965**	1.915**
	(0.428)	(0.441)	(0.453)	(0.442)	(0.452)	(0.456)	(0.488)	(0.473)
R&D geographic conc.	0.589	0.660	0.655	0.770	0.644	0.763	0.607	0.722
	(0.191)	(0.213)	(0.210)	(0.251)	(0.209)	(0.246)	(0.194)	(0.234)
R&D team size	0.771***	0.613***	0.624***	0.638***	0.625***	0.651***	0.658***	0.664***
	(0.059)	(0.073)	(0.074)	(0.074)	(0.075)	(0.075)	(0.079)	(0.078)
R&D alliance duration	0.956	0.950	0.948+	0.958	0.953	0.957	0.957	0.963
	(0.031)	(0.031)	(0.030)	(0.032)	(0.031)	(0.031)	(0.030)	(0.031)
R&D alliance strength	1.112	1.095	1.107	0.956	1.032	0.960	0.981	0.913
	(0.155)	(0.154)	(0.151)	(0.139)	(0.152)	(0.134)	(0.140)	(0.133)
R&D alliance structure	1.336	1.327	1.353	1.408+	1.368+	1.443+	1.457*	1.486*
	(0.253)	(0.250)	(0.255)	(0.267)	(0.259)	(0.274)	(0.277)	(0.284)
R&D alliances	1.027*	1.010	0.997	1.048***	1.023	1.034*	1.014	1.038*
	(0.012)	(0.012)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
Intrafirm connections		1.293***	1.318***	1.259**	1.249**	1.278***	1.237**	1.244**
		(0.095)	(0.096)	(0.090)	(0.096)	(0.090)	(0.095)	(0.092)
Intrafirm clustering		1.017***	1.023***	1.021***	1.016***	1.029***	1.026***	1.030***
		(0.004)	(0.005)	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)
Intrafirm efficiency		1.075	1.018	1.101	0.952	1.012	0.746	0.860
		(0.189)	(0.177)	(0.184)	(0.181)	(0.166)	(0.149)	(0.178)
R&D alliances x Intrafirm connect.			1.022*			1.028**	1.039**	1.035**
			(0.011)			(0.010)	(0.012)	(0.012)
R&D alliances x Intrafirm clustering				1.000***		0.999***		1.000***
				(0.000)		(0.000)		(0.000)
R&D alliances x Intrafirm efficiency					1.038		1.080**	1.034
					(0.024)		(0.028)	(0.027)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	0.630	1.593	1.610	1.923	1.699	2.039	1.861	2.141
	(0.289)	(0.840)	(0.849)	(0.990)	(0.896)	(1.049)	(0.977)	(1.103)
Observations	483	483	483	483	483	483	483	483
Number of firms	49	49	49	49	49	49	49	49

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Robustness Checks for Chapter 2

Table 8 Robustness checks for network reach and clusters

	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)	(Model 7)	(Model 8)	(Model 9)
	Transfer	Transfer	Transfer	Diversity	Diversity	Diversity	Firm inno.	Firm inno.	Firm inno.
Firm size	0.070	0.205**	0.091	0.149	0.242**	0.158+	0.310***	0.476***	0.330***
	(0.084)	(0.075)	(0.077)	(0.091)	(0.089)	(0.094)	(0.063)	(0.062)	(0.061)
Medical device focus	0.596	0.342	0.620+	-0.206	-0.307	-0.202	0.304	-0.004	0.262
	(0.362)	(0.425)	(0.355)	(0.310)	(0.338)	(0.309)	(0.259)	(0.265)	(0.258)
Firm performance	2.240*	1.993*	2.053*	0.248	0.456	0.186	1.609*	1.321*	1.447*
	(0.882)	(0.941)	(0.858)	(0.634)	(0.683)	(0.676)	(0.690)	(0.667)	(0.709)
Firm leverage	0.873	0.927	0.772	-0.244	-0.092	-0.197	0.304	0.421	0.342
	(0.706)	(0.669)	(0.710)	(0.437)	(0.458)	(0.436)	(0.548)	(0.450)	(0.560)
R&D intensity	1.558	2.717*	1.554	3.450**	4.127***	3.464**	4.345*	3.656*	4.013*
	(1.319)	(1.153)	(1.170)	(1.131)	(1.190)	(1.126)	(1.754)	(1.820)	(1.769)
Firm slack	-0.020	-0.036	-0.010	0.050	0.040	0.054	-0.023	-0.024	-0.012
	(0.046)	(0.054)	(0.038)	(0.030)	(0.031)	(0.034)	(0.017)	(0.023)	(0.016)
Acquisitions	0.271	0.290	0.255	0.115	0.113	0.108	0.259+	0.200+	0.264+
	(0.247)	(0.263)	(0.251)	(0.107)	(0.118)	(0.103)	(0.133)	(0.117)	(0.135)
Divestments	-0.040	-0.019	-0.062	-0.806+	-0.772	-0.794+	-0.315	-0.398+	-0.368
	(0.201)	(0.213)	(0.214)	(0.467)	(0.499)	(0.476)	(0.249)	(0.225)	(0.257)
R&D concentration	2.274***	1.284*	1.989**	0.411	-0.100	0.319	0.624*	0.249	0.494
	(0.652)	(0.649)	(0.707)	(0.442)	(0.430)	(0.428)	(0.312)	(0.322)	(0.311)
R&D recruitment	0.565	0.433	0.621	0.551*	0.548*	0.539+	0.048	0.047	0.036
	(0.567)	(0.493)	(0.551)	(0.268)	(0.261)	(0.280)	(0.280)	(0.275)	(0.288)
R&D scientists	0.000	0.000	-0.000	0.001	0.001	0.000	0.001***	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Network density	0.250*	0.067	0.261*	0.219**	0.159*	0.226**	0.194+	0.116	0.194+
	(0.124)	(0.085)	(0.120)	(0.079)	(0.069)	(0.080)	(0.102)	(0.097)	(0.101)
Network isolate ratio	0.238	-0.482	-0.537	-0.445	-0.818	-0.800	-1.147	-1.933*	-1.659*
	(1.201)	(1.426)	(1.388)	(1.179)	(1.368)	(1.415)	(0.812)	(0.784)	(0.819)
R&D team size	-0.599**	-0.250	-0.377+	-0.241*	-0.154	-0.178	-0.440*	-0.343+	-0.340+
	(0.212)	(0.226)	(0.226)	(0.108)	(0.113)	(0.126)	(0.223)	(0.190)	(0.205)
Fragmentation	2.716**		2.496**	1.602**		1.511**	1.512**		1.342**
	(1.008)		(0.926)	(0.522)		(0.528)	(0.522)		(0.518)
Path length	0.283**		0.272**	0.221***		0.211***	0.351***		0.337***
	(0.090)		(0.088)	(0.055)		(0.055)	(0.066)		(0.068)
Ego-network density		-2.367*	-2.026+		-1.114	-0.767		-1.721***	-1.104*
		(1.130)	(1.127)		(0.761)	(0.779)		(0.475)	(0.522)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-6.712***	-3.149***	-5.845***	-3.467***	-1.564*	-3.079***	0.574	2.935***	1.180
	(1.418)	(0.931)	(1.339)	(0.756)	(0.754)	(0.775)	(0.847)	(0.525)	(0.888)
Observations	441	441	441	431	431	431	484	484	484
Number of firms	50	50	50	49	49	49	50	50	50

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 9 Robustness checks for knowledge transfer, diversity and lagged variables

	(Model 1) Transfer^{ALT}	(Model 2) Diversity^{ALT}	(Model 3) Firm inno.	(Model 4) Transfer	(Model 5) Diversity	(Model 6) Firm inno.	(Model 7) Firm inno.
Firm size	-0.035	0.365***	0.384***	0.044	0.129	0.418***	0.331***
	(0.080)	(0.078)	(0.073)	(0.058)	(0.082)	(0.065)	(0.054)
Medical device focus	0.581*	0.792**	0.124	0.260	-0.131	0.067	0.013
	(0.246)	(0.258)	(0.257)	(0.182)	(0.275)	(0.263)	(0.220)
Firm performance	1.813*	-0.382	0.898*	1.253+	0.280	0.829+	1.471*
	(0.745)	(0.738)	(0.404)	(0.674)	(0.675)	(0.474)	(0.631)
Firm leverage	0.079	-0.849	-0.028	0.078	-0.373	-0.144	0.612
	(0.730)	(0.601)	(0.508)	(0.488)	(0.380)	(0.432)	(0.513)
R&D intensity	3.443*	1.250	2.413*	0.219	2.020+	3.421*	4.036**
	(1.668)	(1.619)	(1.228)	(0.909)	(1.211)	(1.527)	(1.476)
Firm slack	0.032	0.025	0.003	0.003	0.043	-0.005	0.002
	(0.043)	(0.027)	(0.024)	(0.030)	(0.036)	(0.023)	(0.016)
Acquisitions	0.235	0.767*	0.311*	0.213	0.144	0.258	0.233
	(0.309)	(0.380)	(0.146)	(0.198)	(0.118)	(0.187)	(0.174)
Divestments	0.081	-0.220	-0.217	-0.063	-0.885+	-0.183	-0.217
	(0.292)	(0.495)	(0.288)	(0.236)	(0.508)	(0.350)	(0.222)
R&D concentration	1.991**	0.497	0.295	0.746*	0.639	0.227	0.925**
	(0.718)	(0.407)	(0.348)	(0.303)	(0.413)	(0.369)	(0.337)
R&D recruitment	1.100*	0.395	-0.092	1.265*	0.484	0.154	-0.082
	(0.522)	(0.423)	(0.317)	(0.531)	(0.327)	(0.382)	(0.302)
R&D scientists	0.000	0.005***	0.002***	-0.000	0.001*	0.001***	0.001**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network density	0.196*	0.250*	0.068	0.062	0.132+	0.085	0.106
	(0.084)	(0.110)	(0.101)	(0.061)	(0.069)	(0.104)	(0.080)
Network isolate ratio	-1.242	0.235	-1.776	1.789+	-0.148	-2.210*	-0.699
	(1.350)	(1.194)	(1.244)	(1.037)	(1.079)	(1.128)	(0.744)
R&D team size	-0.113	-0.271	-0.225	0.193	-0.112	-0.308	-0.151
	(0.170)	(0.235)	(0.178)	(0.170)	(0.121)	(0.213)	(0.169)
Network reach	-6.315***	-3.386***		-3.858***	-2.589**		-2.959***
	(1.336)	(1.022)		(1.046)	(0.948)		(0.697)
Network clusters	-1.804**	-1.447**		-2.121***	-0.651+		-1.352***
	(0.604)	(0.532)		(0.460)	(0.394)		(0.355)
Transfer^{ALT}			1.938***				
			(0.330)				
Diversity^{ALT}			0.911**				
			(0.344)				
Transfer$_{t0}$				3.360***		3.361***	
				(0.482)		(0.311)	
Diversity$_{t0}$					1.048**	0.557*	
					(0.397)	(0.274)	
Firm innovation$_{t0}$						0.000*	0.000***
						(0.000)	(0.000)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-1.668+	-0.383	1.305*	-2.552***	-1.398*	1.703**	3.276***
	(0.885)	(0.787)	(0.571)	(0.686)	(0.678)	(0.585)	(0.515)
Observations	441	431	412	412	405	412	484
Number of firms	50	49	48	48	47	48	50

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

^{ALT} Alternative measures for knowledge transfer and diversity

Table 10 Robustness check for firm innovation

	(Model 1) New products	(Model 2) New products	(Model 3) New products	(Model 4) New products	(Model 5) New products	(Model 6) New products
Firm size	0.419***	0.400***	0.397***	0.384***	0.432***	0.389***
	(0.049)	(0.052)	(0.050)	(0.046)	(0.047)	(0.047)
Medical device focus	0.086	0.028	0.086	0.101	-0.005	0.088
	(0.228)	(0.217)	(0.221)	(0.235)	(0.245)	(0.238)
Firm performance	1.001	0.837	0.705	1.477*	1.455*	1.492*
	(0.993)	(0.964)	(0.911)	(0.709)	(0.739)	(0.698)
Firm leverage	0.675	0.777*	0.741+	0.725+	0.753+	0.789+
	(0.426)	(0.367)	(0.380)	(0.424)	(0.428)	(0.445)
R&D intensity	-3.536+	-3.947*	-4.061*	-4.010*	-3.469*	-4.291**
	(1.819)	(2.003)	(1.962)	(1.651)	(1.580)	(1.634)
Firm slack	-0.046+	-0.059*	-0.053*	-0.042+	-0.044+	-0.039+
	(0.025)	(0.029)	(0.025)	(0.025)	(0.025)	(0.023)
Acquisitions	0.337*	0.326**	0.342**	0.353*	0.321*	0.360*
	(0.148)	(0.120)	(0.126)	(0.149)	(0.144)	(0.145)
Divestments	0.089**	0.063+	0.068+	0.081**	0.118***	0.104**
	(0.033)	(0.038)	(0.039)	(0.030)	(0.035)	(0.037)
R&D concentration	-0.585	-0.224	-0.370	-0.184	-0.537+	-0.140
	(0.372)	(0.384)	(0.385)	(0.329)	(0.287)	(0.322)
R&D recruitment	-0.141	-0.213	-0.245	-0.047	0.017	-0.024
	(0.326)	(0.289)	(0.318)	(0.231)	(0.228)	(0.233)
R&D scientists	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network density	0.076	0.057	0.050	0.131+	0.086	0.117
	(0.102)	(0.100)	(0.102)	(0.078)	(0.082)	(0.074)
Network isolate ratio	-0.299	-0.402	-0.293	-0.522	-0.379	-0.429
	(0.701)	(0.604)	(0.655)	(0.588)	(0.584)	(0.593)
R&D team size	-0.267	-0.263	-0.232	-0.229	-0.246+	-0.180
	(0.213)	(0.211)	(0.216)	(0.143)	(0.130)	(0.129)
Knowledge transfer	0.539		0.563			
	(0.375)		(0.384)			
Knowledge diversity		0.652***	0.654***			
		(0.172)	(0.177)			
Reach				-1.336**		-1.369**
				(0.454)		(0.486)
Clusters					-0.329	-0.354
					(0.431)	(0.412)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)
Constant	0.697	0.647	0.526	0.775	0.818	0.908
	(0.600)	(0.583)	(0.589)	(0.488)	(0.572)	(0.562)
Observations	378	381	378	438	438	438
Number of firms	47	47	47	49	49	49

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 11 Robustness checks for estimation methods

	(Model 1) Firm innovation	(Model 2) Firm innovation	(Model 3) Firm innovation	(Model 4) Firm innovation
Method	Neg. binomial-FE	Neg. binomial-FE	Poisson-QMLE	Poisson-QMLE
Firm size	0.332***	0.209***	0.508**	0.575***
	(0.057)	(0.054)	(0.161)	(0.147)
Medical device focus	-0.212	-0.532**	-0.745	-1.157*
	(0.197)	(0.195)	(0.499)	(0.544)
Firm performance	0.003	0.510	0.222	0.968
	(0.556)	(0.500)	(1.087)	(0.937)
Firm leverage	0.089	0.138	0.384	0.609
	(0.364)	(0.357)	(0.582)	(0.546)
R&D intensity	0.217	1.376	1.081	1.261
	(1.129)	(1.025)	(1.397)	(1.335)
Firm slack	-0.003	0.013	-0.011	0.004
	(0.026)	(0.023)	(0.026)	(0.026)
Acquisitions	0.231*	0.209+	0.098	0.051
	(0.098)	(0.110)	(0.074)	(0.077)
Divestments	-0.530*	-0.579*	-0.562	-0.421
	(0.245)	(0.254)	(0.371)	(0.383)
R&D concentration	0.079	0.711*	-0.506	-0.025
	(0.325)	(0.334)	(0.505)	(0.555)
R&D recruitment	0.203	0.808**	-0.206	0.105
	(0.280)	(0.248)	(0.307)	(0.241)
R&D scientists	0.001***	0.001***	0.001+	0.001+
	(0.000)	(0.000)	(0.000)	(0.000)
Network density	-0.001	0.094	-0.027	-0.023
	(0.064)	(0.058)	(0.058)	(0.058)
Network isolate ratio	-2.086**	-1.797*	-1.508	-1.448
	(0.796)	(0.711)	(1.270)	(1.058)
R&D team size	-0.335*	-0.245*	-0.372**	-0.335*
	(0.141)	(0.117)	(0.120)	(0.138)
Knowledge diversity	0.788***		0.538*	
	(0.188)		(0.273)	
Knowledge transfer	1.987***		1.382***	
	(0.247)		(0.396)	
Reach		-3.484***		-1.879+
		(0.644)		(0.995)
Clusters		-1.330***		-0.605+
		(0.285)		(0.355)
Year dummies	(included)	(included)	(included)	(included)
Constant	-0.925+	0.841+		
	(0.517)	(0.483)		
Observations	407	483	407	483
Number of firms	43	49	43	49

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 12 Robustness checks for mediation effects

	(Model 1) Firm inno.	(Model 2) Firm inno.	(Model 3) Firm inno.	(Model 4) Firm inno.	(Model 5) Firm inno.	(Model 6) Firm inno.	(Model 7) Firm inno.
Firm size	0.361*	0.416**	0.365**	0.214	0.374	0.209	0.322*
	(0.143)	(0.136)	(0.137)	(0.167)	(0.338)	(0.158)	(0.143)
Medical device focus	0.009	-0.685	-0.129	-0.670	-1.029	-0.663	-0.250
	(0.713)	(0.778)	(0.638)	(0.569)	(0.803)	(0.535)	(0.568)
Firm performance	-0.246	-0.727	-0.362	-0.662	-1.290	-0.768	-0.248
	(1.112)	(1.055)	(1.051)	(1.293)	(1.436)	(1.225)	(1.028)
Firm leverage	-0.186	0.030	-0.201	-0.171	0.132	-0.156	-0.194
	(0.595)	(0.602)	(0.577)	(0.685)	(0.747)	(0.660)	(0.573)
R&D intensity	0.902	0.073	0.797	-2.074	-1.096	-2.152	-0.051
	(1.796)	(1.692)	(1.717)	(1.848)	(2.407)	(1.740)	(2.035)
Firm slack	0.031	-0.013	0.024	-0.078*	-0.056	-0.081*	-0.006
	(0.042)	(0.057)	(0.039)	(0.039)	(0.056)	(0.037)	(0.057)
Acquisitions	0.182	0.220	0.207	0.266	0.228	0.247	0.223
	(0.204)	(0.150)	(0.188)	(0.197)	(0.146)	(0.181)	(0.180)
Divestments	-0.326	-0.320	-0.329	-0.476	-0.353	-0.473	-0.379
	(0.346)	(0.342)	(0.345)	(0.393)	(0.418)	(0.386)	(0.365)
R&D concentration	-0.724	-0.153	-0.609	0.443	0.046	0.333	-0.188
	(0.696)	(0.801)	(0.643)	(0.765)	(0.790)	(0.700)	(0.829)
R&D recruitment	0.093	0.233	0.127	-0.074	0.220	-0.045	0.042
	(0.429)	(0.350)	(0.400)	(0.406)	(0.615)	(0.385)	(0.372)
R&D scientists	0.001***	0.002***	0.001***	0.002***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network density	-0.039	-0.139	-0.048	-0.256*	-0.230*	-0.260**	-0.112
	(0.109)	(0.132)	(0.104)	(0.101)	(0.095)	(0.096)	(0.131)
Network isolate ratio	-0.876	-1.708	-1.022	-1.049	-1.548	-0.902	-1.169
	(1.041)	(1.256)	(0.974)	(1.186)	(1.701)	(1.115)	(0.905)
Knowledge transfer	5.911*	2.489	5.403*				3.823
	(2.517)	(3.530)	(2.234)				(2.755)
Knowledge diversity				2.976**	0.577	2.815**	1.101
				(1.133)	(4.310)	(1.036)	(1.392)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Observations	381	381	381	386	386	386	381
Number of firms	40	40	40	42	42	42	40
First-stage model:							
Instrument(s):	Network reach	Network clusters	Reach and clusters	Network reach	Network clusters	Reach and clusters	Reach and clusters
Model validity (F-test):	4.71*	1.77	2.45+	15.30***	1.41	9.59***	9.66***
Hansen J statistic:	(e.e.i.)	(e.e.i.)	0.649	(e.e.i.)	(e.e.i.)	0.217	(e.e.i.)
Hansen J p-value:			0.421			0.641	

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 13 Robustness checks for network size

	Networks of at least 15 R&D scientists				Networks of at least 50 R&D scientists			
	(Model 1) Transfer	(Model 2) Diversity	(Model 3) Firm inno.	(Model 4) Firm inno.	(Model 5) Transfer	(Model 6) Diversity	(Model 7) Firm inno.	(Model 8) Firm inno.
Firm size	-0.003	0.065	0.351***	0.332***	-0.057	0.099	0.182*	0.283**
	(0.090)	(0.098)	(0.078)	(0.069)	(0.079)	(0.166)	(0.071)	(0.093)
Medical device focus	0.119	-0.372	0.098	0.205	-0.201	-0.990*	0.031	0.202
	(0.426)	(0.338)	(0.225)	(0.208)	(0.480)	(0.397)	(0.218)	(0.244)
Firm performance	2.140+	1.389	2.111*	0.794	1.518	0.926	0.505	-1.236
	(1.167)	(1.101)	(0.847)	(0.768)	(1.495)	(1.765)	(1.183)	(1.048)
Firm leverage	0.786	0.059	0.781	0.110	0.628	0.215	0.201	-0.414
	(0.828)	(0.450)	(0.508)	(0.390)	(0.865)	(0.548)	(0.654)	(0.390)
R&D intensity	0.282	0.420	1.091	2.477	0.201	0.159	2.606+	2.765+
	(1.430)	(1.230)	(1.661)	(1.896)	(1.906)	(1.747)	(1.391)	(1.501)
Firm slack	0.051*	0.047+	0.000	-0.040*	0.061	0.196+	0.156	0.128
	(0.023)	(0.026)	(0.017)	(0.020)	(0.144)	(0.109)	(0.122)	(0.126)
Acquisitions	0.215	0.080	0.122	0.154	0.388*	-0.062	0.056	0.222
	(0.224)	(0.125)	(0.098)	(0.119)	(0.166)	(0.128)	(0.134)	(0.176)
Divestments	0.034	-0.460	-0.139	-0.228	0.063	-0.600*	-1.193***	-1.589***
	(0.164)	(0.377)	(0.196)	(0.239)	(0.158)	(0.304)	(0.205)	(0.134)
R&D concentration	2.218**	0.690	0.488	0.011	3.938*	1.323	0.764	0.092
	(0.819)	(0.577)	(0.394)	(0.351)	(1.636)	(1.143)	(0.565)	(0.417)
R&D recruitment	0.578	0.975*	0.465	0.263	0.644	0.519	0.689+	-0.268
	(0.514)	(0.448)	(0.284)	(0.323)	(0.422)	(0.494)	(0.404)	(0.576)
R&D scientists	0.000	0.001+	0.001**	0.001***	0.000	0.001+	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network density	0.113	0.186*	-0.012	0.056	0.166	-0.004	0.189+	0.148+
	(0.122)	(0.074)	(0.078)	(0.099)	(0.213)	(0.163)	(0.108)	(0.088)
Network isolate ratio	0.178	-0.559	-0.428	-0.151	0.070	1.425	0.306	0.377
	(1.547)	(1.074)	(1.206)	(1.270)	(1.792)	(1.428)	(1.018)	(1.057)
R&D team size	-0.091	-0.017	-0.217	-0.261	0.241	0.593	-0.188	-0.542*
	(0.232)	(0.127)	(0.171)	(0.217)	(0.187)	(0.414)	(0.244)	(0.264)
Reach	-7.205*	-4.246**	-1.630		-13.825*	-4.560	-6.519*	
	(3.127)	(1.347)	(1.089)		(6.222)	(4.300)	(2.628)	
Clusters	-1.678**	-1.031*	-2.037***		-0.994	-1.797*	-3.795***	
	(0.549)	(0.434)	(0.503)		(0.805)	(0.850)	(0.759)	
Knowledge diversity				0.425				0.941***
				(0.277)				(0.244)
Knowledge transfer				3.031***				2.628***
				(0.337)				(0.512)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-1.902*	-0.123	4.060***	2.337***	-2.553+	-0.896	5.890***	2.775**
	(0.894)	(0.714)	(0.556)	(0.596)	(1.543)	(1.617)	(0.857)	(0.924)
Observations	343	343	343	343	233	233	233	233
Number of firms	39	39	39	39	25	25	25	25

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 14 Robustness checks for outliers

	Without outliers				Winsorized outliers			
	(Model 1) Firm inno.	(Model 2) Firm inno.	(Model 3) Firm inno.	(Model 4) Firm inno.	(Model 5) Firm inno.	(Model 6) Firm inno.	(Model 7) Firm inno.	(Model 8) Firm inno.
Firm size	0.337***	0.429***	0.329***	0.410***	0.342***	0.439***	0.334***	0.418***
	(0.064)	(0.057)	(0.056)	(0.068)	(0.062)	(0.056)	(0.055)	(0.066)
Medical device focus	0.143	-0.044	0.042	0.081	0.146	-0.031	0.047	0.090
	(0.248)	(0.247)	(0.224)	(0.269)	(0.250)	(0.250)	(0.225)	(0.267)
Firm performance	1.316+	1.602**	1.422*	0.785	1.275+	1.553**	1.382*	0.713
	(0.693)	(0.536)	(0.622)	(0.486)	(0.680)	(0.528)	(0.607)	(0.492)
Firm leverage	0.349	0.502	0.503	-0.289	0.548	0.734	0.703	-0.052
	(0.444)	(0.481)	(0.502)	(0.422)	(0.457)	(0.506)	(0.517)	(0.439)
R&D intensity	3.825*	4.093**	3.801*	3.284*	3.984*	4.243**	3.942**	3.333*
	(1.834)	(1.489)	(1.532)	(1.541)	(1.797)	(1.468)	(1.495)	(1.564)
Firm slack	-0.020	-0.024	-0.001	-0.005	-0.022	-0.028	-0.003	-0.008
	(0.021)	(0.020)	(0.016)	(0.024)	(0.021)	(0.021)	(0.016)	(0.024)
Acquisitions	0.358*	0.280*	0.375*	0.351+	0.203	0.125	0.221	0.236
	(0.164)	(0.140)	(0.183)	(0.210)	(0.154)	(0.160)	(0.172)	(0.187)
Divestments	-0.314	-0.213	-0.219	-0.186	-0.307+	-0.206	-0.210	-0.180
	(0.195)	(0.249)	(0.225)	(0.357)	(0.186)	(0.238)	(0.214)	(0.346)
R&D concentration	0.920**	0.367	0.919**	0.221	0.940**	0.369	0.939**	0.203
	(0.326)	(0.338)	(0.343)	(0.381)	(0.321)	(0.335)	(0.338)	(0.379)
R&D recruitment	-0.101	0.143	-0.067	0.168	-0.132	0.117	-0.087	0.191
	(0.272)	(0.266)	(0.292)	(0.377)	(0.281)	(0.277)	(0.300)	(0.380)
R&D scientists	0.002***	0.002***	0.002***	0.002***	0.002**	0.001**	0.001**	0.002**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network density	0.174*	0.045	0.116	0.088	0.190*	0.060	0.129	0.104
	(0.086)	(0.093)	(0.080)	(0.104)	(0.087)	(0.095)	(0.081)	(0.110)
Network isolate ratio	-0.965	-0.684	-0.646	-2.179+	-0.874	-0.560	-0.548	-2.020+
	(0.686)	(0.810)	(0.732)	(1.141)	(0.683)	(0.802)	(0.721)	(1.124)
R&D team size	-0.332+	-0.349+	-0.173	-0.313	-0.329+	-0.353+	-0.166	-0.316
	(0.191)	(0.187)	(0.166)	(0.215)	(0.190)	(0.189)	(0.167)	(0.224)
Reach	-2.871***		-2.908***		-2.995***		-3.018***	
	(0.719)		(0.704)		(0.731)		(0.711)	
Clusters		-1.330***	-1.364***			-1.333***	-1.378***	
		(0.389)	(0.356)			(0.387)	(0.353)	
Knowledge diversity				0.524+				0.550*
				(0.272)				(0.273)
Knowledge transfer				3.383***				3.393***
				(0.324)				(0.330)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	2.565***	3.082***	3.328***	1.783**	2.500***	2.986***	3.265***	1.670**
	(0.446)	(0.593)	(0.532)	(0.606)	(0.434)	(0.597)	(0.527)	(0.588)
Observations	467	467	467	395	484	484	484	412
Number of firms	50	50	50	48	50	50	50	48

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 15 Robustness checks for interaction effects

	(Model 1) Transfer	(Model 2) Transfer	(Model 3) Diversity	(Model 4) Diversity	(Model 5) Firm innov.	(Model 6) Firm innov.	(Model 7) Firm innov.	(Model 8) Firm innov.
Firm size	0.073	0.072	0.152+	0.152+	0.416***	0.417***	0.347***	0.319***
	(0.102)	(0.094)	(0.089)	(0.089)	(0.066)	(0.066)	(0.057)	(0.055)
Medical device focus	0.398	0.398	-0.298	-0.297	0.087	0.088	0.010	0.044
	(0.334)	(0.326)	(0.313)	(0.313)	(0.267)	(0.265)	(0.224)	(0.217)
Firm performance	2.331**	2.323**	0.158	0.156	0.884+	0.881+	1.477*	1.605*
	(0.787)	(0.795)	(0.647)	(0.647)	(0.476)	(0.472)	(0.639)	(0.695)
Firm leverage	0.658	0.667	-0.180	-0.177	-0.186	-0.188	0.506	0.484
	(0.771)	(0.769)	(0.428)	(0.430)	(0.425)	(0.429)	(0.496)	(0.546)
R&D intensity	0.767	0.759	3.154**	3.148**	3.515*	3.507*	3.885**	4.138**
	(1.290)	(1.336)	(1.207)	(1.207)	(1.534)	(1.545)	(1.490)	(1.577)
Firm slack	0.006	0.006	0.062+	0.062+	-0.006	-0.006	-0.002	0.003
	(0.033)	(0.033)	(0.036)	(0.035)	(0.024)	(0.024)	(0.016)	(0.015)
Acquisitions	0.292	0.290	0.129	0.129	0.273	0.274	0.296+	0.283+
	(0.236)	(0.237)	(0.116)	(0.117)	(0.173)	(0.174)	(0.153)	(0.145)
Divestments	-0.007	0.001	-0.797+	-0.797+	-0.187	-0.187	-0.220	-0.197
	(0.215)	(0.209)	(0.475)	(0.473)	(0.354)	(0.354)	(0.220)	(0.237)
R&D concentration	2.624***	2.613***	0.621	0.621	0.199	0.197	0.932**	0.927**
	(0.626)	(0.618)	(0.492)	(0.490)	(0.378)	(0.378)	(0.346)	(0.337)
R&D recruitment	0.706	0.711	0.536*	0.535*	0.147	0.150	-0.109	-0.045
	(0.675)	(0.664)	(0.270)	(0.269)	(0.383)	(0.382)	(0.295)	(0.295)
R&D scientists	0.000	0.000	0.001+	0.001+	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network density	0.168+	0.173*	0.181*	0.180*	0.090	0.091	0.096	0.131
	(0.087)	(0.085)	(0.077)	(0.078)	(0.105)	(0.104)	(0.079)	(0.086)
Network isolate ratio	0.445	0.417	-0.185	-0.181	-2.222+	-2.229+	-0.761	-0.978
	(1.476)	(1.574)	(1.259)	(1.248)	(1.142)	(1.153)	(0.763)	(0.815)
R&D team size	-0.248	-0.268	-0.068	-0.065	-0.316	-0.318	-0.159	-0.226
	(0.232)	(0.293)	(0.104)	(0.111)	(0.212)	(0.204)	(0.167)	(0.190)
$Reach_{mc}$	-5.843**	-5.861**	-2.939**	-2.923**			-2.897***	-3.414***
	(2.015)	(1.846)	(1.010)	(0.921)			(0.701)	(0.772)
$Clusters_{mc}$	-1.326	-1.260	-0.866*	-0.870*			-1.422***	-1.483***
	(0.808)	(0.977)	(0.367)	(0.368)			(0.361)	(0.370)
$Reach_{mc}$ x $Clusters_{mc}$		1.632		-0.207				2.795
		(6.835)		(3.257)				(2.275)
Knowledge $diversity_{mc}$					0.563*	0.568*		
					(0.274)	(0.268)		
Knowledge $diffusion_{mc}$					3.474***	3.464***		
					(0.326)	(0.329)		
$Diversity_{mc}$ x $Diffusion_{mc}$						0.139		
						(1.371)		
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-4.885***	-4.842***	-2.244**	-2.249**	2.430***	2.431***	1.831***	1.947***
	(0.761)	(0.820)	(0.722)	(0.735)	(0.618)	(0.618)	(0.492)	(0.492)
Observations	441	441	431	431	412	412	484	484
Number of firms	50	50	49	49	48	48	50	50

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

mc: mean-centered variable

Table 16 Robustness checks for knowledge transfer at patent level

	(Model 1) Times cited	(Model 2) Times cited	(Model 3) Times cited	(Model 4) Dummy cited	(Model 5) Dummy cited	(Model 6) Dummy cited
Method	Neg. binom.	Neg. binom.	Neg. binom.	Probit	Probit	Probit
Year t+2	0.740***	0.738***	0.745***	0.393***	0.392***	0.396***
	(0.038)	(0.038)	(0.037)	(0.020)	(0.020)	(0.020)
Year t+3	1.089***	1.080***	1.098***	0.541***	0.537***	0.547***
	(0.037)	(0.038)	(0.038)	(0.020)	(0.020)	(0.020)
Nr cites made	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Self-citations	5.334***	6.022***	4.986***	2.461***	2.701***	2.196***
	(0.538)	(0.573)	(0.583)	(0.269)	(0.283)	(0.290)
% Patents in same class	1.174***	1.206***	1.169***	0.508***	0.520***	0.501***
	(0.101)	(0.101)	(0.101)	(0.050)	(0.050)	(0.051)
% Patents in proximity	1.015***	1.029***	0.901***	0.415***	0.420***	0.362***
	(0.082)	(0.082)	(0.083)	(0.044)	(0.044)	(0.044)
Number of inventors	0.001	-0.002	-0.005	0.007	0.006	0.005
	(0.009)	(0.009)	(0.009)	(0.005)	(0.005)	(0.005)
Closeness centrality	2.259***	2.533***	3.424***	1.294***	1.419***	1.787***
	(0.169)	(0.186)	(0.210)	(0.088)	(0.099)	(0.107)
Reach		-1.235***	0.231		-0.468**	0.304
		(0.344)	(0.374)		(0.173)	(0.191)
Closeness x Reach			-7.851***			-3.565***
			(0.858)			(0.408)
Firm dummies	(included)	(included)	(included)	(included)	(included)	(included)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)
Patent class dummies	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-2.986***	-3.025***	-2.858***	-1.594***	-1.605***	-1.528***
	(0.194)	(0.194)	(0.196)	(0.098)	(0.098)	(0.098)
Observations	44,112	44,112	44,112	43,983	43,983	43,983

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 17 Robustness checks for knowledge transfer at citation level

	(Model 1) Citation	(Model 2) Citation	(Model 3) Citation	(Model 4) Citation	(Model 5) Citation	(Model 6) Citation
	Probit	Probit	Probit	RE logit	RE logit	RE logit
Time difference	0.180***	0.193***	0.198***	0.626***	0.658***	0.672***
	(0.005)	(0.005)	(0.005)	(0.019)	(0.020)	(0.021)
Same tech main class	0.442***	0.406***	0.413***	1.337***	1.231***	1.243***
	(0.008)	(0.009)	(0.009)	(0.033)	(0.034)	(0.034)
Same tech subclass	0.866***	0.732***	0.720***	2.301***	2.151***	2.118***
	(0.011)	(0.012)	(0.012)	(0.057)	(0.063)	(0.063)
Spatial distance	-0.099***	-0.028***	-0.031***	-0.260***	-0.088***	-0.094***
	(0.001)	(0.002)	(0.002)	(0.005)	(0.007)	(0.007)
Social proximity		1.162***			2.758***	
		(0.015)			(0.068)	
Same inventor(s)			1.051***			2.540***
			(0.015)			(0.068)
Past collaborators			0.523***			1.143***
			(0.014)			(0.057)
Shared acquaintance			0.199***			0.557***
			(0.015)			(0.058)
Indirect tie			-0.117***			-0.362***
			(0.013)			(0.045)
Firm dummies	(included)	(included)	(included)	(included)	(included)	(included)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)
Firm-year citation mean	(included)	(included)	(included)	(included)	(included)	(included)
Patent citation mean	17.790***	17.798***	17.706***	133.557***	127.478***	126.016***
	(0.197)	(0.200)	(0.199)	(5.224)	(5.366)	(5.401)
Constant	-3.097***	-3.676***	-3.637***	-7.784***	-9.339***	-8.924***
	(0.052)	(0.055)	(0.055)	(0.061)	(0.078)	(0.081)
Observations	5,612,009	5,612,009	5,612,009	66,441	66,441	66,441

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Robustness Checks for Chapter 3

Table 18 Robustness checks for non-linear effects

	(Model 1) Innovation	(Model 2) Innovation	(Model 3) Innovation	(Model 4) Innovation	(Model 5) Innovation	(Model 6) Innovation	(Model 7) Innovation	(Model 8) Innovation
Firm size	0.231***	0.195***	0.225***	0.195***	0.234***	0.192***	0.250***	0.203***
	(0.053)	(0.053)	(0.053)	(0.054)	(0.053)	(0.053)	(0.053)	(0.054)
Medical device focus	-0.324	-0.363+	-0.386+	-0.362+	-0.300	-0.324	-0.306	-0.326
	(0.214)	(0.212)	(0.214)	(0.216)	(0.214)	(0.218)	(0.218)	(0.221)
Firm performance	0.826	0.791	0.813	0.791	0.774	0.859+	0.629	0.795
	(0.511)	(0.498)	(0.511)	(0.498)	(0.507)	(0.497)	(0.504)	(0.500)
Firm leverage	-0.018	-0.231	-0.097	-0.230	-0.214	-0.421	-0.261	-0.434
	(0.393)	(0.392)	(0.397)	(0.393)	(0.396)	(0.404)	(0.403)	(0.408)
Firm slack	-0.011	-0.004	-0.006	-0.004	-0.010	-0.008	-0.000	-0.004
	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.024)	(0.024)
Firm tech. diversity	-0.192	-0.189	-0.208	-0.188	-0.206	-0.213	-0.237	-0.225
	(0.298)	(0.293)	(0.297)	(0.293)	(0.292)	(0.288)	(0.290)	(0.288)
Acquisitions	0.139	0.149	0.155	0.149	0.140	0.079	0.135	0.079
	(0.115)	(0.108)	(0.116)	(0.108)	(0.110)	(0.104)	(0.110)	(0.105)
Divestments	-0.541*	-0.586*	-0.559*	-0.586*	-0.577*	-0.532*	-0.541*	-0.520*
	(0.245)	(0.238)	(0.243)	(0.238)	(0.240)	(0.240)	(0.242)	(0.241)
R&D intensity	2.927**	2.539**	2.819**	2.541**	2.834**	2.872**	2.624**	2.783**
	(0.998)	(0.963)	(0.996)	(0.964)	(0.981)	(0.962)	(0.983)	(0.969)
R&D scientists	-0.002**	-0.001+	-0.002**	-0.001	-0.003***	-0.001	-0.004***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D recruitment	0.615*	0.646**	0.663**	0.645**	0.633*	0.597*	0.653**	0.608*
	(0.248)	(0.248)	(0.250)	(0.250)	(0.247)	(0.249)	(0.249)	(0.249)
R&D geographic conc.	-0.395	-0.122	-0.450	-0.120	-0.365	-0.173	-0.429	-0.222
	(0.322)	(0.326)	(0.321)	(0.331)	(0.321)	(0.327)	(0.322)	(0.333)
R&D team size	-0.426***	-0.360**	-0.379**	-0.361**	-0.454***	-0.418***	-0.457***	-0.423***
	(0.122)	(0.120)	(0.125)	(0.121)	(0.119)	(0.120)	(0.123)	(0.121)
R&D alliance duration	-0.054	-0.065*	-0.052	-0.065*	-0.055+	-0.037	-0.040	-0.032
	(0.033)	(0.032)	(0.032)	(0.032)	(0.033)	(0.032)	(0.032)	(0.033)
R&D alliance strength	0.020	-0.142	-0.068	-0.140	-0.031	-0.082	-0.062	-0.094
	(0.157)	(0.159)	(0.164)	(0.165)	(0.145)	(0.145)	(0.151)	(0.150)
R&D alliance structure	0.348+	0.439*	0.421*	0.438*	0.354+	0.406*	0.330+	0.393*
	(0.194)	(0.193)	(0.198)	(0.197)	(0.192)	(0.190)	(0.195)	(0.194)
R&D alliances[(1)]	0.112	0.169*	0.129	0.169*	0.031+	0.031+	0.030+	0.030+
	(0.081)	(0.078)	(0.081)	(0.079)	(0.017)	(0.018)	(0.017)	(0.018)
R&D alliances sq.					-0.004***	0.002	-0.002	0.002
					(0.001)	(0.002)	(0.001)	(0.002)
Intrafirm connections	0.233**	0.178*	0.180*	0.179*	0.244***	0.214**	0.220**	0.206**
	(0.074)	(0.074)	(0.080)	(0.078)	(0.073)	(0.075)	(0.077)	(0.077)
Intrafirm clustering	0.019***	0.025***	0.020***	0.025***	0.028***	0.027***	0.032***	0.028***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
Intrafirm efficiency	0.052	0.073	-0.207	0.079	-0.062	0.017	-0.298	-0.095
	(0.172)	(0.165)	(0.218)	(0.230)	(0.172)	(0.168)	(0.201)	(0.213)
R&D alliances[(1)] x Intrafirm connect.	0.064	0.092*	0.140*	0.090	0.023*	0.018	0.018	0.017
	(0.047)	(0.047)	(0.062)	(0.063)	(0.012)	(0.011)	(0.016)	(0.016)
R&D alliances sq. x Intrafirm connect.					0.001	0.000	0.003*	0.001
					(0.001)	(0.001)	(0.001)	(0.001)
R&D alliances[(1)] x Intrafirm clustering		-0.006***		-0.006***		-0.001***		-0.001**
		(0.001)		(0.001)		(0.000)		(0.000)
R&D alliances sq. x Intrafirm clustering						0.000+		0.000
						(0.000)		(0.000)
R&D alliances[(1)] x Intrafirm efficiency			0.408+	-0.009			-0.031	-0.007
			(0.211)	(0.230)			(0.055)	(0.060)
R&D alliances sq. x Intrafirm efficiency							0.007+	0.002
							(0.004)	(0.004)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	0.400	0.598	0.518	0.596	0.744	0.736	0.802	0.769
	(0.530)	(0.523)	(0.533)	(0.526)	(0.537)	(0.527)	(0.536)	(0.533)
Observations	483	483	483	483	483	483	483	483
Number of firms	49	49	49	49	49	49	49	49

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
[(1)] In models 1 to 4, this variables is the natural log of R&D alliances

Table 19 Robustness checks for R&D alliances

	(Model 1) Innovation	(Model 2) Innovation	(Model 3) Innovation	(Model 4) Innovation	(Model 5) Innovation	(Model 6) Innovation	(Model 7) Innovation	(Model 8) Innovation
Firm size	0.285***	0.228***	0.225***	0.214***	0.229***	0.207***	0.221***	0.210***
	(0.052)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
Medical device focus	-0.652***	-0.287	-0.300	-0.306	-0.302	-0.333	-0.353+	-0.363+
	(0.193)	(0.211)	(0.212)	(0.210)	(0.211)	(0.210)	(0.211)	(0.211)
Firm performance	0.466	0.812	0.811	0.757	0.771	0.741	0.714	0.692
	(0.492)	(0.506)	(0.508)	(0.495)	(0.503)	(0.495)	(0.502)	(0.496)
Firm leverage	-0.062	0.099	0.088	0.032	0.096	-0.004	0.049	-0.013
	(0.379)	(0.379)	(0.380)	(0.380)	(0.379)	(0.381)	(0.380)	(0.381)
Firm slack	-0.012	-0.011	-0.012	-0.010	-0.008	-0.012	-0.009	-0.010
	(0.024)	(0.024)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Firm tech. diversity	-0.434	-0.252	-0.242	-0.200	-0.258	-0.179	-0.236	-0.190
	(0.294)	(0.297)	(0.298)	(0.296)	(0.296)	(0.297)	(0.296)	(0.297)
Acquisitions	0.250*	0.173	0.175	0.158	0.172	0.160	0.175	0.164
	(0.123)	(0.118)	(0.118)	(0.115)	(0.118)	(0.115)	(0.119)	(0.116)
Divestments	-0.518*	-0.494*	-0.494*	-0.548*	-0.514*	-0.551*	-0.538*	-0.562*
	(0.251)	(0.245)	(0.244)	(0.241)	(0.245)	(0.239)	(0.243)	(0.239)
R&D intensity	2.790**	2.869**	2.853**	2.604**	2.754**	2.522*	2.540*	2.392*
	(0.983)	(1.000)	(0.998)	(0.985)	(1.003)	(0.981)	(0.998)	(0.989)
R&D scientists	0.001***	-0.001**	-0.002**	-0.001*	-0.001*	-0.002**	-0.002**	-0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D recruitment	0.589*	0.568*	0.585*	0.552*	0.572*	0.579*	0.630*	0.608*
	(0.237)	(0.248)	(0.248)	(0.247)	(0.249)	(0.246)	(0.248)	(0.247)
R&D geographic conc.	-0.532	-0.421	-0.411	-0.339	-0.441	-0.313	-0.453	-0.358
	(0.324)	(0.323)	(0.323)	(0.325)	(0.323)	(0.324)	(0.322)	(0.326)
R&D team size	-0.260***	-0.487***	-0.475***	-0.469***	-0.480***	-0.441***	-0.430***	-0.423***
	(0.077)	(0.118)	(0.118)	(0.117)	(0.119)	(0.117)	(0.120)	(0.118)
R&D alliance duration	-0.028	-0.037	-0.039	-0.023	-0.032	-0.024	-0.031	-0.021
	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)	(0.035)
R&D alliance strength	0.109	0.073	0.084	0.026	0.040	0.040	0.025	0.013
	(0.138)	(0.141)	(0.140)	(0.142)	(0.144)	(0.140)	(0.142)	(0.142)
R&D alliance structure	0.307	0.303	0.308	0.351+	0.334+	0.368+	0.402*	0.408*
	(0.189)	(0.189)	(0.189)	(0.189)	(0.190)	(0.190)	(0.193)	(0.193)
New R&D alliances	0.039*	0.026	0.014	0.065**	0.046+	0.050*	0.039	0.057*
	(0.020)	(0.020)	(0.024)	(0.024)	(0.026)	(0.025)	(0.026)	(0.026)
Intrafirm connections		0.258***	0.257***	0.259***	0.244***	0.251***	0.214**	0.227**
		(0.072)	(0.072)	(0.071)	(0.073)	(0.070)	(0.074)	(0.073)
Intrafirm clustering		0.017***	0.019***	0.019***	0.017***	0.021***	0.021***	0.022***
		(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Intrafirm efficiency		0.069	0.057	0.172	0.007	0.167	-0.130	0.037
		(0.174)	(0.175)	(0.175)	(0.180)	(0.175)	(0.188)	(0.205)
New R&D alliances x Intrafirm connect.			0.016			0.029+	0.052*	0.045*
			(0.017)			(0.017)	(0.022)	(0.022)
New R&D alliances x Intrafirm cluster				-0.001**		-0.001**		-0.001*
				(0.000)		(0.000)		(0.000)
New R&D alliances x Intrafirm effici.					0.062		0.162*	0.084
					(0.050)		(0.065)	(0.072)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-0.498	0.469	0.469	0.550	0.507	0.547	0.558	0.576
	(0.459)	(0.527)	(0.526)	(0.523)	(0.527)	(0.521)	(0.524)	(0.521)
Observations	483	483	483	483	483	483	483	483
Number of firms	49	49	49	49	49	49	49	49

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 20 Robustness checks for intrafirm networks and small worlds

	(Model 1) Innovation	(Model 2) Innovation	(Model 3) Innovation	(Model 4) Innovation	(Model 5) Innovation	(Model 6) Innovation	(Model 7) Innovation	(Model 8) Innovation
Firm size	0.195***	0.186***	0.198***	0.194***	0.191***	0.232***	0.221***	0.220***
	(0.054)	(0.054)	(0.055)	(0.054)	(0.055)	(0.053)	(0.053)	(0.053)
Medical device focus	-0.478*	-0.448*	-0.477*	-0.474*	-0.439*	-0.279	-0.337	-0.339
	(0.197)	(0.199)	(0.197)	(0.197)	(0.198)	(0.212)	(0.216)	(0.216)
Firm performance	0.471	0.464	0.471	0.471	0.461	0.786	0.743	0.732
	(0.489)	(0.490)	(0.488)	(0.489)	(0.489)	(0.511)	(0.500)	(0.499)
Firm leverage	0.156	0.182	0.154	0.165	0.175	0.127	-0.361	-0.345
	(0.361)	(0.361)	(0.362)	(0.362)	(0.362)	(0.379)	(0.404)	(0.405)
Firm slack	0.012	0.010	0.012	0.012	0.008	-0.009	-0.002	-0.001
	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)	(0.024)	(0.024)	(0.024)
Firm tech. diversity	-0.675*	-0.727*	-0.685*	-0.686*	-0.768**	-0.272	-0.217	-0.228
	(0.282)	(0.286)	(0.282)	(0.284)	(0.286)	(0.297)	(0.288)	(0.290)
Acquisitions	0.201+	0.192+	0.207+	0.203+	0.202+	0.145	0.106	0.106
	(0.110)	(0.109)	(0.111)	(0.110)	(0.109)	(0.117)	(0.106)	(0.106)
Divestments	-0.556*	-0.525*	-0.583*	-0.560*	-0.585*	-0.510*	-0.585*	-0.587*
	(0.256)	(0.261)	(0.258)	(0.256)	(0.259)	(0.245)	(0.237)	(0.237)
R&D intensity	1.273	1.204	1.273	1.246	1.212	2.893**	2.749**	2.842**
	(1.019)	(1.028)	(1.018)	(1.024)	(1.024)	(1.010)	(0.964)	(0.989)
R&D scientists	0.001***	0.001***	0.001***	0.001***	0.001***	-0.001**	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
R&D recruitment	0.536*	0.510*	0.541*	0.537*	0.511*	0.568*	0.641**	0.637*
	(0.247)	(0.246)	(0.247)	(0.247)	(0.246)	(0.248)	(0.247)	(0.247)
R&D geographic	0.579	0.496	0.572	0.554	0.478	-0.422	-0.329	-0.329
conc.	(0.354)	(0.361)	(0.353)	(0.359)	(0.364)	(0.323)	(0.324)	(0.324)
R&D team size	-0.018	-0.011	-0.020	-0.015	-0.018	-0.483***	-0.406***	-0.409***
	(0.081)	(0.080)	(0.081)	(0.081)	(0.080)	(0.118)	(0.117)	(0.117)
R&D alliance	-0.033	-0.019	-0.035	-0.032	-0.019	-0.053	-0.039	-0.040
duration	(0.031)	(0.032)	(0.031)	(0.031)	(0.032)	(0.033)	(0.033)	(0.033)
R&D alliance	0.099	0.157	0.089	0.094	0.168	0.094	-0.087	-0.078
strength	(0.142)	(0.146)	(0.144)	(0.143)	(0.148)	(0.140)	(0.145)	(0.147)
R&D alliance	0.144	0.132	0.145	0.145	0.127	0.278	0.390*	0.386*
structure	(0.181)	(0.180)	(0.181)	(0.181)	(0.180)	(0.188)	(0.191)	(0.191)
R&D alliances	0.022+	-0.007	0.027+	0.029	-0.019	0.011	0.039**	0.040**
	(0.012)	(0.022)	(0.015)	(0.021)	(0.033)	(0.012)	(0.015)	(0.015)
Intrafirm connections[1]	-4.270***	-4.957***	-4.241***	-4.342***	-5.065***	0.258***	0.219**	0.220**
	(0.940)	(1.047)	(0.940)	(0.953)	(1.047)	(0.073)	(0.074)	(0.074)
Intrafirm clustering[1]	-1.025**	-1.015**	-0.938*	-1.003**	-0.792*	0.017***	0.029***	0.029***
	(0.334)	(0.333)	(0.365)	(0.338)	(0.366)	(0.004)	(0.004)	(0.004)
Intrafirm efficiency[1]	-0.413	-0.339	-0.377	-0.363	-0.285	0.093	-0.127	-0.120
	(0.301)	(0.303)	(0.307)	(0.323)	(0.320)	(0.177)	(0.209)	(0.210)
Intrafirm small world						0.000	0.000	0.000
						(0.000)	(0.000)	(0.000)
New R&D alliances x		-0.303			-0.450*		0.034**	0.034**
Intrafirm connect.[1]		(0.197)			(0.230)		(0.011)	(0.011)
New R&D alliances x			0.043		0.127		-0.000***	-0.000***
Intrafirm clustering[1]			(0.075)		(0.091)		(0.000)	(0.000)
New R&D alliances x				-0.019	0.033		0.033	0.032
Intrafirm efficiency[1]				(0.044)	(0.052)		(0.027)	(0.027)
R&D alliances x								-0.000
Intrafirm small w.								(0.000)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-0.468	-0.527	-0.462	-0.468	-0.532	0.444	0.740	0.732
	(0.457)	(0.458)	(0.458)	(0.457)	(0.460)	(0.528)	(0.515)	(0.516)
Observations	483	483	483	483	483	483	483	483
Number of firms	49	49	49	49	49	49	49	49

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

[1] Models 1 to 5 use alternative intrafirm network measures (density, transitivity, largest component)

Table 21 Robustness checks for firm innovation

	(Model 1) New prod.	(Model 2) New prod.	(Model 3) New prod.	(Model 4) New prod.	(Model 5) New prod.	(Model 6) New prod.	(Model 7) New prod.	(Model 8) New prod.
Firm size	0.429***	0.398***	0.390***	0.376***	0.397***	0.361***	0.381***	0.361***
	(0.076)	(0.078)	(0.078)	(0.078)	(0.079)	(0.078)	(0.079)	(0.078)
Medical device focus	0.302	0.376	0.393	0.395	0.372	0.421	0.375	0.419
	(0.256)	(0.260)	(0.261)	(0.261)	(0.261)	(0.262)	(0.262)	(0.263)
Firm performance	-1.105	-0.922	-0.746	-1.004	-0.940	-0.815	-0.793	-0.819
	(0.728)	(0.756)	(0.769)	(0.746)	(0.761)	(0.756)	(0.767)	(0.757)
Firm leverage	0.270	0.269	0.170	0.106	0.266	-0.041	0.104	-0.045
	(0.335)	(0.334)	(0.341)	(0.340)	(0.334)	(0.349)	(0.346)	(0.351)
Firm slack	-0.007	-0.015	-0.019	-0.009	-0.014	-0.013	-0.013	-0.013
	(0.030)	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.031)	(0.031)
Firm tech. diversity	-0.035	0.083	0.005	0.081	0.086	-0.021	-0.014	-0.022
	(0.291)	(0.300)	(0.304)	(0.299)	(0.300)	(0.304)	(0.305)	(0.304)
Acquisitions	0.345**	0.332**	0.312*	0.313*	0.334**	0.287*	0.321*	0.288*
	(0.128)	(0.128)	(0.127)	(0.124)	(0.129)	(0.123)	(0.127)	(0.123)
Divestments	0.099	0.098	0.068	0.075	0.099	0.036	0.060	0.035
	(0.110)	(0.112)	(0.113)	(0.115)	(0.113)	(0.115)	(0.115)	(0.115)
R&D intensity	-9.892***	-10.700***	-9.957***	-10.848***	-10.771***	-9.950***	-10.110***	-9.967***
	(1.878)	(1.996)	(2.022)	(1.942)	(2.026)	(1.954)	(2.010)	(1.961)
R&D scientists	0.001***	0.000	-0.001	0.000	0.000	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
R&D recruitment	0.307	0.340	0.327	0.337	0.343	0.321	0.342	0.322
	(0.232)	(0.236)	(0.237)	(0.239)	(0.237)	(0.240)	(0.238)	(0.240)
R&D geographic conc.	-0.346	-0.358	-0.396	-0.373	-0.365	-0.423	-0.464	-0.428
	(0.368)	(0.367)	(0.365)	(0.368)	(0.368)	(0.366)	(0.369)	(0.370)
R&D team size	-0.212*	-0.215	-0.248+	-0.203	-0.211	-0.244+	-0.235	-0.243
	(0.096)	(0.145)	(0.148)	(0.145)	(0.147)	(0.148)	(0.149)	(0.149)
R&D alliance duration	-0.027	-0.026	-0.036	-0.016	-0.025	-0.028	-0.033	-0.027
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
R&D alliance strength	0.046	0.054	0.082	0.014	0.049	0.047	0.061	0.046
	(0.125)	(0.126)	(0.125)	(0.129)	(0.129)	(0.126)	(0.126)	(0.127)
R&D alliance structure	-0.279+	-0.238	-0.252	-0.219	-0.233	-0.234	-0.227	-0.232
	(0.155)	(0.156)	(0.158)	(0.157)	(0.158)	(0.159)	(0.160)	(0.160)
R&D alliances	0.015	0.011	0.001	0.030*	0.013	0.019	0.005	0.019
	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.014)
Intrafirm connections		0.061	0.090	0.047	0.056	0.077	0.068	0.075
		(0.085)	(0.087)	(0.085)	(0.088)	(0.086)	(0.089)	(0.088)
Intrafirm clustering		0.006+	0.010*	0.007*	0.006+	0.013**	0.012**	0.013**
		(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Intrafirm efficiency		-0.042	-0.071	-0.060	-0.060	-0.105	-0.210	-0.117
		(0.161)	(0.160)	(0.157)	(0.184)	(0.157)	(0.196)	(0.202)
R&D alliances x			0.016			0.020*	0.024*	0.021+
Intrafirm connections			(0.010)			(0.010)	(0.012)	(0.012)
R&D alliances x				-0.000**		-0.000**		-0.000**
Intrafirm clustering				(0.000)		(0.000)		(0.000)
R&D alliances x					0.004		0.030	0.003
Intrafirm efficiency					(0.021)		(0.025)	(0.027)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	0.335	0.596	0.760	0.816	0.607	1.057	0.908	1.067
	(0.639)	(0.718)	(0.724)	(0.716)	(0.720)	(0.724)	(0.732)	(0.730)
Observations	422	422	422	422	422	422	422	422
Number of firms	47	47	47	47	47	47	47	47

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 22 Robustness checks for outliers

	Without outliers				Winsorized outliers			
	(Model 1) Innovation	(Model 2) Innovation	(Model 3) Innovation	(Model 4) Innovation	(Model 5) Innovation	(Model 6) Innovation	(Model 7) Innovation	(Model 8) Innovation
Firm size	0.219***	0.201***	0.217***	0.202***	0.228***	0.211***	0.226***	0.213***
	(0.053)	(0.053)	(0.054)	(0.053)	(0.052)	(0.052)	(0.052)	(0.052)
Medical device focus	-0.369+	-0.417+	-0.417+	-0.422*	-0.349	-0.394+	-0.345	-0.395+
	(0.216)	(0.213)	(0.214)	(0.214)	(0.213)	(0.214)	(0.212)	(0.214)
Firm performance	0.858+	0.858+	0.840+	0.854+	0.836+	0.712	0.840+	0.712
	(0.510)	(0.498)	(0.510)	(0.499)	(0.500)	(0.478)	(0.498)	(0.479)
Firm leverage	-0.055	-0.289	-0.216	-0.299	0.167	-0.059	0.064	-0.082
	(0.392)	(0.401)	(0.403)	(0.405)	(0.385)	(0.388)	(0.390)	(0.390)
Firm slack	-0.015	-0.010	-0.012	-0.010	-0.014	-0.008	-0.007	-0.006
	(0.026)	(0.025)	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Firm tech. diversity	-0.234	-0.309	-0.297	-0.313	-0.343	-0.402	-0.394	-0.414
	(0.298)	(0.293)	(0.297)	(0.294)	(0.296)	(0.286)	(0.295)	(0.287)
Acquisitions	0.188	0.188	0.209	0.190	0.009	-0.040	0.022	-0.036
	(0.170)	(0.168)	(0.169)	(0.169)	(0.130)	(0.121)	(0.130)	(0.122)
Divestments	-0.493*	-0.530*	-0.551*	-0.534*	-0.432+	-0.510*	-0.443+	-0.510*
	(0.240)	(0.237)	(0.238)	(0.238)	(0.243)	(0.236)	(0.240)	(0.235)
R&D intensity	3.060**	2.988**	2.972**	2.979**	3.319***	3.034**	3.244**	3.016**
	(0.999)	(0.972)	(0.993)	(0.973)	(1.002)	(0.958)	(0.994)	(0.959)
R&D scientists	-0.003***	-0.001	-0.003***	-0.001	-0.002**	-0.002**	-0.003***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D recruitment	0.616*	0.665**	0.690**	0.672**	0.622*	0.642**	0.662**	0.653**
	(0.250)	(0.249)	(0.253)	(0.251)	(0.246)	(0.243)	(0.248)	(0.244)
R&D geographic conc.	-0.446	-0.238	-0.439	-0.245	-0.460	-0.311	-0.522	-0.334
	(0.324)	(0.329)	(0.322)	(0.330)	(0.318)	(0.320)	(0.318)	(0.321)
R&D team size	-0.484***	-0.419***	-0.451***	-0.418***	-0.496***	-0.439***	-0.469***	-0.436***
	(0.119)	(0.117)	(0.120)	(0.117)	(0.119)	(0.117)	(0.120)	(0.117)
R&D alliance duration	-0.047	-0.046	-0.047	-0.046	-0.062+	-0.056+	-0.058+	-0.054+
	(0.033)	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)	(0.032)	(0.032)
R&D alliance strength	0.065	-0.035	-0.033	-0.042	0.141	-0.001	0.044	-0.024
	(0.138)	(0.139)	(0.145)	(0.144)	(0.135)	(0.137)	(0.140)	(0.142)
R&D alliance structure	0.253	0.311+	0.326+	0.317+	0.243	0.307+	0.286	0.315+
	(0.188)	(0.188)	(0.191)	(0.190)	(0.186)	(0.186)	(0.189)	(0.186)
R&D alliances	-0.002	0.024	0.016	0.025	-0.018	0.022	-0.003	0.024
	(0.014)	(0.015)	(0.016)	(0.016)	(0.014)	(0.014)	(0.015)	(0.015)
Intrafirm connections	0.277***	0.205**	0.227**	0.201**	0.273***	0.219**	0.227**	0.208**
	(0.073)	(0.074)	(0.077)	(0.076)	(0.074)	(0.072)	(0.076)	(0.074)
Intrafirm clustering	0.028***	0.026***	0.029***	0.026***	0.022***	0.026***	0.025***	0.027***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
Intrafirm efficiency	-0.082	-0.048	-0.263	-0.070	-0.111	-0.123	-0.376+	-0.202
	(0.193)	(0.182)	(0.205)	(0.212)	(0.179)	(0.169)	(0.202)	(0.208)
New R&D alliances x Intrafirm connect.	0.016	0.021*	0.034**	0.023+	0.018+	0.023*	0.033**	0.027*
	(0.011)	(0.010)	(0.013)	(0.013)	(0.011)	(0.010)	(0.012)	(0.011)
New R&D alliances x Intrafirm clustering		-0.001***		-0.001***		-0.001***		-0.001***
		(0.000)		(0.000)		(0.000)		(0.000)
New R&D alliances x Intrafirm efficiency			0.097*	0.009			0.070**	0.018
			(0.039)	(0.047)			(0.026)	(0.027)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	0.861	0.827	1.007+	0.844	0.619	0.877+	0.787	0.912+
	(0.535)	(0.519)	(0.532)	(0.525)	(0.528)	(0.513)	(0.528)	(0.516)
Observations	466	466	466	466	483	483	483	483
Number of firms	49	49	49	49	49	49	49	49

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 23 Robustness checks for estimation method

	(Model 1) Innovation	(Model 2) Innovation	(Model 3) Innovation	(Model 4) Innovation	(Model 5) Innovation	(Model 6) Innovation	(Model 7) Innovation	(Model 8) Innovation
Method	Random-effect negative binomial				Fixed-effect Poisson QMLE			
Firm size	0.213***	0.192***	0.217***	0.198***	0.517***	0.408**	0.514***	0.408**
	(0.045)	(0.043)	(0.045)	(0.043)	(0.134)	(0.131)	(0.136)	(0.131)
Medical device focus	0.132	0.154	0.064	0.121	-0.984+	-0.806	-0.981+	-0.804
	(0.185)	(0.178)	(0.183)	(0.180)	(0.532)	(0.502)	(0.535)	(0.498)
Firm performance	1.482**	1.411**	1.352**	1.355**	0.445	0.255	0.435	0.262
	(0.451)	(0.431)	(0.451)	(0.434)	(0.713)	(0.575)	(0.702)	(0.575)
Firm leverage	-0.093	-0.286	-0.206	-0.328	0.669	0.625	0.656	0.638
	(0.361)	(0.364)	(0.367)	(0.367)	(0.540)	(0.479)	(0.537)	(0.484)
Firm slack	-0.012	-0.002	-0.000	0.002	-0.013	0.000	-0.009	-0.003
	(0.022)	(0.021)	(0.022)	(0.021)	(0.024)	(0.024)	(0.030)	(0.028)
Firm tech. diversity	0.124	0.128	0.086	0.117	-0.064	-0.164	-0.063	-0.167
	(0.258)	(0.247)	(0.255)	(0.247)	(0.486)	(0.451)	(0.480)	(0.454)
Acquisitions	0.086	0.054	0.111	0.066	-0.017	-0.012	-0.015	-0.014
	(0.105)	(0.095)	(0.106)	(0.096)	(0.076)	(0.065)	(0.077)	(0.064)
Divestments	-0.495*	-0.568*	-0.525*	-0.572*	-0.428	-0.455	-0.429	-0.455
	(0.242)	(0.236)	(0.241)	(0.235)	(0.351)	(0.348)	(0.350)	(0.349)
R&D intensity	4.131***	3.842***	3.854***	3.735***	1.289	1.013	1.219	1.080
	(0.880)	(0.829)	(0.877)	(0.836)	(1.113)	(0.979)	(1.143)	(1.020)
R&D scientists	-0.003***	-0.003***	-0.004***	-0.003***	-0.002**	-0.002**	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D recruitment	0.672**	0.716**	0.739**	0.742**	0.131	0.148	0.145	0.134
	(0.245)	(0.243)	(0.247)	(0.244)	(0.258)	(0.253)	(0.278)	(0.273)
R&D geographic conc.	-0.342	-0.162	-0.415	-0.211	-0.704	-0.660	-0.738	-0.624
	(0.282)	(0.278)	(0.280)	(0.280)	(0.480)	(0.435)	(0.534)	(0.483)
R&D team size	-0.644***	-0.593***	-0.586***	-0.575***	-0.393**	-0.401**	-0.394**	-0.400**
	(0.115)	(0.110)	(0.116)	(0.111)	(0.133)	(0.130)	(0.134)	(0.129)
R&D alliance duration	-0.063*	-0.068*	-0.057+	-0.064*	-0.001	0.010	0.000	0.008
	(0.030)	(0.031)	(0.030)	(0.031)	(0.038)	(0.039)	(0.038)	(0.039)
R&D alliance strength	0.166	0.020	0.039	-0.026	-0.196	-0.229*	-0.205+	-0.220*
	(0.130)	(0.132)	(0.136)	(0.137)	(0.120)	(0.110)	(0.113)	(0.109)
R&D alliance structure	0.280	0.342+	0.365+	0.372*	0.183	0.204	0.184	0.203
	(0.186)	(0.187)	(0.188)	(0.188)	(0.147)	(0.136)	(0.146)	(0.136)
R&D alliances	-0.004	0.038**	0.014	0.042**	0.005	0.027	0.007	0.026
	(0.013)	(0.014)	(0.014)	(0.014)	(0.010)	(0.017)	(0.010)	(0.017)
Intrafirm connections	0.438***	0.400***	0.373***	0.375***	0.114	0.109+	0.113	0.110+
	(0.069)	(0.066)	(0.072)	(0.069)	(0.073)	(0.066)	(0.072)	(0.065)
Intrafirm clustering	0.029***	0.034***	0.032***	0.035***	0.015**	0.019***	0.016*	0.018**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Intrafirm efficiency	-0.003	-0.001	-0.324+	-0.151	0.054	0.018	0.012	0.063
	(0.170)	(0.158)	(0.190)	(0.195)	(0.162)	(0.155)	(0.201)	(0.201)
R&D alliances x Intrafirm connect.	0.021*	0.026**	0.038***	0.033**	0.021**	0.021**	0.023*	0.019*
	(0.010)	(0.009)	(0.011)	(0.011)	(0.007)	(0.008)	(0.009)	(0.009)
R&D alliances x Intrafirm clustering		-0.001***		-0.001***		-0.000**		-0.000**
		(0.000)		(0.000)		(0.000)		(0.000)
R&D alliances x Intrafirm efficiency			0.084***	0.032			0.008	-0.008
			(0.024)	(0.025)			(0.019)	(0.017)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	0.412	0.627	0.579	0.681				
	(0.486)	(0.467)	(0.483)	(0.469)				
Observations	483	483	483	483	483	483	483	483
Number of firms	49	49	49	49	49	49	49	49

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 24 Robustness checks for intrafirm network size

	(Model 1) Innovation	(Model 2) Innovation	(Model 3) Innovation	(Model 4) Innovation	(Model 5) Innovation	(Model 6) Innovation	(Model 7) Innovation	(Model 8) Innovation
Network size	15 R&D scientists		30 R&D scientists		50 R&D scientists		100 R&D scientists	
Firm size	0.291***	0.248***	0.273**	0.210*	0.099	0.034	0.097	0.034
	(0.068)	(0.067)	(0.093)	(0.094)	(0.112)	(0.108)	(0.134)	(0.122)
Medical device focus	-0.045	-0.067	-0.313	-0.293	-0.264	-0.143	-0.640	-0.494
	(0.231)	(0.232)	(0.263)	(0.265)	(0.314)	(0.309)	(0.442)	(0.405)
Firm performance	1.181	1.082	-0.094	-0.065	-0.361	-0.255	-0.759	-0.508
	(0.874)	(0.844)	(1.085)	(1.032)	(1.259)	(1.144)	(1.685)	(1.402)
Firm leverage	0.086	-0.230	0.044	-0.244	-0.096	-0.465	-0.909	-0.966+
	(0.401)	(0.418)	(0.432)	(0.453)	(0.472)	(0.488)	(0.602)	(0.543)
Firm slack	-0.006	0.007	0.005	0.069	0.019	0.163+	0.212*	0.314***
	(0.032)	(0.029)	(0.078)	(0.075)	(0.086)	(0.085)	(0.098)	(0.091)
Firm tech. diversity	-0.211	-0.241	-0.601+	-0.664+	-0.636	-0.640+	-0.176	-0.266
	(0.317)	(0.308)	(0.355)	(0.345)	(0.398)	(0.383)	(0.584)	(0.539)
Acquisitions	0.080	0.057	0.105	0.081	0.103	0.064	0.005	-0.000
	(0.108)	(0.098)	(0.113)	(0.101)	(0.118)	(0.100)	(0.110)	(0.093)
Divestments	-0.480+	-0.554*	-0.764*	-0.829**	-0.803**	-0.855**	-0.499	-0.391
	(0.263)	(0.256)	(0.309)	(0.298)	(0.290)	(0.279)	(0.621)	(0.589)
R&D intensity	0.001	0.076	-0.568	-0.124	-0.332	0.358	2.570	2.516
	(1.463)	(1.364)	(1.700)	(1.578)	(1.790)	(1.615)	(1.923)	(1.737)
R&D scientists	-0.003***	-0.003***	-0.002**	-0.003**	-0.002+	-0.002*	-0.003**	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D recruitment	0.793**	0.856**	0.962**	0.876**	0.475	0.385	0.635	0.523
	(0.283)	(0.280)	(0.336)	(0.328)	(0.406)	(0.381)	(0.491)	(0.439)
R&D geographic conc.	-0.550	-0.605	-0.933*	-1.043*	-1.646**	-1.844**	-0.929	-1.274
	(0.388)	(0.398)	(0.457)	(0.475)	(0.620)	(0.631)	(0.927)	(0.898)
R&D team size	-0.375**	-0.325*	-0.162	-0.160	-0.264	-0.209	-0.635+	-0.478
	(0.136)	(0.135)	(0.188)	(0.183)	(0.260)	(0.245)	(0.363)	(0.318)
R&D alliance duration	-0.012	0.016	0.014	0.043	0.027	0.070*	-0.046	0.015
	(0.033)	(0.032)	(0.032)	(0.032)	(0.034)	(0.033)	(0.037)	(0.037)
R&D alliance strength	0.029	-0.116	-0.090	-0.239	-0.178	-0.353+	-0.196	-0.357+
	(0.141)	(0.148)	(0.162)	(0.167)	(0.199)	(0.199)	(0.199)	(0.207)
R&D alliance structure	0.025	0.113	0.047	0.130	0.059	0.140	0.943**	0.981***
	(0.192)	(0.195)	(0.199)	(0.200)	(0.208)	(0.210)	(0.306)	(0.296)
R&D alliances	-0.007	0.030*	-0.010	0.028+	-0.000	0.052**	-0.029+	0.027
	(0.013)	(0.015)	(0.014)	(0.015)	(0.015)	(0.017)	(0.018)	(0.020)
Intrafirm connections	0.188*	0.155+	0.115	0.104	0.058	0.070	0.355*	0.348*
	(0.081)	(0.082)	(0.094)	(0.093)	(0.117)	(0.111)	(0.171)	(0.157)
Intrafirm clustering	0.022***	0.029***	0.020***	0.027***	0.016**	0.025***	0.024***	0.033***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Intrafirm efficiency	-0.121	-0.305	-0.068	-0.314	-0.131	-0.514*	0.013	-0.419+
	(0.159)	(0.195)	(0.159)	(0.202)	(0.174)	(0.219)	(0.178)	(0.236)
R&D alliances x	0.034**	0.047***	0.035**	0.048***	0.031*	0.046***	0.052***	0.058***
Intrafirm connections	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
R&D alliances x		-0.000***		-0.000***		-0.000***		-0.000***
Intrafirm clustering		(0.000)		(0.000)		(0.000)		(0.000)
R&D alliances x		0.035		0.044+		0.066*		0.060*
Intrafirm efficiency		(0.025)		(0.026)		(0.027)		(0.027)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	0.024	0.529	0.407	1.108	2.304*	2.782*	3.003+	3.212*
	(0.673)	(0.658)	(0.918)	(0.892)	(1.147)	(1.097)	(1.563)	(1.366)
Observations	372	372	284	284	233	233	171	171
Number of firms	39	39	29	29	24	24	18	18

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 25 Robustness checks for potential endogeneity

	(Model 1) Innovation	(Model 2) Innovation	(Model 3) Innovation	(Model 4) Innovation	(Model 5) Innovation	(Model 6) Innovation	(Model 7) Innovation	(Model 8) Innovation
Firm size	0.265***	0.217***	0.242***	0.145**	0.216***	0.163**	0.246***	0.173**
	(0.053)	(0.053)	(0.052)	(0.053)	(0.053)	(0.053)	(0.052)	(0.054)
Medical device focus	-0.630**	-0.289	-0.389+	-0.239	-0.285	-0.317	-0.403+	-0.343
	(0.192)	(0.210)	(0.212)	(0.205)	(0.210)	(0.208)	(0.210)	(0.209)
Firm performance	0.592	0.862+	0.968+	1.051*	0.850+	1.165*	0.876+	1.087*
	(0.499)	(0.509)	(0.507)	(0.497)	(0.510)	(0.493)	(0.504)	(0.496)
Firm leverage	0.043	0.168	-0.151	-0.130	0.170	-0.369	-0.225	-0.401
	(0.380)	(0.379)	(0.386)	(0.376)	(0.379)	(0.378)	(0.387)	(0.381)
Firm slack	-0.006	-0.007	-0.005	-0.007	-0.006	-0.007	0.002	-0.003
	(0.023)	(0.024)	(0.024)	(0.023)	(0.024)	(0.023)	(0.024)	(0.023)
Firm tech. diversity	-0.440	-0.247	-0.222	-0.089	-0.255	-0.088	-0.281	-0.113
	(0.289)	(0.295)	(0.287)	(0.291)	(0.297)	(0.285)	(0.288)	(0.287)
Acquisitions	0.204+	0.152	0.120	0.111	0.155	0.077	0.140	0.086
	(0.114)	(0.110)	(0.107)	(0.093)	(0.111)	(0.091)	(0.110)	(0.093)
Divestments	-0.522*	-0.503*	-0.517*	-0.513*	-0.498*	-0.516*	-0.475*	-0.499*
	(0.249)	(0.244)	(0.244)	(0.239)	(0.245)	(0.237)	(0.241)	(0.237)
R&D intensity	2.990**	2.955**	3.535***	2.640**	2.911**	3.202***	3.351***	3.115***
	(0.964)	(0.989)	(0.968)	(0.920)	(0.996)	(0.910)	(0.965)	(0.915)
R&D scientists	0.001***	-0.001**	-0.004***	-0.000	-0.001*	-0.003***	-0.004***	-0.003***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
R&D recruitment	0.598*	0.570*	0.537*	0.651**	0.580*	0.647**	0.620*	0.681**
	(0.236)	(0.247)	(0.243)	(0.246)	(0.249)	(0.243)	(0.246)	(0.245)
R&D geographic conc.	-0.579+	-0.440	-0.474	-0.102	-0.443	-0.174	-0.520+	-0.212
	(0.323)	(0.322)	(0.315)	(0.322)	(0.322)	(0.317)	(0.313)	(0.318)
R&D team size	-0.274***	-0.473***	-0.456***	-0.437***	-0.471***	-0.446***	-0.443***	-0.437***
	(0.077)	(0.118)	(0.117)	(0.114)	(0.119)	(0.115)	(0.119)	(0.116)
R&D alliance duration	-0.061*	-0.061+	-0.068*	-0.044	-0.060+	-0.049+	-0.058+	-0.045
	(0.031)	(0.032)	(0.031)	(0.030)	(0.032)	(0.030)	(0.030)	(0.029)
R&D alliance strength	0.112	0.077	0.050	-0.056	0.070	-0.079	-0.030	-0.110
	(0.137)	(0.139)	(0.133)	(0.135)	(0.141)	(0.131)	(0.135)	(0.133)
R&D alliance structure	0.315+	0.332+	0.325+	0.406*	0.336+	0.388*	0.359+	0.405*
	(0.191)	(0.191)	(0.187)	(0.187)	(0.191)	(0.184)	(0.187)	(0.185)
R&D alliances(1)	0.080***	0.060*	0.037	0.078***	0.059*	0.061**	0.026	0.057*
	(0.024)	(0.026)	(0.025)	(0.023)	(0.026)	(0.023)	(0.025)	(0.023)
Intrafirm connections		0.241***	0.303***	0.223**	0.233**	0.274***	0.257***	0.253***
		(0.073)	(0.074)	(0.070)	(0.076)	(0.072)	(0.077)	(0.075)
Intrafirm clustering		0.016***	0.030***	0.024***	0.015***	0.035***	0.033***	0.036***
		(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
Intrafirm efficiency		0.081	-0.030	0.154	0.042	0.047	-0.383+	-0.117
		(0.167)	(0.161)	(0.153)	(0.199)	(0.150)	(0.204)	(0.211)
R&D alliances(1) x Intrafirm connect.			0.052***			0.043***	0.069***	0.051***
			(0.012)			(0.011)	(0.013)	(0.013)
R&D alliances(1) x Intrafirm clustering				-0.001***		-0.001***		-0.001***
				(0.000)		(0.000)		(0.000)
R&D alliances(1) x Intrafirm efficiency					0.012		0.091**	0.036
					(0.032)		(0.034)	(0.033)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-0.202	0.561	0.764	0.908+	0.568	1.157*	0.891+	1.180*
	(0.469)	(0.526)	(0.525)	(0.516)	(0.526)	(0.522)	(0.526)	(0.522)
Observations	483	483	483	483	483	483	483	483
Number of firms	49	49	49	49	49	49	49	49

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

(1) Instrumented value of R&D alliances (bases on non-R&D alliances)

APPENDIX A – SAMPLE SELECTION

Initial data was collected on all firms active in the medical device industry included in WRDS Compustat using firm segment data. This database covers all North-American public firms. The sampling frame consists of all firms with any sales in the medical devices industry in 1990. A sample of medical device firms was selected using three criteria: (1) the size of a firm in terms of medical device sales in 1990, (2) the number of medical device patents during 1986-1990, and (3) the number of medical devices during 1986-1990. Medical device sales were measured as the sum of sales in segments with SICs 3841-3851. For convenience, the original patent concordance details and ownership data as provided in the NBER Patent Data Project (Hall et al., 2001) were used. The number of medical devices was measured as the raw number of PMA approvals and 510(k) notifications for each firm. I realize that these data are rather crude (and are re-collected in more detail later on), but sufficient enough for sample selection. The initial sampling frame contained 180 firms which were ranked based on a factor analysis of sales, patents and products (all three variables strongly loaded on a single factor). The first fifty firms form my final sample. I considered including more firms, but these firms generally did not have patents or devices (e.g. distributors, importers or start-ups). The final sample is shown in the table below.

Table 26 Sample of fifty North-American medical device firms

Firm	Observation period[1]	R&D scientists[2]	R&D alliance partners[3]
Abbott Laboratories	1990-2005	535	34
American Cyanamid Co	1990-1993 (acquired by Wyeth in 1994)	124	3
Wyeth (AKA: American Home Products)	1990-1997 (divested by selling subsidiaries)	219	12
Ballard Medical Products	1990-1998 (acquired by Kimberly-Clark in 1999)	34	5
Bard (C.R.) Inc	1990-2005	529	25

Bausch & Lomb Inc	1990-2005 (acquired by Warburg Pincus in 2007)	160	24
Baxter International Inc	1990-2005	844	28
Becton Dickinson & Co	1990-2005	553	27
Bristol-Myers Squibb Co	1990-1999 (divested by selling subsidiaries)	460	10
Circon Corp	1990-1997 (acquired by Maxxim Med. in 1998)	25	0
Coherent Inc	1990-2001 (divested by selling subsidiaries)	36	14
Collagen Aesthetic Inc (AKA: Collagen Corp)	1990-1998 (acquired by Inamed in 1999)	53	16
Cooper Companies Inc (AKA: CooperVision)	1990-2005	30	11
Cordis Corp	1990-1995 (acquired by J&J in 1996)	171	7
Datascope Corp	1990-2005 (acquired by Getinge AB in 2008)	62	8
OEC Medical Systems Inc (AKA: Diasonics Inc)	1990-1998 (acquired by GE Healthcare in 1999)	30	11
Eastman Kodak Co (AKA: Kodak)	1990-2005	160	20
Empi Inc	1990-1998 (acquired by Carlyle Group in 1999)	25	1
General Electric Co	1990-2005	1118	44
Gish Biomedical Inc	1990-2002 (acquired by CardioTech in 2002)	9	6
Grace (W R) & Co	1990-1993 (left industry)	9	1
Healthdyne Inc	1990-1994 (merged with Tokos Medical in 1995)	9	0
Hewlett-Packard Co	1990-1998 (divested by spinning off subsidiary)	242	11
Mallinckrodt (AKA: International Minerals & Chemicals Corp/IMCERA)	1990-2000 (acquired by Tyco in 2000)	229	18
Invacare Corp	1990-2005	20	3
Johnson & Johnson	1990-2005	2533	68
Lilly (Eli) & Co	1990-1994 (divested by selling subsidiaries)	348	11
Medex Inc	1990-1996 (acquired by Furon in 1997)	33	0
Medtronic Inc	1990-2005	2201	68
Mentor Corp (AKA: Mentor Medical)	1990-2005 (acquired by J&J in 2009)	80	26
Optical Radiation Corp (AKA: ORC)	1990-1993 (merged with Benson Eyecare in 1994)	11	2
PPG Industries Inc	1990-1993 (divested by selling subsidiary)	16	1
Pfizer Inc	1990-1997 (divested by selling subsidiaries)	392	12
Puritan-Bennett Corp	1990-1994 (acquired by Nellcor in 1995)	45	3

St Jude Medical Inc	1990-2005	529	23
Schering-Plough	1990-1998 (divested by selling subsidiary)	45	3
Scimed Life Systems Inc	1990-1993 (acquired by Boston Sci. in 1994)	53	5
Stryker Corp	1990-2005	435	10
Meridian Medical Technologies Inc (AKA: Survival Technology Inc/STI)	1990-2002 (acquired by King Pharma. in 2003)	30	13
Thermo Fisher Scientific Inc (AKA: Thermo Electron)	1990-2003 (divested by selling subsidiaries)	115	14
Trimedyne Inc	1990-2005	24	15
U.S. Surgical Corp (AKA: U.S.S.C.)	1990-1997 (acquired by Tyco in 1998)	297	8
Acuson Corp	1990-1999 (acquired by Siemens in 2000)	139	4
Cabot Medical Corp	1990-1994 (acquired by Circon Corp in 1995)	7	4
Kirschner Medical Corp	1990-1993 (acquired by Biomet in 1994)	12	0
Nellcor Puritan Bennett Inc (AKA: Nellcor Inc)	1990-1996 (acquired by Mallinckrodt in 1997)	61	4
Dentsply International Inc (AKA: Gendex Corp)	1990-2005	139	8
Orthomet Inc[4]	1990-1994 (acquired by Wright Medical in 1994)	7	2
Allergan Inc	1990-2001	102	7
Target Therapeutics Inc	1990-1995 (acquired by Boston Sci. in 1997)	37	11

(1) Period a firm is included in the panel and, if exited before 2005, the cause of leaving the sample
(2) Number of unique medical device inventors mentioned on firm's patents
(3) Number of unique medical device R&D alliance partners
(4) Orthomet Inc is not included in Chapter 3 (only one observation)

APPENDIX B – VARIABLES AND DATA COLLECTION

This appendix describes the process of data collection and variable construction. The table below provides a summary by defining each variable and stating its source.

Name	Definition	Data source	Updated
Firm's innovation			
Firm innovation	Number of patents the firm successfully applied for at t0 plus the number of non-self-citations they received in the next five years	USPTO/NBER/ Dataverse	Updated annually
New products*	Number of new or technologically improved medical devices observed via PMA approvals and 510(k) notifications	FDA	Updated annually
Firm's knowledge			
Knowledge transfer	The percentage of patents and backward citations at t-1 that are (re)cited by another (set of) inventor(s) during [t0;t+2]	USPTO/NBER/ Dataverse	Updated annually
Knowledge diversity	Blau's index (one minus Herfindahl concentration index) of a firm's medical device patents applied for at t0 by technological class	USPTO/NBER/ Dataverse	Updated annually
Intrafirm networks			
Network reach	Average inversed path length among all R&D scientists (with zero if disconnected)	USPTO/NBER/ Dataverse	Updated annually using 5y window
Network clusters	Three times the number of triads divided by the number of triples (likelihood of triadic closure)	USPTO/NBER/ Dataverse	Updated annually using 5y window
Network density	Average degree centrality of all connected R&D scientists in an intrafirm network	USPTO/NBER/ Dataverse	Updated annually using 5y window
Network isolate ratio	Number of non-connected R&D scientists as a percentage of all R&D scientists	USPTO/NBER/ Dataverse	Updated annually using 5y window
Network largest component*	Number of R&D scientists in largest connected component divided by total number of scientists	USPTO/NBER/ Dataverse	Updated annually using 5y window
Network component ratio*	The number of components as a fraction of the number of scientists in a network	USPTO/NBER/ Dataverse	Updated annually using 5y window
Network fragmentation*	The percentage of R&D scientists that are not (in)directly connected	USPTO/NBER/ Dataverse	Updated annually using 5y window
Network path length*	The average path length among all R&D scientists (corrected for network density and size)	USPTO/NBER/ Dataverse	Updated annually using 5y window
Ego-network density*	Average ego-network density of all R&D scientists	USPTO/NBER/ Dataverse	Updated annually using 5y window
Intrafirm connections	Average degree centrality of all connected R&D scientists in an intrafirm network	USPTO/NBER/ Dataverse	Updated annually using 5y window
Intrafirm clustering	Average ego-network density of all R&D scientists scaled for similar density in random networks	USPTO/NBER/ Dataverse	Updated annually using 5y window
Intrafirm efficiency	Inverse of average shortest path length scaled for similar path length in random networks	USPTO/NBER/ Dataverse	Updated annually using 5y window
Largest component*	Number of R&D scientists in largest connected component divided by total number of scientists	USPTO/NBER/ Dataverse	Updated annually using 5y window
Interfirm networks			
R&D alliances	The number of R&D alliance partners (independent of multipartner alliances or repeated ties)	SDC/ReCap/ 10K/Factiva/ LexisNexis	Updated annually
New R&D alliances*	The number of new R&D alliance partners in at t0	SDC/ReCap/	Updated annually

		10K/Factiva/ LexisNexis	
Interfirm controls			
R&D alliance duration	The average age of a firm's ongoing R&D alliance partnerships	SDC/ReCap/ 10K/Factiva/ LexisNexis	Updated annually
R&D alliance strength	The average number of partnerships between a firm and each R&D alliance partner	SDC/ReCap/ 10K/Factiva/ LexisNexis	Updated annually
R&D alliance structure	The percentage of R&D partnerships that is based on a new, equity-based entity (i.e. joint venture)	SDC/ReCap/ 10K/Factiva/ LexisNexis	Updated annually
Non-R&D alliances*	Number of alliance partners that are purely downstream and do not involve any R&D (e.g. production, distribution, marketing)	SDC/ReCap/ 10K/Factiva/ LexisNexis	Updated annually
R&D controls			
R&D intensity	R&D expenses as fraction of total sales	Compustat	Updated annually
Acquisitions	Amount spent on acquisitions of medical device firms scaled by the firm's sales in medical devices	SDC Platinum/ Compustat	Updated annually
Divestments	Amount earned from sales (or spin-off) of medical device units scaled by the firm's sales in medical devices	SDC Platinum/ Compustat	Updated annually
R&D scientists	Number of R&D scientists observed on medical device patent applications	USPTO/NBER/ Dataverse	Updated annually using 5y window
R&D recruitment	Number of R&D scientists observed for first time within firm at t0 as fraction of total R&D scientists	USPTO/NBER/ Dataverse	Updated annually
R&D concentration	One minus a Herfindahl index of R&D scientists by US state and by country (for foreign scientists)	Harvard Patent Dataverse	Updated annually using 5y window
R&D team size	Average number of inventors on each patent	USPTO/NBER/ Dataverse	Updated annually using 5y window
Patent stock*/**	Number of medical device patents the firm successfully applied for in the past five years	USPTO/NBER/ Dataverse	Updated annually using 5y window
Technological diversity**	One minus a Herfindahl index of firm medical device patents by technological class	USPTO/NBER/ Dataverse	Updated annually using 5y window
Firm controls			
Firm size	Natural log of total firm sales in medical device segments in $millions	Compustat	Updated annually
Medical device focus	Percentage of total sales earned in medical devices	Compustat	Updated annually
Firm performance	Return on sales (EBIT ÷ sales)	Compustat	Updated annually
Firm slack	Current ratio (current assets ÷ current liabilities)	Compustat	Updated annually
Firm leverage	Debt-to-asset ratio	Compustat	Updated annually
Firm age**	Current year minus year of establishment	Mergent	Updated annually
Diversification**	One minus Herfindahl index of firm sales by SIC	Compustat	Updated annually

* These variables are only used the robustness checks
** These variables were excluded for multicollinearity reasons

Firm Data

Financial data for sample firms were obtained from WRDS Compustat North America and WRDS Compustat Segment data. In case variables were missing, data were retrieved from firm SEC filings (obtained via Thomson One and SEC Edgar). Firm years of establishment were mentioned in Mergent WebReports. All variables were updated annually until the end of the panel or until a firm was acquired or left the medical devices industry.

In addition, I manually created corporate trees for each firms by listing all their subsidiaries based on SEC 10K filings (updated annually). Subsidiaries are included in case the parent has majority ownership (leaving out CVC investments)

Patent Data

Full patent data were obtained via Harvard Patent Dataverse which includes bibliographic characteristics for all patents granted by the USPTO during 1976-2010. Using the corporate trees, the names of each firm and all its subsidiaries are then matched against patent assignee names. This is important since some firms do not use their corporate name when applying for patents. For instance, Johnson & Johnson often uses the names of its main subsidiaries (Cilag, Cordis, Ethicon, Janssen, etc.) as patent assignees. So patents are matched to the ultimate owner of the assignee at the time of invention.

To correct for highly diversified firms, I only focus on medical device patents as indicated by the USPTO Patent Technology Monitoring Team (2012). These are USPTO main classes 128, 433, 600, 601, 602, 604, 606, 607, and 623 and certain subclasses of technological classes 227, 323, 351, 356, 362, 378, 382, 422, 424, 436, and 705. Other concordances, like these by Hall et al. (2001), were considered. While they largely overlapped with the Patent Technology Monitoring Team's concordance, they are not as fine-grained.

Publication Data

Publication data were obtained from Elsevier Scopus. This database contains bibliographic characteristics of a large number of publications including journals and conference proceedings. It also lists all authors and their individual affiliations. I extracted all publications for each firm by searching for firm and subsidiary names in the publication affiliation field. I then manually filtered for each publication to correct for false positives (name similarities between a focal firm and an unrelated organization). I filtered out all co-authors not related to a focal firm. Publications with over 15 co-authors were also excluded for computational reasons (this was only a very tiny fraction).

These publication data are subject to one major limitation. Contrary to patents, publications are not categorized in fine-grained classes. Though Scopus allows for filtering, the group of life sciences includes biotech and pharmaceutical in addition to medical devices. Since some of the sample firms are active in both industries, this needed to be corrected when constructing intraorganizational networks.

Product Data

Product data were obtained from FDA PMA and 510(k) archival data. Any medical device sold in the United States must be registered with the FDA. Premarket approval (PMA) is required for potentially high-risk medical devices (e.g. implants) before being marketed. Further approval is needed each time devices are changed. 510(k) notifications (also known as PMN) are required for lower-risk medical devices (e.g. sphygmomanometer) before being marketed. PMA and 510(k) data are publicly available and updated annually.

It is important to understand that the approval procedure for medical devices is significantly different from the approval procedure for new pharmaceutical products. Pharmaceutical products need to pass through various stages of clinical testing. The entire process from early clinical testing to market often takes multiple years. For medical devices, however, the process is much simpler and faster. First, medical device firms perform independent clinical testing of their device to compare its efficacy with alternative devices.

As one interviewee explained, this process can be extremely quick for often used devices (like stethoscopes) and clinical testing only takes weeks or months. Upon submission of the application that includes the results of these tests, the FDA aims to provide approval within 180 days. The large majority of these devices were approved within a year.

For my study, I used the historical medical device registrant to avoid changes caused by M&A. I match each registrant to the names of a focal firm and all its subsidiaries. I measure product innovation as the sum of (i) the number of successful PMA applications for new devices, (ii) the number of successful PMA applications for technological changes to existing devices, and (iii) the number of 510(k) notifications. Though the approval procedures tend to be very short, all is measured using application dates.

M&A Data

M&A data were obtained from SDC Platinum. Firm and subsidiary names were matched to acquirer and vendor names (the 'immediate', 'parent' and 'ultimate parent' fields) to obtain all deals done by sample firms. Non-medical device deals were excluded as well as non-realized deals and deals that involved minority stakes (e.g. a 10% stake or a share increase from 95% to 100%). This provided the number and amount of acquisitions and divestitures of medical devices units.

Intrafirm Network Data

Intrafirm networks were observed via R&D scientists and their co-invention and co-authorship activities. I used a complicated procedure to weed out non-medical device scientists. First, of the ca. 114,000 patents belonging to the focal firms, only 18,797 were related to medical devices. As explained above, such filtering was unfortunately not possible for publications. Therefore I limit the nodes in intrafirm networks to all R&D scientists mentioned on medical device patents. Second, ties are added by looking at the instances in which any potential dyad of medical device R&D scientists co-invented a patent or co-authored a paper. I use five-year moving windows since ties tend to persist over time (Singh, 2005). An intrafirm network at t0 thus consists of all medical device inventors during [t-4;t0] and their co-invention and co-authorship ties during this period.

Name disambiguation is an important issue since R&D scientists tend to use different names over time by adding or removing initials and middle names. While Lai et al. (2011) made a serious effort in creating coherent identifiers, a manually inspection showed that their method was too restrictive: since they only compare inventor characteristics (name, address) and ignore assignee, their method generally provides too many false negatives (the same person getting two different identifiers). Therefore I use a method similar by Paruchuri (2010) and create unique identifiers based on first name initial and last name. A similar name disambiguation was applied to authors of publications.

Using five-year windows, the collaboration data on R&D scientists, patents and publications form a bipartite network. I used the iGraph plug-in for R to collapse these two-mode networks into undirected, non-weighted one-mode networks and calculate all network characteristics. As a robustness check, all measures were recalculated using three-year windows which provided highly correlated results.

Interfirm Network Data

Interfirm network data were obtained from three sources. First, I scanned two alliance databases for any alliance announcement by a focal firm or any of its subsidiaries. SDC provided a number of alliance announcements but mainly for the larger firms. Recombinant Capital (ReCap) provided mainly alliances for sample firms also active in pharmaceuticals.

Second, I scanned firms' annual reports (ARS and 10K) from 1985 till 2005. These are around 1,500 documents that ranged between 50 and 500 pages each. It proved to be very useful for smaller firms: the legal obligation to mention any agreement that could substantially impact their financial results forced them to disclose many alliances.

Third, I scanned news announcements via the LexisNexis and Factiva databases. In particular, I searched for the keywords joint*, alliance*, link*, partner*, agree*, licen*, coop*, collab*, tie, team, accord or pact in combination with firm and subsidiary names. This resulted in over 122,000 news articles that were manually scanned and coded.

Each alliance in any of the three sources was coded in a similar fashion. Dummies were used to code for medical device focus, upstream elements, downstream elements, and equity arrangement (joint venture). If upstream, dummies were used to code for in-licensing, out-licensing, cross-licensing, and joint R&D/technology transfer. Downstream elements included OEM, manufacturing, marketing, and distribution. Starting dates and ending dates were coded as much as possible. In case termination was not announced, I assumed three-year duration unless there was evidence otherwise (e.g. an extension mentioned four years later). Licensing agreements for unique patents were limited to three years as well: though patent lifetime could be up to twenty years, licensing contracts showed that actual technology transfer and training only occurs in the first years.

As pointed out by Schilling (2009), commercial alliance databases are often incomplete. Table 27 below shows what percentage of all alliances was found in each source of data as well as the overlap between data sources. Each cell represents the number of alliances that were covered by both the source mentioned in the column and the row. The percentage underneath shows which fraction this is of the total number of alliances identified in this source. For example, 143 medical device alliances are both mentioned in SDC and in ReCap. This composes 26% of all relevant medical device alliances obtained from SDC but

33% of all relevant alliances obtained from ReCap. It reveals that news announcements are by far the most complete: of all alliances announced, over half was mentioned in Factiva or LexisNexis.

Table 27 Alliance announcements by data source

	SDC	ReCap	10K/ARS	Factiva	LexisNexis	Total
SDC	559 (100%)	143 (33%)	72 (18%)	346 (24%)	318 (23%)	559 (24%)
ReCap	143 (26%)	428 (100%)	51 (13%)	285 (20%)	260 (18%)	428 (19%)
10K/ARS	72 (13%)	51 (12%)	406 (100%)	165 (11%)	179 (13%)	406 (18%)
Factiva	346 (62%)	285 (67%)	165 (41%)	1438 (100%)	1007 (71%)	1438 (63%)
LexisNexis	318 (57%)	260 (61%)	179 (44%)	1007 (70%)	1413 (100%)	1413 (62%)
Total	559	428	406	1438	1413	2294 (100%)

The numbers in each cell represent the number of medical device alliances of the fifty sample firms that are both covered by the source mentioned in the column and in the row (e.g. overlap).
The percentage in each cell represents the fraction of these overlapping alliances as the total number of alliances mentioned by the source mentioned in the column.

APPENDIX C – ROBUSTNESS CHECKS AT PATENT AND CITATION LEVEL

The first hypothesis of chapter 2 argues that intrafirm network reach has a positive effect on knowledge transfer. However, the empirical results consistently show a negative effect of network reach on knowledge transfer. This appendix performs additional robustness checks at different levels of analysis. While the main analysis was performed at the level of a firm, these robustness checks perform a similar assessment at the patent- and citation-level.

Patent-level Robustness Checks

Each patent harbors one or more components of knowledge, i.e. unique knowledge, skills or technologies (Fleming, 2001). If new R&D projects build upon these components of knowledge, this tacit process is observable via a paper trail of patent citations (see Alcacer & Gittelman, 2006). Past studies have shown that patent citations are robust proxies for knowledge reuse and knowledge transfer (e.g. Mowery et al., 1996; Rosenkopf & Nerkar, 2001). In this robustness check, I will repeat earlier analysis at the level of a firm's patents.

Data collection and sample construction. The sample consists of all 16,205 medical device patents successfully applied for by the fifty sample firms between 1989 and 2004. These patents enter a panel dataset the year after their invention. They leave the panel after three years, after their firm was acquired, or after 2005 (whichever came first). This results in 44,112 firm-patent-year observations. This corresponds to the three-year windows used for measuring knowledge transfer at the organizational level.

Co-patent networks. To measure distance between patents, firm co-patent networks are created in a fashion similar to co-inventor networks above. In such networks, patents are the nodes while ties are based on common inventors, e.g. a patent has a direct connection to another patent if both patents have at least one inventor in common. As above, I use a five-year moving window to construct unweighted, undirected networks for each firm for each year.

Dependent variables. *Times cited* is a count variable indicating how many times the focal patent is cited on any new patent by the same firm during the focal year. *Dummy cited* is a dummy variable indicating if the focal patent is cited at least once on any of the new patents by the same firm during the focal year.

Independent variable. Network *reach* is a firm level variable indicating the average closeness centrality of all patents. Specifically, I calculate the average closeness centrality of all patents from a given application year in regard to new patents in the focal year. For example, if an organization had five patents in 1998 and seven patents in 1999, I first calculate the closeness centrality of each of the five patents from 1998 towards the seven new patents in 1999. An older patent's closeness centrality is the average of the inverse of the number of steps from the older, focal patent to each new patent. Reach is then the average of all older patents' closeness centrality. This is similar to the network reach measure in the main chapter, but adapted to correct for time.

Control variables. The likelihood of a patent being cited is not only influenced by the social proximity of its inventors. Therefore I add a number of different control variables. First, the likelihood of knowledge transfer depends on the time since the invention. Therefore I add dummies to correct for the number of *years since patent application* (either one, two or three). Second, a firm's R&D strategy influences the probability of citing a particular patent. Therefore I add the total *number of citations* a firm makes in a focal year, the *percentage of self-citations* and the *percentage of patents in the same class*. To correct for the effects of geographical proximity in knowledge flows, I calculate the *percentage of patents in proximity* (inventors of the same firm living within a 100 kilometer radius from focal patent's inventors). The *number of inventors* and the patents *closeness centrality* are added to correct for other effects of social proximity. Finally, I added firm, year, and technological class dummies to control for firm, time and technology specific effects.

Results. The results of negative binomial regressions are shown in the table below. The results indicate that intrafirm network structure and position have significant effects on patent citations. First, patent closeness centrality increases the likelihood of being cited. This means that patents with inventors that are more central in an intrafirm network have a higher chance of being cited, confirming Paruchuri (2010). Second, network reach has a negative effect on citations. This implies that cohesive intrafirm networks with shorter paths reduce knowledge transfer. An interaction effect (model 3) indicates that this effect is stronger for patents with a higher closeness centrality. Computed incident rate ratios reveal that this effect is strong. The regression was repeated using a probit estimation and the binary dependent variable. Results are virtually the same and margin plots showed again a negative effect of network reach, particularly for patents central in an intrafirm network. In summary, knowledge transfer from one R&D scientist to another increases if this R&D scientist is well-connected. However, this effect is weaker in firms where all R&D scientists are well-connected.

Table 16 – Robustness checks for knowledge transfer at patent level (p. 168)

Citation-level Robustness Checks

This robustness check aims to replicate the results for the first hypothesis using the method of Singh (2005). In this article, Singh demonstrated that knowledge transfer increases with physical proximity, social proximity and with working in the same organization. Since my analysis does not support the argument for social proximity, I replicate my study using this approach.

Data collection and sample construction. In line with Singh (2005), the unit of analysis consists of the dyad of an existing patent and a new patent. Therefore I took all medical device patents by the fifty sample firms between 1989 and 2005. For each patent between 1989 and 2004 (*focal patent*), I created dyadic relationships to all other medical device patents (*alter patents*) by the same firm in the next three years, until the firm was acquired, or until 2005 (whichever came first). This results in 5,689,161 dyadic observations.

Co-patent networks. To measure distance between focal and alter patents, firm co-patent networks are created in a fashion similar to the robustness check above. In these networks, patents are the nodes while ties are based on common inventors, e.g. a focal patent has a direct connection to an alter patent if both patents have at least one inventor in common. As above, I use a five-year moving window to construct unweighted, undirected networks for each firm for each year.

Dependent variable. *Cited* is a dummy variable indicating if the alter patent cites the focal patent.

Independent variable. *Social proximity* is the inverse path length between social and alter patent in a firm's co-patent network. It ranges from 0 (no social tie among inventors) to 1 (same inventor(s)). Furthermore, I split social distance into five categories. *Same inventor(s)* means at least one of the inventors mentioned on focal and alter patent is the same R&D scientist. *Past collaborators* means that one or more inventors on each patent have collaborated on another R&D project during the past five years. *Shared acquaintance* means that one or more inventors on each patent share a common acquaintance, that is, an R&D scientist they collaborated with during the past five years. *Indirect tie* implies that inventors of focal and alter patent are indirectly connected via longer paths. The reference group, *Non-connected*, has no collaborative ties between focal and alter patent inventors.

Control variables. The likelihood of an alter patent citing a focal patent is not only influenced by the social proximity of their inventors. Therefore I add a number of different control variables. First, like Singh (2005), I add two dummy variables indicating if focal and alter patent belong to the *same technological main class* and *same technological subclass*. Second, to control for geographical proximity, the *spatial distance* between inventors of the focal and alter patent is added. Using the Patent Network Dataverse dataset, I calculate the distance between all inventors on the two patents and take its log value for the nearest inventors. Since knowledge transfer takes time, the *time difference* (in years) between focal and alter patent is added. In addition, firm and year dummies are added to control for unobserved organizational and temporal effects. Finally, patents themselves differ largely in importance and impact. Since the estimation method does not allow for fixed effects, I add the focal *patent citation mean* to control for this effect.

Results. To start, social ties among R&D scientists of focal and alter patent are present in 49% of the dyads. In 1.7% of the dyads, both patents share the same inventor(s). In 4.8% of the cases, inventors of focal and alter patent have collaborated in the past. In 7.2% of the cases, these R&D scientists share a common acquaintance and in 35.4% of the cases there is a longer indirect tie.

The results of a probit regression are shown in the table below. The results indicate that intrafirm network structure influences knowledge transfer and recombination. As expected, the higher the social proximity, the more likely it is that the alter patent cites the focal patent (model 2). However, when looking at the different levels of social distance between two patents (model 3), results become interesting. First, an alter patent is more likely to cite a focal patent if both patents have one R&D scientist in common. Second, an alter patent is also more likely to cite a focal patent if scientists of both patents have collaborated. Third, an alter patent is still more likely to cite the focal patent if its inventors have a common acquaintance. Fourth, an alter patents is significantly less likely to cite a focal patent if the social tie is longer. Contrary to Singh (2005), I find that R&D scientists are more likely to build upon knowledge components of colleagues they do not share a connection with than to use knowledge components of distant colleagues. These results provide support for the effects of network reach on knowledge transfer, namely that shorter ties (13.7% of the cases) increase knowledge transfer but that longer ties (35.4% of the cases) decrease knowledge transfer.

Since the likelihood of an alter patent citing a focal patent is only 0.18%, the regressions are repeated in models 4 to 6 using a rare events logit specification (Tomz, King, & Zeng, 2003). This procedure uses a subsample of all zero observations to obtain more efficient standard errors. Since this method is computationally intensive, year and firm dummies are replaced with firm-year averages of the dependent variable. The results are similar to those obtained earlier in models 1 to 3.

Table 17 – Robustness checks for knowledge transfer at citation level *(p. 169)*

ACKNOWLEDGEMENTS

All previous pages are the outcome of a five-year journey that involved many enjoyable and challenging, exciting and monotonous, and organized and chaotic periods. I would or could definitely not have persisted or pursued this path without the help and support of many people around me.

First, I would like to thank all people on my dissertation committee: Corey Phelps, Pierre Dussauge, Denisa Mindruta, Srikanth Paruchuri, Emmanual Lazega, and Stéphane Saussier. Corey has been of incredible support over the entire course of my doctoral studies in shaping the ideas as well as executing all analyses. And it was Pierre's class on interorganizational relationships that aroused my interest on the role of interfirm cooperation for firm innovation. Denisa, with her expertise on innovation, has helped me strongly in thinking pragmatically and meticulously about research design. Srikanth was very instructive in framing my research and even invited me to spend one semester within the wonderful academic community of Penn State University. Dr Lazega and Dr Saussier have spent substantial time and effort by joining this committee and their insightful feedback, during earlier and later stages of this dissertation, definitely contributed to the research quality.

Second, many parts of the HEC Paris institute have helped in substantive and pragmatic ways. The Strategy department offered a thriving academic atmosphere. Specialized courses given by the various professors provided the knowledge and skills required to pursue my research. Various (planned or random) discussions with the permanent and visiting faculty have always been enjoyable and supportive. The secretaries of the department, Anne, Nathalie and Veronique, were always ready with pragmatic advice and assistance, which definitely made my life easier. The HEC PhD Program office has made a valuable contribution to my work in many ways: by facilitating conference participation, dealing with the Doctoral School requirements, and solving the institutional challenges expats face. Dr Hege, Caroline, Cecile, Françoise, and Melanie have always been supportive in any of these matters. In addition, this dissertation would not have been possible without the financial support of the Fondation HEC and the HEC Paris Leadership Center Chair that I graciously received

Thirdly, I am indebted to over three dozen of anonymous experts working on innovation, collaboration, and business development in the medical industry. Your experiences and stories definitely took the magic out of innovation. Instead, you provided me with a more realistic view of the phenomenon under study which increased the pragmatic relevance. I would have liked to mention you all individually, but understand the importance of confidentiality and secrecy in this industry.

Fourthly, on a more personal level, I would like to thank all my friends, colleagues, and family. An exhaustive list would significantly influence the length of this document, but there are many memories on the occasions we met: the many hours spent in PhD office 2.17 (HEC) or 4.16A (PSU), during a hasty lunch or coffee break, the evening drinks in Expansiel, the Friday nights at Pasquerilla building, the after-conference drinks, and the rare holidays spent back home or elsewhere.

Fifth, I am heavily indebted to Ming. Many of our weekends, aimed to spend together in Jouy, Sarcelles, Brussels, Cologne, Prague and Paris, were too often filled with work, conferences and e-mails. Thanks for your continuous support all this time!

Finally, now that I am about to finish this important part of my life, it is time to put this individual and joint accomplishment in its right perspective. Therefore,

Soli Deo gloria

RÉSUMÉ GÉNÉRAL EN FRANÇAIS

Introduction

Cette thèse développe la notion de 'réseaux d'innovation à plusieurs niveaux', c'est-à-dire, l'idée que le rendement innovateur d'une entreprise est influencé conjointement par des réseaux à l'intérieur et à l'extérieur d'une organisation. L'innovation est une source importante de compétitivité de l'entreprise sur le marché et l'innovation d'une entreprise est un déterminant majeur du rendement financieret de la survie de celle-ci sur le long terme (Cefis & Marsili, 2005; Roberts, 1999). L'innovation permet à une entreprise de briser le cycle continu d'améliorations de l'efficacité et de la concurrence des prix par le développement de produits ou de procédés nouveaux ou améliorés. Cela permet à une entreprise de fixer les prix du marché, d'obtenir des rendements excédentaires et d'obtenir un avantage concurrentiel.

De nombreuses études antérieures ont mis l'accent sur l'importance des réseaux et de la collaboration pour les innovations de l'entreprise (Borgatti & Foster, 2003; Brass et al., 2004). Un corps de littérature a complètement étudié le rôle des réseaux intra-organisationnels et de l'innovation (Smith et al., 1995; Van Wijk et al., 2008). Ce volet de recherche, principalement intégré dans la discipline du comportement organisationnel, se penche sur le rôle des relations entre les (groupes d') employés pour expliquer la créativité individuelle (ou de l'équipe). Les liens sociaux entre les employés donnent une possibilité d'accès et d'échange d'informations, de connaissances et de ressources entre eux. Ceci, à son tour, augmente la productivité et le rendement. Les chercheurs dans ce domaine ont montré que la taille, la structure et la force des liens sociaux ont une forte influence sur la créativité et l'innovation des employés (Phelps et al., 2012; Van Wijk et al., 2008). Un deuxième corps de la littérature a mis l'accent sur le rôle des réseaux inter-organisationnels dans l'innovation de l'entreprise. Basées sur la littérature de gestion stratégique, ces études soutiennent que les relations de collaboration entre les organisations, créées par des alliances et des coentreprises, donnent lieu à l'échange de connaissances et de ressources qui permettent d'améliorer par la suite le rendement innovateur des entreprises (Shan et al., 1994). Puisant dans la littérature des réseaux sociaux, les chercheurs dans ce domaine ont montré que le nombre et la structure de ces liens inter-entreprises influencent l'innovation de l'entreprise (Phelps et al., 2012).

Malgré le nombre important d'études dans les deux volets de recherche, la plupart des recherches se sontelles-mêmes limitées à un seul niveau. Avec quelques exceptions notables (e.g. Lazega et al., 2006; Moliterno & Mahony, 2011; Paruchuri, 2010), la nature multi-niveaux des réseaux et de l'innovation est un domaine de recherche peu développé. Cela est surprenant, en particulier pour la recherche regardant l'innovation de l'entreprise, car l'innovation est en fin de compte le résultat de ces processus à plusieurs niveaux (Gupta et al., 2007). Par conséquent, je soutiens que les réseaux inter et intra-organisationnels d'une entreprise doivent être considérés simultanément pour expliquer l'innovation de l'entreprise. Dans une conceptualisation de réseau à plusieurs niveaux, les acteurs à un niveau inférieur forment un réseau qui devient lui-même un nœud à un niveau supérieur (Harary & Batell, 1981; Moliterno & Mahony, 2011). Dans ce cas, une organisation crée des liens avec d'autres organisations par le biais d'accords de collaboration et ainsi elle crée et maintient un réseau inter-organisationnel. Simultanément, cette organisation abrite un réseau intra-organisationnel créé par les liens sociaux entre ses employés. Dans ces réseaux imbriqués, les nœuds ne sont plus des entités cohérentes, mais deviennent eux-mêmes des réseaux.

L'application d'une optique à plusieurs niveaux pour les réseaux et les recherches de l'innovation pose des défis pour les études passées sur trois points importants. Tout d'abord, la plupart des études ont porté sur les effets microéconomiques des réseaux sociaux et ont négligé les conséquences potentielles de niveau macroéconomique. Autrement dit, ces études ont examiné l'effet des caractéristiques des réseaux sociaux (position, taille, ou structure) sur la performance d'un acteur individuel et n'ont pas examiné l'impact de ces dernières sur la performance cumulée de tous les acteurs. Cette recherche suppose implicitement que les avantages au niveau microéconomique sont similaires à ceux du niveau macroéconomique. Cependant, il ya des raisons de douter de cette hypothèse. Par exemple, être dans une position de courtage est souvent liée à l'amélioration de la créativité et de la performance (Burt, 1992; Fleming et al., 2007). Cependant, le courtage d'un réseau a une forte incidence défavorable sur les collègues d'un courtier et réduit leur performance (Bizzi, 2013). Donc, ce qui peut être bon pour la performance individuelle, à l'échelle microéconomique, peut-ne pas être automatiquement avantageux pour la performance organisationnelle, à l'échelle macroéconomique. Deuxièmement, la littérature existante a obtenu des résultats confus en ce qui concerne les mécanismes expliquant le lien entre la structure du réseau et l'innovation. Les quelques études portant empiriquement sur ces mécanismes ont démontré que les connexions dans les réseaux intra-organisationnels accroissent l'innovation de l'entreprise, mais donnent des résultats opposés pour les coefficients d'agglomération (comparent Cowan et Jonard (2004) à Fang et al. (2011)) et la reach (comparent Lazer and Friedman (2007) à Fang et al. (2011)). Une explication plausible de ces résultats contradictoires peut être liée à des processus médiateurs concurrents. Troisièmement, la recherche sur les réseaux et l'innovation a accordé peu d'attention aux effets potentiels d'un niveau conjoint. Les effets d'un niveau conjoint sont les effets combinés d'un niveau inférieur et d'un réseau de plus haut niveau sur l'innovation de l'acteur. Pour l'innovation de l'entreprise, cela signifie comment les réseaux inter et intra-organisationnels non seulement influencent individuellement l'innovation de l'entreprise, mais qu'ils ont aussi un effet conjoint. Par exemple, les entreprises peuvent bénéficier davantage de la collaboration inter-organisationnelle si leurs réseaux internes sont moins liés et partagent moins d'informations entre les unités commerciales. Dans un tel cas, les unités commerciales sont plus susceptibles d'obtenir de nouvelles connaissances et des ressources via des alliances inter-entreprises. Ainsi, il convient d'examiner les deux réseaux simultanément afin de saisir pleinement leur influence sur l'innovation de l’entreprise.

L'objectif de cette thèse est de combler ces lacunes par l'intégration des réseaux à différents niveaux et d'évaluer leur effet sur les processus qui expliquent la relation des réseaux et de l'innovation. Je le fais en répondant à la question suivante: comment les réseaux d’entreprise inter et intra-organisationnels, indépendamment et conjointement, influencent l'innovation de l’entreprise? Pour répondre à cette question, je me concentre sur deux niveaux de réseaux: les réseaux intra-organisationnels des employés au sein des entreprises et les réseaux inter-organisationnels entre les entreprises. Ces réseaux intra-organisationnels sont constitués de réseaux de collaboration entre les scientifiques travaillant dans les services de recherche et de développement d'une organisation. Leur collaboration sur des projets de R & D mène à la communication et l'interaction ce qui facilitent la circulation de l'information et de la connaissance, et affecte ultimement l'innovation (Brown & Duguid, 1991; Paruchuri, 2010; Singh, 2005). Les réseaux inter-organisationnels sont composés d'organisations qui établissent des partenariats inter-entreprises à des fins d'innovation. Une telle collaboration inter-organisationnelle conduit à la diffusion des connaissances entre les entreprises et constitue une source importante d'innovation (Ahuja, 2000; Hamel, 1991; Shan et al., 1994). Pour comprendre comment les réseaux influencent l'innovation de l’entreprise, j’adopte une approche de système imbriqué (Harary & Batell, 1981). Dans cette perspective, un acteur à un niveau supérieur se compose d'un ou plusieurs acteurs de niveau inférieur. Cela signifie qu'un nœud dans le réseau inter-entreprises est en fait lui-même un réseau de personnes. Lorsque deux entreprises collaborent, les employés des deux organisations coopéreront par projets d’équipes communs. Il en résulte de nouveaux liens interpersonnels qui traversent les frontières organisationnelles. Les liens inter-entreprises sont donc représentés à un niveau inférieur par la création de nouveaux liens interpersonnels entre les (certaines) personnes des deux entreprises.

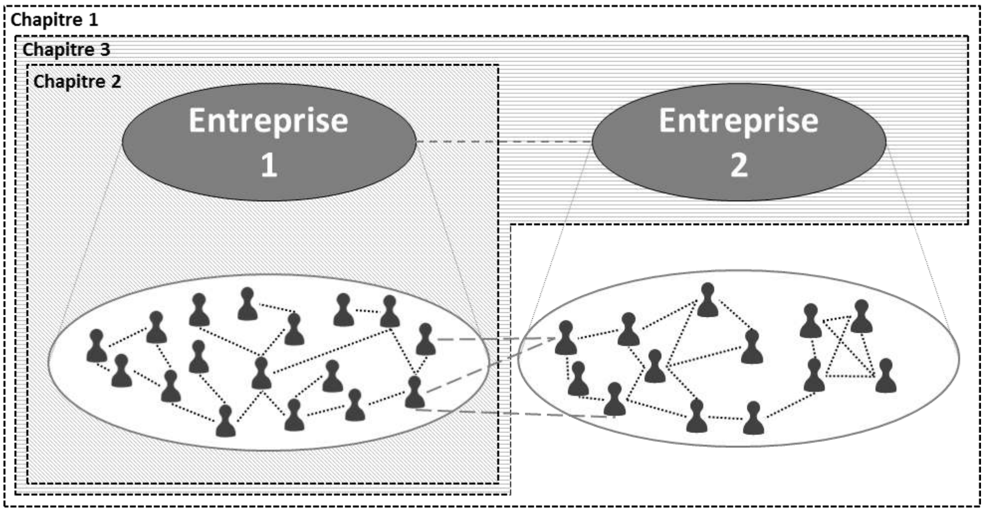


Figure 9 Structure de thèse

Pour répondre à la question de recherche ci-dessus, je développe trois sous-questions connexes qui sont traitées dans trois articles différents, chacun constituant un chapitre distinct de cette thèse. Le premier chapitre développe un modèle conceptuel des réseaux d'innovation à plusieurs niveaux et développe le rôle crucial des passeurs de frontières dans ce processus. Le deuxième chapitre examine les mécanismes qui interviennent dans la structure du réseau et de l'innovation en utilisant une approche à l'échelle macroéconomique. Le dernier chapitre explore la nature commune des réseaux inter et intra-organisationnels pour l'innovation de l'entreprise.

Chapitre 1: Réseaux Inter-organisationnels, Réseaux Intra-organisationnels et Innovation

Le premier chapitre intègre les littératures sur les réseaux inter-organisationnels et intra-organisationnels. Il est motivé par l'absence d'un perspectif multi-niveau dans la littérature des réseaux et de l'innovation. Au lieu de cela, la plupart des recherches sur les réseaux et l'innovation ne portent que sur un seul niveau d'analyse et ne tiennent pas compte des influences potentielles des réseaux à des niveaux plus ou moins élevés (Moliterno & Mahony, 2011). En particulier, il répond à deux lacunes de la recherche existante. Tout d'abord, la littérature sur les réseaux inter-organisationnels perçoit les entreprises comme individuelles, des entités «atomistique». Les entreprises peuvent varier dans leurs caractéristiques, mais sont considérées comme homogène en interne. Cela signifie que les collaborations entre deux organisations conduisent à des niveaux similaires de diffusion de connaissances et d'innovation. En conséquence, il suppose que chaque entreprise est affectée également par sa structure, et sa position au sein d'un réseau organisationnel. Cependant, la littérature du réseau intra-organisationnel a montré que les entreprises sont en fait des réseaux d'individus qui ont tous leurs propres caractéristiques. Parce que les organisations sont en interne hétérogène, les effets de la collaboration inter-organisationnelle varient selon la firme. Pour mieux comprendre quand les réseaux inter-entreprises influencent l'innovation de l'entreprise, le rôle des individus et de leurs réseaux intra-organisationnels doit être inclus. Deuxièmement, la littérature sur les réseaux inter organisationnels a prêté peu d'attention au rôle des individus dans ce processus. La plupart des études de réseaux inter-organisationnels considère que seulement le nombre, la structure et le type d'alliances interentreprises concerne directement l'apprentissage organisationnel et l'innovation de l'entreprise (Van Wijk et al, 2008). Cependant, l'apprentissage inter-organisationnel et le transfert de connaissances sont ultimement des processus de niveau individuel qui se produisent entre les employés des deux organisations partenaires (Janowicz-Panjaitan & Noorderhaven, 2009). Pour comprendre comment et quand la collaboration inter-organisationnelle conduit à l'innovation de l'entreprise, le rôle des employés et de leurs réseaux personnels doivent être intégré davantage. Par conséquent, ce chapitre aborde la question de la façon dont les réseaux inter-organisationnels et intra-organisationnels influencent conjointement l'innovation de l'entreprise.

Afin de développer le concept de réseaux d'innovation à plusieurs niveaux, nous commençons par expliquer comment les réseaux inter-organisationnels, en collaboration avec les réseaux intra-organisationnels ont des rôles complémentaires dans le transfert des connaissances inter-organisationnelles et la diffusion des connaissances intra-organisationnelles. Nous nous appuyons sur le modèle en bateau de Coleman pour décrire la façon dont les actions à l'échelle macroéconomique ont des résultats à l'échelle macroéconomique, par procédés microéconomique (Coleman, 1994). En particulier, nous l'utilisons pour décrire comment la formation de lien au niveau organisationnel influence l'innovation de l'entreprise par les processus au niveau individuel. Nous soutenons que la formation d'alliances influence l'innovation de l'entreprise via un processus en quatre étapes. Dans la première étape, comprenant la liaison macro-micro dans le bateau de Coleman, une organisation nomme des employés comme passeurs de frontières après la création d'une alliance avec une organisation partenaire. Ces personnes passeurs de frontières sont ensuite assignées à des projets qui font partie des accords d'alliance. Dans la deuxième étape, une partie de la liaison micro-micro, ces passeurs de frontières nouent des relations professionnelles avec les passeurs de frontières dans l'organisation partenaire. Ces liens interpersonnels se traduisent dans la connaissance et le partage d'informations entre les passeurs de frontières qui traversent les frontières organisationnelles. Dans la troisième étape, qui est également une partie de la liaison micro-micro, les passeurs de frontières partagent leurs nouvelles informations avec leur contact professionnel au sein de leur propre organisation. De cette façon la connaissance, les nouvelles connaissances sont partagées et réparties au sein de l'organisation focale. Dans la quatrième étape, constituant la liaison micro-macro, les employés appliquent ces nouvelles connaissances dans leurs projets et deviennent plus créatifs. Cela augmente les niveaux globaux d'innovation de l'entreprise.

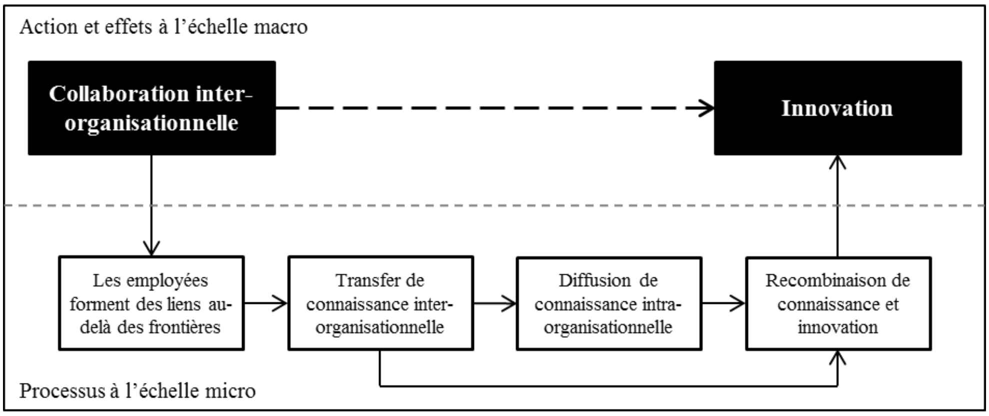


Figure 10 Le modèle en bateau de Coleman pour collaboration inter-organisationelle

Subséquemment, nous séparons ce modèle en quatre étapes en deux parties distinctes et générons des prévisions significatives sur l'efficacité de ces deux processus. Le premier processus est l'assimilation des connaissances et comprend les deux premières étapes du modèle en bateau de Coleman. Ce processus implique l'absorption de connaissances résidant dans une organisation partenaire par (un ou plusieurs) passeurs de frontières dans l'organisation focale. Nous soutenons que la mesure dans laquelle un passeur de frontière de l'organisation focale peut obtenir la connaissance de l'organisation partenaire dépend des caractéristiques de la source, du lien, et du destinataire. En ce qui concerne la source, un passeur de frontière apprendra plus si son homologue dans une organisation partenaire a des niveaux plus élevés de capital humain ou social. En ce qui concerne le lien, un passeur de frontière apprendra plus s'il / elle a un lien plus fort avec sa contrepartie dans une organisation partenaire. Considérant le destinataire, un passeur de frontière apprendra plus si il / elle a plus de capital humain, ce qui est, une meilleure capacité à apprendre de nouvelles connaissances et compétences. Dans une perspective à l'échelle macroéconomique, ce transfert de connaissances inter-organisationnelles change légèrement nos propositions. Tout d'abord, l'organisation focale en apprendra plus de son partenaire si le partenaire implique plus de passeurs de frontière et si ces passeurs de frontières ont plus de capital humain et social non-cumulable. Deuxièmement, l'organisation focale en apprendra plus de son partenaire si ses passeurs de frontières des deux organisations développent des liens de plus en plus forts avec les passeurs de frontières dans l'organisation partenaire. Troisièmement, l'organisation focale en apprendra plus en nommant des employés plus nombreux et plus qualifiés comme passeurs de frontières.

Le processus d'absorption de connaissances est suivi par un processus de diffusion des connaissances au sein d'une organisation. Ce processus, qui constitue les deux dernières étapes du modèle en bateau de Coleman, décrit comment les nouvelles connaissances se propagent des employés passeurs de frontières aux autres collègues dans une organisation. Au niveau microéconomique, un passeur de frontière peut encore apprendre des connaissances d'une organisation partenaire via ses connexions dans le réseau intra-organisationnelle. L'efficacité de ce processus dépend de sa / ses relations avec les employés passeurs de frontières. Nous prévoyons qu'un passeur de frontière peut encore apprendre des connaissances de l'organisation partenaire s'il / elle a plus de liens, des liens plus forts, et des liens plus étroits avec des collègues passeurs de frontière. Plus de liens avec les passeurs de frontières sont bénéfiques puisque chaque lien est l'occasion d'échanger des connaissances. Des liens plus étroits avec les passeurs de frontière augmentent la volonté et la capacité des passeurs de frontièreà partagé leur nouvelle information. Des liens plus étroits rendent les mécanismes de conseil et d'orientation plus efficace. En passant à un point de vue macroéconomique de la diffusion des connaissances, nous développons des prévisions un peu différentes. Tout d'abord, les connaissances acquises d'une organisation partenaire est plus susceptible de diffuser à partir des passeurs de frontière à d'autres employés de l'organisation si les passeurs de frontières ont une position plus centrale dans le réseau intra-organisationnel. Deuxièmement, cette connaissance est plus susceptible d'être diffusée si le réseau intra-organisationnel est moins fragmenté (mieux connecté) ou si les passeurs de frontière font partie des différents éléments dans un réseau intra-organisationnel fragmenté.

Pour conclure, les organisations sont simultanément impliquées dans deux réseaux différents. Leur réseau inter-organisationnel des alliances et des projets communs leur permet d'absorber de nouvelles connaissances par les organisations partenaires. Leur réseau intra-organisationnel de liens professionnels entre les employés leur permet de partager et d'employer cette connaissance afin de renforcer l'innovation de l'entreprise. En examinant une situation particulière, à savoir lier la formation dans le réseau inter-organisationnel, nous décrivons l'efficacité de ce processus en fonction de diverses caractéristiques individuelles et de l'entreprise. Le modèle de réseau d'innovation à plusieurs niveaux développé dans ce chapitre contribue à divers volets de recherche. Tout d'abord, il contribue à la recherche sur les réseaux et à l'innovation en intégrant et en identifiant les rôles complémentaires des réseaux inter et intra-organisationnels. Deuxièmement, il contribue à la littérature sur le fondement microéconomique en identifiant le rôle des individus dans le processus de transfert de connaissances inter-entreprises. Troisièmement, il contribue à notre compréhension de la capacité d'absorption en décrivant les mécanismes qui sous-tendent la capacité d'une entreprise à absorber et d'exploiter les connaissances externes.

Chapitre 2: Structure de Réseau Intra-organisationnel et Innovation de l'Entreprise

De nombreuses recherches ont discuté les conséquences de la structure du réseau interpersonnel sur la créativité individuelle et l'innovation (Carpenter et al., 2012; Phelps et al, 2012). Toutefois, on en sait moins sur les effets à l'échelle macroéconomique de la structure du réseau intra-entreprises, à savoir les effets de la structure de l'ensemble du réseau sur l'innovation de l'entreprise. Cette question est importante pour deux raisons. Tout d'abord, plusieurs études indiquent qu'il existe un micro / macro paradoxe entre la structure du réseau au niveau individuel et organisationnel (Operti & Carnabuci, 2012). Cela signifie que les structures du réseau favorisant la performance d'un employé peuvent le faire au détriment d'autres personnes dans l'entreprise et, éventuellement, diminuer l'innovation de l'entreprise. Par exemple, Burt (1992) propose que les personnes améliorent leurs performances en comblant les trous structurels. Cependant, Bizzi (2013) affirme que l'augmentation des courtiers de trous structuraux nuit au capital social des employés et démontre que plus de courtage réduit en fait le rendement des employés. Cette question est pertinente dans la recherche de gestion qui tente d'expliquer l'innovation au niveau des entreprises. Deuxièmement, une recherche existante utilisant la structure du réseau à l'échelle macroéconomique pour expliquer l'innovation de l'entreprise a fourni des résultats incomplets. Par exemple, Carnabuci et Operti (2013) confirment que les réseaux intra-organisationnels sont un mécanisme important pour le partage des connaissances en montrant que la connectivité du réseau augmente la réutilisation des connaissances. Cependant, Guler et Nerkar (2012) concluent que la connectivité du réseau réduit l'innovation de l'entreprise, ce qui impliquerait que le partage des connaissances nuit à l'innovation de l'entreprise. Pour comprendre comment la structure du réseau influence l'innovation de l'entreprise, il faut identifier les mécanismes qui interviennent dans cette relation.

Le deuxième chapitre demande donc: comment la structure du réseau intra-entreprise n'a aucune influence sur l'innovation de l'entreprise? Il vise à créer une clarté théorique et empirique par l'identification des processus qui interviennent dans la relation structure-performance. Spécifiquement, je me concentre sur deux caractéristiques dominantes des réseaux intra-organisationnels, à savoir le reach et le clusters (Provan et al., 2007). Le reach du réseau se réfère au degré avec lequel tous les employés sont reliés par des chemins relativement étroit et est un équivalent au niveau macro de la proximité de centralité. Je soutiens que le reach du réseau sera faciliter le transfert des connaissances entre les employés par le partage des connaissances, la communication informelle et la résolution conjointe de problèmes, mais cela diminuera la diversité des connaissances entre les employés. Le coefficient de clustering du réseau se réfère à la présence de groupes connectés d'employés à forte densité dans une organisation et est l'équivalent au niveau macro à la clôture du réseau. Les clusters sont des mécanismes efficaces pour le développement de nouveaux domaines d'expertise et pour augmenter la diversité des connaissances, mais ont un double effet sur le transfert de connaissances entre les employés. Subséquemment, la diversité et le transfert de connaissances d'une entreprise renforcent les performances d'innovation de l'entreprise: alors que la diversité des connaissances fournit à l'entreprise des possibilités de recombinaison des connaissances et de l'innovation, sa capacité à le faire est déterminée par le degré auquel les connaissances détenues par les divers employés sont partagées et transférées.

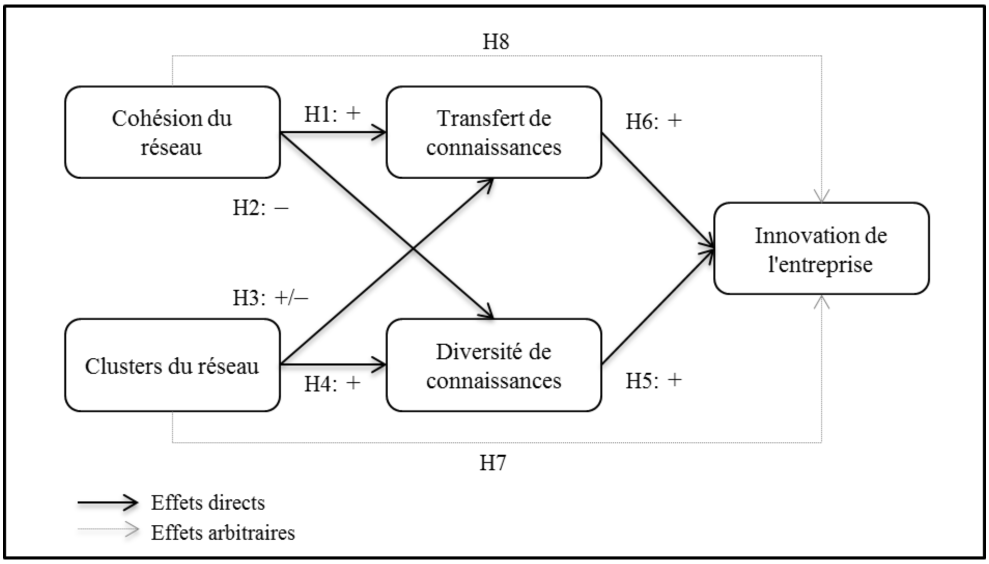


Figure 11 Modèle théorique des reseaux, connaissances et innovation

Ce modèle théorique est testé sur un ensemble de données de cinquante entreprises actives dans l'industrie des dispositifs médicaux nord-américains entre 1990 et 2005. Cette industrie fournit un cadre approprié en raison de son haut degré d'innovation technologique qui est le résultat d'un processus de recombinaison par des personnes ayant des spécialisations diverses. Les réseaux intra-organisationnels sont observés en regardant la collaboration entre les employés dans les projets de R & D qui résultent soit en brevets soit en publications. La diversité et le transfert des connaissances sont mesurés par les classes et les citations de brevets de chaque entreprise. Enfin, l'innovation technologique est observée par le nombre de nouveaux brevets et de produits obtenus par chaque entreprise dans une année. Les résultats, bien que significatifs, sont souvent en contradiction avec les prévisions antérieures. Pour commencer, les réseaux intra-entreprises dont le niveau de reach est plus grand affichent des niveaux inférieurs de diversité de connaissances et de transfert de connaissances. De plus, les réseaux intra-entreprises avec de grands clusters ont également des niveaux inférieurs de diversité des connaissances et de transfert des connaissances. Comme prévu, la diversité des connaissances et le transfert ont un effet positif sur l'innovation de l'entreprise. Dans l'ensemble, la structure des réseaux intra-entreprises influe sur l'innovation de l'entreprise par un processus qui est entièrement ou partiellement médiés par la diversité de connaissances et le transfert de connaissances.

Ce chapitre contribue à notre compréhension des réseaux et de l'innovation de deux façons. Premièrement, il permet une meilleure compréhension de la relation entre la structure du réseau et l'innovation en identifiant le transfert de connaissances et la diversité comme processus de médiation. Ces mécanismes pourraient être testés de façon empirique en déplaçant le niveau d'analyse de l'individu à l'ensemble de l'organisation. Deuxièmement, il fournit de plus amples informations potentiellement divergentes des effets micro / macroéconomique de la structure du réseau en examinant les effets à l'échelle macroéconomique de la centralité de proximité des salariés, ou le reach du réseau, et la clôture de l'ego-réseau des employés, ou le coefficient de clustering du réseau, sur l'innovation de l'entreprise.

Chapitre 3: La Collaboration Inter-organisationnelle, Réseaux Intra-organisationnels et Innovation de l'Entreprise

Le troisième chapitre relie les réseaux intra-organisationnels à la collaboration inter-organisationnelle et à l'innovation de l'entreprise. La collaboration inter-organisationnelle via des alliances et à des projets communs conduit à l'apprentissage inter-organisationnelle et à la diffusion des connaissances (Hamel, 1991; Lavie, 2006). L'afflux de nouvelles connaissances et d'information par l'intermédiaire de partenariats inter-entreprises stimule aussi l'innovation de l'entreprise (Shan et al., 1994). Les travaux existants sur les réseaux de collaboration inter-organisationnelle ont montré les effets significatifs de la taille du réseau, de la structure et de la composition sur l'innovation des entreprises (par exemple Ahuja, 2000a; Phelps, 2010). Malgré le vaste corpus de littérature sur la collaboration inter-organisationnelle, elle a prêté peu d'attention au rôle des réseaux intra-organisationnels. Ceci est surprenant puisque les réseaux intra-organisationnels remplissent un autre rôle, très lié à l'innovation de l'entreprise. Les réseaux de collaboration au sein des organisations permettent le transfert des connaissances et la diffusion parmi les employés (Brown & Duguid, 1991). Ces relations personnelles entre les employés constituent le fondement de la circulation des connaissances au sein d'une organisation (Paruchuri, 2010). La performance individuelle des employés est donc fortement influencée par le nombre et la structure de leurs liens (Fleming, Mingo, et al., 2007). Le nombre et la structure des connexions entre employés ont également un effet profond sur la capacité d'une organisation à transformer ses connaissances et ressources en innovation (Carnabuci & Operti, 2013). Les réseaux de collaboration inter-entreprises et intra-entreprises assurent ainsi des rôles très similaires en agissant comme des conduits de connaissances qui stimulent la créativité et l'innovation. Peu d'études ont examiné l'effet conjoint des réseaux inter-organisationnels et intra-organisationnels et ont démontré que les deux réseaux influencent la performance individuelle de chaque employé (Lazega et al., 2008; 2006; Paruchuri, 2010). Cependant, la recherche n'a pas encore évalué la façon dont les réseaux inter-organisationnels et intra-organisationnels influencent simultanément l'innovation organisationnelle, qui est un élément clé dans la recherche en gestion. Par conséquent, le troisième chapitre de cette thèse pose la question: comment les réseaux intra-organisationnels et la collaboration inter-organisationnelle influencent conjointement l'innovation de l’entreprise ?

Je soutiens que la collaboration inter-organisationnelle via des alliances et des projets communs façonne l'opportunité d'une entreprise pour l'absorption de la connaissance alors que son réseau intra-organisationnel constitue sa capacité à absorber ces connaissances et à les appliquer dans de nouveaux produits et procédés. La coopération avec d'autres organisations donne accès aux connaissances et aux capacités des organisations partenaires (Hamel, 1991; Lavie, 2006). Initialement, les employés passeurs de frontière apprennent de nouvelles informations et compétences d'une organisation partenaire via leur participation à des projets communs. Par la suite, ils peuvent partager leurs connaissances et leurs expériences avec d'autres collègues dans leur entreprise par le biais de son réseau intra-organisationnel. Il en résulte un processus de diffusion des connaissances à travers l'entreprise. Le degré de diffusion dépendra alors du nombre et de la structure de connexion dans le réseau intra-organisationnel d'une entreprise (Lazer & Friedman, 2007). Par conséquent, l'influence de la collaboration inter-organisationnelle sur l'innovation est modérée par la structure du réseau des employés intra-organisationnel de l'entreprise. En particulier, je propose que l'effet positif de la collaboration inter-organisationnelle sur l'innovation soit plus fort si le réseau intra-organisationnel d'une entreprise a une densité supérieure, plus ou moins de clusters, et un plus grand reach.

Les propositions sont examinées de façon empirique sur le même jury de cinquante entreprises de dispositifs médicaux nord-américains. La collaboration inter-organisationnelle est observée via l'annonce d'alliances et d'une formation de projets communs annoncée dans des articles de presse et des bases de données spécialisées. Pour chaque entreprise, je calcule le degré de sa centralité dans ses réseaux inter-organisationnels, c'est-à-dire, le nombre unique de partenaires alliés dans une année donnée. Ce terme est en interaction avec les caractéristiques structurelles du réseau des employés intra-organisationnel de l'entreprise. Comme prévu, les résultats montrent un effet positif du nombre d'alliances sur l'innovation de l'entreprise. L'effet de modération de la structure du réseau intra-organisationnel est partiellement pris en charge: alors que le nombre total de connexions a un effet positif, les clusters ont un effet négatif et son reach n'a aucun effet. Ces résultats obtenus au cours de nombreux tests de robustesse effectués pour corriger l'observation et la mesure potentiels. Dans l'ensemble, les résultats indiquent que les réseaux inter et intra-organisationnels ont un effet sur l'innovation conjointe en plus de leurs effets individuels.

Ce chapitre apporte des contributions à la littérature sur les réseaux et l'innovation, à la littérature sur la complémentarité des alliances, et à la recherche sur la capacité d'absorption. Premièrement, en considérant les effets conjoints des réseaux individuels et organisationnels, cette étude révèle que l'innovation de l'entreprise est le résultat d'une interaction entre les réseaux inter et intra-organisationnels. En particulier, la connectivité des réseaux intra-organisationnels d'une entreprise renforce l'effet positif des réseaux inter-entreprises sur l'innovation de l'entreprise. Cette étude contribue également à la recherche sur la complémentarité des alliances (Rothaermel, 2001) en examinant comment les réseaux intra-entreprises complètent les alliances inter-entreprises dans la poursuite de l'innovation. Finalement, ce document déballe le concept de capacité d'absorption. La capacité d'une entreprise « à reconnaître la valeur des nouvelles, informations externes, à les assimiler et à les appliquer » (Cohen & Levinthal, 1990: 128) est partiellement expliquée par le réseau intra-organisationnel d'une entreprise qui diffuse de nouvelles connaissances à travers l'entreprise.

Contributions

Les résultats de cette thèse contribuent à trois flux connectés de la littérature: les réseaux et l'innovation, la recherche du fondement microéconomique, et le paradigme ouvert de l'innovation. Premièrement, cette thèse contribue tout d'abord à la littérature sur les réseaux multi-niveaux en explorant les effets des liens de collaboration internes et externes sur l'innovation de l'entreprise. La recherche multi-niveaux dans la gestion a révélé comment les effets des réseaux à un niveau sont tributaires sur les réseaux supérieurs et inférieurs (Moliterno & Mahony, 2011), donc il ya des effets sur le niveau transversal et le niveau commun (Maison et al., 1995; Rousseau, 1985). Cette thèse explore la nature multi-niveau des réseaux organisationnels et l'innovation de l'entreprise en combinant les effets individuels et conjoints du partenariat inter-organisationnel et de la collaboration intra-organisationnelle. Dans le premier chapitre, on expose comment les individus et leurs liens personnels effectuent une tâche fondamentale dans la réalisation des opportunités offertes par les relations inter-organisationnelles. L'efficacité de la collaboration interentreprises pour l'innovation dépend fortement des caractéristiques du réseau intra-organisationnel ainsi que du capital social des passeurs de frontière. Le troisième chapitre fournit un test préliminaire de ce modèle multi-niveaux du réseau en combinant le réseau de collaboration intra-entreprises avec les alliances interentreprises R & D, à savoir le degré de centralité dans le réseauinter-organisationnel de l'entreprise. Les résultats indiquent que les réseaux interentreprises et intra-entreprises façonnent conjointement l'innovation de l'entreprise. Cette thèse soulève donc le fait que les recherches futures devraient combiner les réseaux à différents niveaux pour examiner leur impact sur l'innovation de l'entreprise.

Deuxièmement, cette thèse contribue également à la masse croissante de la littérature sur les fondements microéconomiques dans la recherche en gestion (Felin et al., 2012). Une approche du fondement microéconomique de la recherche en gestion fait valoir que la recherche sur les actions et les résultats de l'entreprise devrait examiner les processus exacts par lesquels une cause conduit à un effet, y compris les processus à un niveau inférieur de l'analyse. Coleman (1994) a fourni un outil utile pour l'analyse du fondement microéconomique et a démontré son utilisation dans un cadre politique. Dans le premier chapitre, j'applique une approche similaire aux alliances de R & D, au transfert des connaissances inter-organisationnelles et à l'innovation l'entreprise. L'utilisation de cette approche révèle l'importance liée aux individus, à leurs connexions et le rôle des réseaux intra-entreprise. Il démontre comment les effets au niveau de l'organisation des alliances de R & D reposent sur de nombreux facteurs au niveau individuel. Les fondements microéconomiques des alliances R & D sont donc les individus, et leur capital social est essentiel pour le succès de la collaboration inter-organisationnelle. Il met aussi en lumière les fondements microéconomiques de la capacité recombinante de l'entreprise (Garud & Nayyar, 1994).Les organisations sont des instruments essentiels pour l'apprentissage, le partage et la combinaison des connaissances qui résulte en l'innovation (Grant, 1996; Kogut & Zander, 1992). Le deuxième chapitre identifie les réseaux intra-entreprises comme d'importants mécanismes pour le partage des connaissances et l'innovation. La structure de ce réseau émerge par un processus ascendant et a des effets importants sur le transfert et la diversité des connaissances et de l'expertise. Par conséquent, la capacité recombinante d'une entreprise est finalement façonnée par la structure de son réseau de collaboration intra-entreprise qui facilite le partage de l'information et le transfert parmi ses employés. Le troisième chapitre traite de la littérature sur la capacité d'absorption par l'identification des fondements microéconomiques de la capacité d'une entreprise à absorber et exploiter les connaissances externes. Dans leur article pivot, Cohen et Levinthal (1990) ont déjà soutenu que la connaissance et l'expertise externe obtenue en traversant les frontières organisationnelles ne sont pas suffisantes. Au lieu de cela, les organisations ont besoin de procédures de transfert de connaissances absorbées au bon (s) endroit (s) de l'organisation où elles peuvent être utilisées et développées davantage. Le troisième chapitre décrit comment les passeurs de frontière dans les alliances de R & D peuvent partager et transférer leurs nouvelles connaissances à d'autres scientifiques R & D via leurs connections personnelles avec des collègues. Le réseau intra-entreprise, avec tous les flux de son savoir informel, est donc comme un complément important de la connaissance externe absorbée.

Enfin, cette dissertation contribue au paradigme de l'innovation ouverte. Dans un cadre et une époque où l'innovation n’est plus le résultat de la recherche et du développement par une organisation, des idées dans un rôle précis de collaboration à plusieurs niveaux sont une nécessité. Une approche d'innovation ouverte souligne l'importance de la collaboration entre les différents acteurs pour stimuler la recherche et le développement, mais révèle également les risques liés à ces stratégies (Chesbrough, 2003). Dans le premier chapitre, j'étudie comment les organisations peuvent structurer leur coopération inter-organisationnelle pour influencer la quantité et la diversité des apports de connaissances. Il révèle un certain nombre d'éléments importants de la stratégie de l'entreprise et de la politique de l'entreprise. Pour commencer, l'apprentissage par l'innovation ouverte dépend directement des passeurs de frontière ainsi que de la structure et des politiques de l'alliances R & D. Consacrer davantage de ressources à des alliances R & D en augmentant le nombre de scientifiques va augmenter l’apprentissage inter-entreprises. De plus, permettre la communication et la collaboration interpersonnelle et informelle, par exemple via la colocation, conduit à des liens plus étroits entre les passeurs de frontière et résulte en plus de transfert des connaissances. En outre, les alliances des réseaux inter-entreprises et intra-entreprise ne doivent pas être considérées individuellement pour comprendre les effets de la collaboration interne et externe sur l'innovation. La combinaison d'une perspective de portefeuille d'alliance avec les réseaux intra-entreprise est très utile pour comprendre comment la coopération des alliances inter-entreprises influence l'innovation de l'entreprise. Le portefeuille de recherche d'une alliance affirme déjà qu'il ya des effets complémentaires et de remplacement survenant lorsqu'une organisation est impliquée dans de multiples alliances (Wassmer, 2010). En outre, la recherche d'alliances a identifié le capital humain au sein des organisations en tant que compléments aux alliances R & D pour l'innovation de l'entreprise (Hess & Rothaermel, 2011). Cette thèse ajoute les réseaux intra-entreprises comme un autre facteur qui vient compléter la collaboration inter-organisationnelle. En particulier, elle explique comment des réseaux de collaboration intra-entreprise plus forts renforcent les effets positifs des alliances sur l'innovation. Cela indique que la collaboration R & D interne et externe est un élément complémentaire de la stratégie d'innovation d'une organisation.

Intraorganizational Networks, Interorganizational Collaboration and Firm Innovation

Abstract. This dissertation explores how intraorganizational networks and interorganizational collaboration, individually and jointly, shape firm innovation. Organizations rely on both external and internal collaboration to obtain and integrate knowledge in new products and processes. Internal collaboration networks among R&D scientists facilitate knowledge sharing and transfer whereas external collaboration via alliances and joint ventures provide an organization with access to new knowledge. This model is empirically tested in the North-American medical devices industry between 1990 and 2005. Contrary to the expectations, intrafirm networks with shorter paths and more clusters actually reduce knowledge transfer and diversity, which then reduces firm innovation. But well-connected intrafirm networks augment the effects of interorganizational collaboration on firm innovation. This dissertation contributes to the networks and innovation literature by examining the mechanisms that mediate the effects of network structure on firm innovation. It also explores the multilevel nature of networks by combining both intrafirm and interfirm relationships to explain firm innovation.

Keywords. Intraorganizational networks, Interorganizational relations, Multilevel collaboration, Firm innovation.

Réseaux Intra-organisationnels, Collaboration Inter-organisationnelle et Innovation d'Entreprise

Résumé. Cette thèse explore comment les réseaux intra-organisationnels et la collaboration inter-organisationnelle déterminent, séparément et conjointement l'innovation d'entreprise. Les organisations s'appuient à la fois sur la collaboration externe et interne pour obtenir et intégrer des connaissances sur de nouveaux produits et procédés. Les réseaux de collaboration interne entre les scientifiques en recherche et développement facilitent le partage et le transfert de connaissances tandis que la collaboration externe, via des alliances et des "joint ventures", offre accès à de nouvelles connaissances. Ce modèle a été testé empiriquement en utilisant des données de l'industrie des dispositifs médicaux en Amérique du nord entre 1990 et 2005. Contrairement aux attentes, les réseaux intra-organisationnels plus cohésifs et plus regroupés réduisent le transfert de connaissances et la diversité, ce qui réduit aussi l'innovation d'entreprise. Alors que les réseaux intra-organisationnels très connectés augmentent les effets de la collaboration inter-organisationnelle sur l'innovation d'entreprise. Cette thèse contribue à la littérature des réseaux et de l'innovation en examinant les mécanismes qui interviennent dans les effets de la structure du réseau sur l'innovation d'entreprise. Elle explore également le caractère multi-niveaux des réseaux en combinant à la fois les relations intra-entreprise et inter-entreprises pour expliquer l'innovation d'entreprise.

Mots-clés. Réseaux intra-organisationnels, Relations inter-organisationnelles, Collaboration multi-niveaux, Innovation d'entreprise.