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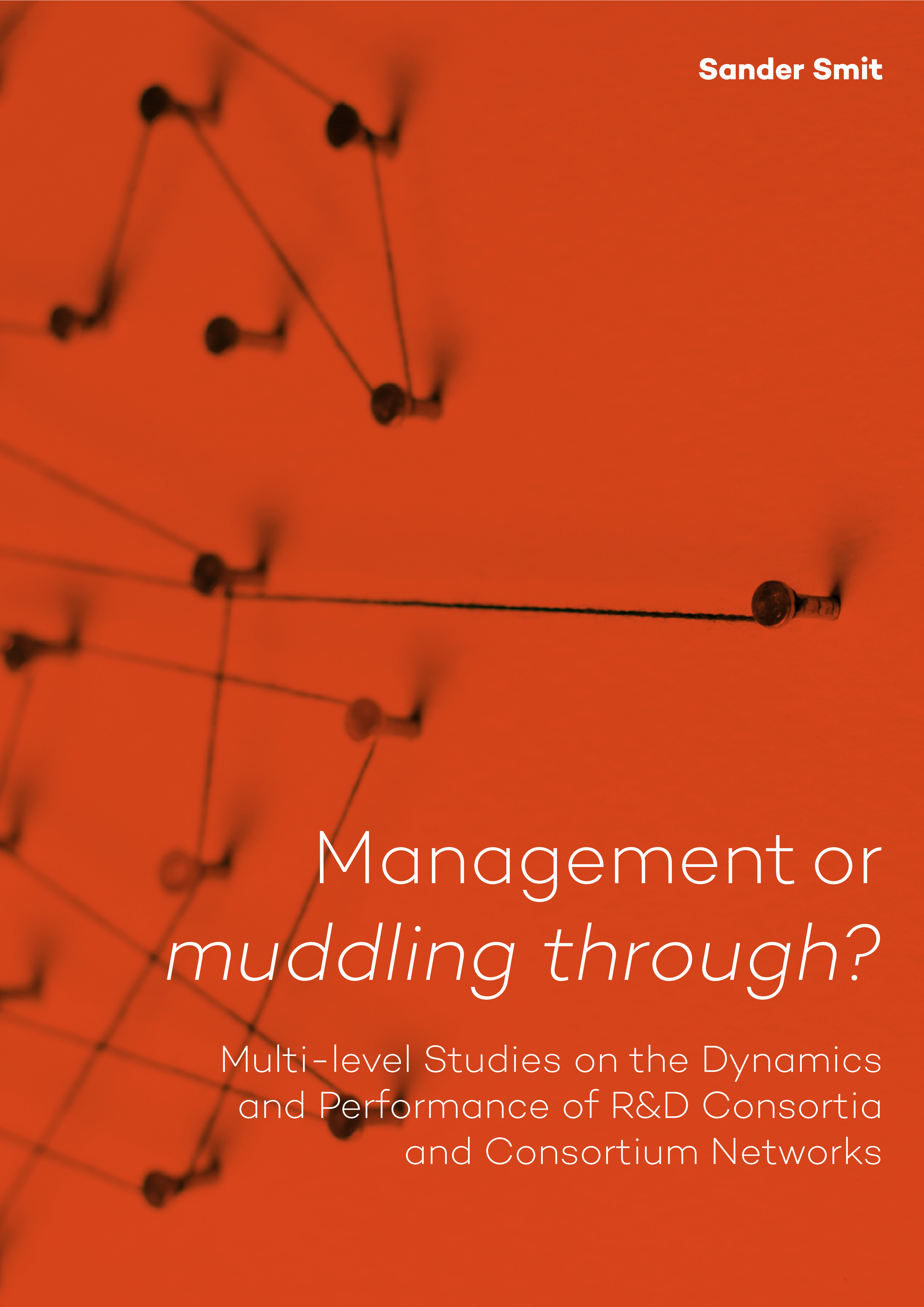

Sander Smit

Management or *muddling through?*

Multi-level Studies on the Dynamics and Performance of R&D Consortia and Consortium Networks

Management or Muddling Through? Multi-level Studies on the Dynamics and Performance of R&D Consortia and Consortium Networks

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Management or Muddling Through? Multi-level Studies on the Dynamics and Performance of R&D Consortia and Consortium Networks

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1. Introduction

1.1 Setting the stage

On January 18, 2005, a large production hall in the French town of Blagnac was the decor of the official presentation of the Airbus A380. More than 15 years after Airbus made its first steps in developing the biggest passenger jet airliner the world had seen, the plane was revealed to numerous dignitaries and journalists after a grand ceremony (Clark, 2006). With a height of 24 meters, a wing span of nearly 80 meters and an overall length of almost 73 meters, this newly born giant made a stunning impression on all attendants. An aspect that might be even more impressive than the plane's size, yet invisible to the audience, was that the A380 was the first plane that contained a considerable amount of a new material in its primary structure: Glass Laminated Aluminium Reinforced Epoxy, or GLARE (Vlot, 2001). The implementation of this product marked the start of the take-off of a material that, amongst other applications, solved several of the challenges the airplane industry had faced ever since the first aluminium aircraft went airborne (Vlot, Vogelesang, & de Vries, 1999; Vogelesang & Gunnink, 1986).

An interesting aspect of the development of GLARE is that, when reconstructing the history of its development, it is impossible to pinpoint one single actor to which its developmental success can be attributed. Instead, the development of the fibre-metal laminates that resulted in the large-scale use of GLARE in the A380 has been referred to by one of the key players involved as a typical example of a successful co-operation between science and industry (Vogelesang, 2001). As from the first moment that Anthony Fokker envisioned the use of laminated structures in aircrafts in the 1920s (Vlot, 2001), several research and development consortia have been formed around the material and its precursors, involving players from industry (e.g. AKZO, Alcoa, 3M, Boeing, Bombardier), research institutes (e.g. Delft University of Technology and the Dutch Aerospace Laboratory) as well as governmental organizations (e.g. the Dutch Ministry of Economic Affairs) (Berends, van Burg, & van Raaij, 2011; Vlot, 2001).

More generally, the importance of collaboration between science and industry in the generation of technological innovation such as GLARE has been often underlined (Freeman, 1991; Grant, 1996; Meeus, Oerlemans, & Hage, 2001; von Hippel, 1988). Take, for example, the following quote of an associate professor of Eindhoven University of Technology who together with several partners from industry and an energy research centre, developed a power electronic converter that integrates sustainable energy sources with existing energy delivery systems: *"The good thing about this consortium is that, as a researcher, one can surrender to scientific curiosity while at the same time the user committee keeps you level-headed. That combination has proven to be a very fruitful one" (STW, 2009, p. 86).* Or consider the following quote by the head of a package applications department of a Dutch industrial steel company who together with several large industrial partners and a full professor of applied physics from the University of Groningen, participated in a consortium that focused on improving industrial protective coatings: *"Our research department holds just a small percentage of all knowledge available in the world. The rest of this knowledge must come from our external network. We can't afford to conduct all the research that is needed to suit our products to the requirements of the customer ourselves. That is one of the reasons why participating in consortia is so helpful. This involvement helps to develop applications in an early stage" (STW, 2010, p. 9).* Both quotes illustrate the synergetic effect of collaboration for innovation.

The importance of collaboration between science and industry is not only illustrated by the experiences of individual actors involved. On the societal level as well, many "grand challenges" are faced. Such challenges are barriers that require the coordinated and sustained effort by multiple stakeholders for their removal. Removing such barriers helps solving an important societal problem with a high global impact (Coenen, Hansen, & Rekers, 2015; George, Howard-Grenville, Joshi, & Tihanyi, 2016). Hence, grand challenges shape the joint goals, and guide the actions of a broad stakeholders' community (Coenen, Benneworth, & Truffer, 2012; Eisenhardt, Graebner, & Sonenshein, 2016), and have become an established theme for policy makers across the world. For example, about 43% (€31 billion) of the budget that is available for the EU research programme Horizon 2020 is reserved for collaborative projects that address societal challenges, such as improving health and well-being for all, realizing the transition to a reliable, sustainable and competitive energy system, or the protection of citizens, society and economy as well as infrastructures and services (McGrath et al., 2014; Rhisiart & Carabias, 2013). Although evidently not the all-encompassing solution to any of today's challenges, the creation and adoption of more effective and appropriate technologies is generally considered as a necessary ingredient for addressing at least some of them (Foray, Mowery, & Nelson, 2012). Hence, governmental stimulation of the formation of linkages between industry, knowledge institutes and governments is one of the key elements in addressing such challenges.

In this dissertation we delve deeper into the question how research and development (R&D) collaboration between science and industry can best be organized, at both the consortium level and the network level. The consortium level refers to the combination of organizations that pool resources with the aim of carrying out research and development activities. The network level refers to the network of consortia that emerges because of organizations being involved in multiple consortia simultaneously. This multiple involvement leads to joint member ties between consortia. Although the existing academic literature underlines the importance of networks for innovation, there is considerable debate as to the question which ways of organizing R&D consortia and consortium networks are most effective, and when. In the next sections of this dissertation, this issue will be further elaborated on (section 1.2), which will result in a research question (section 1.3). We then will outline the contributions of this dissertation (section 1.4), which is followed by a description of our research approach (section 1.5) and the layout of this dissertation (section 1.6).

1.2 Research problem

Our focus in this dissertation will be on a specific form of organizing joint innovation: R&D consortia. Basic R&D -activities devoted to increasing scientific or technical knowledge and applying that knowledge in the creation of new and improved products or processes (Hagedoorn, 2002)- is seen as the first step towards the development of new technologies (de Man & Duysters, 2005). As illustrated by the examples in the first paragraph of this chapter, in early stages of technological development, collaboration between industrial and academic actors is of key importance. As we will see, however, the network effects that come with such collaboration at both the level of consortia as well as the network level are not fully understood yet.

Multi-partner consortia such as R&D consortia are a prevalent form of pooling resources, as they are considered to have the potential to influence a host of outcomes beyond what their individual members could achieve on their own (Koschmann, Kuhn, & Pfarrer, 2012). A considerable yet scattered body of literature on multi-partner consortia has emerged in the past decades. This literature focuses on a variety of consortium types, addressing topics such as prevalence (Vaara, Kleymann, & Seristo, 2004), dynamics with respect to consortium formation, collaboration and termination (Bakker, 2016; Berends et al., 2011; Davis, 2016; Heidl, Steensma, & Phelps, 2014; Hwang & Burgers, 1997; Koza & Lewin, 1999; Zhang, Gupta, & Hallen, 2016), issues related to consortium governance, management and strategy (Cummings & Kiesler, 2007; de Man & Roijakkers, 2009; Gil, 2007; Jones, Hesterly, Fladmoe-Lindquist, & Borgatti, 1998; Li, Eden, Hitt, Ireland, & Garrett, 2012; McCarter, Mahoney, & Northcraft, 2011; Postrel, 2002; Zeng & Chen, 2003) as well as consortium outcomes (Cummings & Kiesler, 2007; Tiwana, 2008) and effectiveness (García-Canal, Valdés-Llaneza, & Ariño, 2003; Hoffmann & Schlosser, 2001). More conceptual work has developed a variety of typologies (Biggart & Delbridge, 2004; Das & Teng, 2002) and -based on a problematization of the production of joint action- developed models for enhancing the value-creating capacity of consortia (Koschmann et al., 2012; Monge et al., 1998). We approach the question as to the organization of R&D consortia from two perspectives: the perspective of the consortium manager and the innovation policy perspective.

From the perspective of the consortium manager, one of the aspects that is not explicitly considered in the current academic debate regarding the management of R&D consortia is that consortium members are often involved in multiple research collaborations simultaneously. As a result, R&D consortia are embedded in a larger collaborative network, and delineating to what extent this network affects the innovative outcomes of a consortium is important: scholars have often stressed that in addition to building internal capabilities, actively managing the external network by an organization becomes a crucial issue for effective innovation management and network orchestration (Dhanaraj & Parkhe, 2006; Manning, 2017; Reger, 2003; Tanskanen et al., 2017). The issue at stake here is control: whereas a consortium leader can control which direct ties to other consortia are forged, it is usually much harder to control the establishment of ties between its partner consortia ties, ties between the partners of these partners, and so on (Vanhaverbeke, Gilsing, Beerkens, & Duysters, 2009). Hence, knowing to what extent this network affects the innovative outcomes of a consortium forms the basis for devising strategies for either capitalizing on or mitigating such network effects for by consortium managers.

Yet, the phenomenon of multi-partner consortium network embeddedness is understudied. For example, even though a host of authors have linked network position and structure to nodal outcomes (Borgatti & Foster, 2003; Brass, Galaskiewicz, & Greve, 2004; Schilling & Phelps, 2007), alliance researchers deal rather pragmatically with collaborations in which more than two partners are involved, by either excluding such multi-partner collaborations from the analyses (Hu, McNamara, & Piaskowska, 2017; Kavusan, Noorderhaven, & Duysters, 2016; Wassmer & Dussauge, 2012), or by analytically separating these collaborations into multiple dyadic relations (Ranganathan & Rosenkopf, 2013). Consequently, although research on antecedents of organizational innovation has considered a wide array of both features at the level of the organization (Crossan & Apaydin, 2010; Damanpour, 1991) and the level of the network in which such an organization is embedded (Meeus, Oerlemans, & Kenis, 2008; Pittaway, Robertson, Munir, Denyer, & Neely, 2004), it is not clear to what extent these insights are applicable to networked R&D consortia. In addition, an ongoing concern that is voiced by researchers on organizational networks is that the "nestedness" of phenomena should be considered more often (Lusher, Koskinen, & Robins, 2013). For example, Brass et al. (2004) have argued that organizational performance depends on features that can be specified at multiple levels, for example organizational features but also network features. However, even though insights in the relative effects of aspects specified at different levels of analysis are important for focusing network management efforts, capturing such multilevel effects has shown to be elusive for researchers (Contractor, Wasserman, & Faust, 2006; Zappa & Lomi, 2015).

We seek to contribute to this debate in two related ways. First, we focus on the relative effect of the complete consortium network structure compared to consortium-level features on the innovative outcomes of R&D consortia. Although such a comparison explicitly recognizes the nestedness of organizational phenomena, only few studies have considered such relative effects to date (Schilling & Phelps, 2007; Uzzi & Spiro, 2005). Second, we will compare the effect on innovative outcomes of the brokerage position a consortium has in the complete network structure with the effect on innovative outcomes of the level of closure of the consortium's ego network. With respect to both effects, we are especially interested in the role of time, to tease out which network position is most salient for generating innovative outcomes, and when such a position during the innovation process is most beneficial for generating such outcomes.

From the innovation policy perspective, government has an important role in the formation and subsequent dynamics of interorganizational networks geared towards technological development (Peterman, Kourula, & Levitt, 2014). Similar to the consortium manager, the issue at stake here is control: for the effective spending of public resources, one wants to organize innovation networks as optimally as possible. However, for policy agencies, the focus is on outcomes at the system level rather than on outcomes of individual consortia. The reason for this is that most innovation policies build on two assumptions: the first assumption is that organizational innovation is rarely an outcome generated by one single organization. Instead, conditions of the system in which organizations innovate (e.g. linkages with customers and suppliers as well as the broader institutional and infrastructural context) are considered to be decisive in organizational innovation (Edquist, 1997; Kuhlmann, 2001; Smith, 2000). The second assumption is that because of the very nature of innovation, failures in the innovation system would occur if innovation would be left completely to the market. One of the failures identified is that of network failure. Such network failure refers to problems in the interaction among actors, leading to an inadequate amount of links and a low quality of these links (Coenen et al., 2015; Klein Woolthuis, Lankhuizen, & Gilsing, 2005; Smith, 2000). Hence, policy measures to avoid such market and network failures are needed that -amongst other measures- facilitate the formation and sustenance of research and development consortia involving industrial organizations as well as academic partners in the innovation system for this system to deliver innovative results.

Research considering network outcomes at the system level, however, has predominantly focused on public sector networks (Turrini, Cristofoli, Frosini, & Nasi, 2009). Prevalent models in this research field explain network outcomes as a function of network structural organization and network contextual factors (Provan & Milward, 1995; Provan & Sebastian, 1998). Although this work has generated a sizeable body of knowledge, the role of network structure in generating consortium network-level innovative outcomes has been relatively absent in the existing literature (Turrini et al., 2009). Hence, despite the underlined importance of public funding of R&D collaboration (Defazio, Lockett, & Wright, 2009; Hellsmark, Frishammar, Söderholm, & Ylinenpää, 2016; Thorelli, 1986), the question regarding efficient network structures for generating innovation at the network-level merits further investigation (Dhanaraj & Parkhe, 2006; Klerkx & Aarts, 2013; McDermott, Corredoira, & Kruse, 2009; Peterman et al., 2014; Provan & Lemaire, 2012; Sydow & Windeler, 1998; Turner, Michelet, & Courtial, 1990). In this context, a question that is especially salient is the question to what extent innovation policy aimed at the formation and development of networks of R&D consortia should be homogeneous or heterogeneous. Scholars have, for example, acknowledged that the most appropriate type of instrument aimed at stimulating innovation and technological change depends on sectoral patterns of production and use of innovations (Kivimaa & Kern, 2016; Pavitt, 1984). Although the organization of innovative activities within sectors is often times assumed to be rather homogeneous within sectors, profound differences with respect to this organization have been detected across fields (Audretsch, 1997;

Gort & Klepper, 1982; Lechevalier, Nishimura, & Storz, 2014; Leiponen & Drejer, 2007; Luo, 2003; Malerba & Orsenigo, 1996; Pavitt, 1984). Hence, we expect that technology field dynamics influence dynamics in technological field networks, and if so, the implication is that policy measures should be tailored to specific developmental features of such technology field networks, instead of treating each technological field in the same way. The literature on the formation and development of interorganizational networks in the field of innovation, however, does not offer a solid hold for describing and comparing the dynamics of technological networks across sectors: studies that provide insight in interorganizational network dynamics consider limited time frames (and consequently a limited number of networks), often do not account for the set of nodes amongst which ties can be forged and tend to focus on the life sciences field only (e.g. Gay and Dousset (2005); Orsenigo, Pammolli, and Riccaboni (2001); Powell, White, Koput, and Owen-Smith (2005)).

We seek to contribute to knowledge regarding the dynamics and innovativeness of complete consortium networks in two related ways. First, we will focus on the question if differences exist in the dynamics of different technology field networks. The insights obtained with this study (Chapter 4), in turn, will be used in a second study in which we focus on predicting network-level innovative outcomes using network structural features, as well as features of the network population and the stability of the underlying technology field (Chapter 5). Similar to our approach regarding consortium-level outcomes, we are especially interested in the role of time, for example to detect differences in the developmental pace of networks, as well as time lags between network structure and the generation of network-level innovative performance.

1.3 Research question

As the title of this dissertation suggests, R&D consortia can be managed to a certain extent by both consortium managers and policy makers. Consortium managers can manage several inputs to the consortium, such as selecting the most suitable partners, setting up a clear collaboration structure and organizing a filing system that allows for sharing knowledge embedded in documents such as minutes, research reports and white papers. Policy makers can actively stimulate R&D collaboration at the country level, for example by setting up funding schemes that stimulate joint innovation, bringing potential collaboration partners together and organizing conferences. Yet, the actions of both policy makers and consortium managers in forming and collaborating in R&D consortia involve higher order effects that are beyond the control of both: even though it is possible to select one's partners, for example, choosing the partners of one's partners is beyond one's control. This second order network, as well as the overall network -including its volatility over time- that emerges from the aggregate of partner selection decisions of all consortium managers, however, can affect the outcomes of individual R&D consortia as well as the innovative outcomes of the nation as a whole (Provan & Milward, 1995; Schilling & Phelps, 2007; Uzzi, 1997). Hence, with respect to these higher order effects that result in inputs to R&D consortia and consortium networks that are beyond the control of consortium managers and policy makers, both muddle through: one can only hope for the best with respect to the impact such inputs have on the innovative performance of R&D consortia and consortium networks (Lindblom, 1959).

With this dissertation we want to make both consortium managers and policy makers more aware of the networks they become embedded in or create through setting up R&D consortia, as well as the effect such networks have on the generation of innovative outcomes. This helps managing one's position in these networks as well as the structure of complete networks. For this, however, a more in-depth insight in the effects of these networks is needed. To create this insight, the following related research questions have been formulated:

1) *To what extent does R&D consortium network structure affect innovative outcomes?*

2) *To what extent does the network position of R&D consortia affect innovative outcomes?*

3) *To what extent do network dynamics and technology field dynamics moderate the relationships explored in research question 1 and 2?*

Hence, the focus in this dissertation is on the generation of innovative outcomes at both the level of the consortium and the consortium network level. At the consortium level, we explain outcomes by considering the effects of consortium features, consortium network positional features and features of the complete consortium network. At the network level, we explain outcomes by considering features of the complete consortium network. At both levels, we consider the role of time by either considering the development of the network position of a consortium over time, or the dynamics of the complete consortium network.

1.4 Research contributions

In addition to the contributions of each individual chapter, we distinguish three main overarching contributions of this dissertation. First, we focus on the R&D consortium as a distinct form of organizing. As explained in section 1.2, multi-partner alliances in general are often simplified or ignored in research that considers the effect of an organization's network position on the generation of innovative outcomes. Recent studies that have emerged on the phenomenon of R&D consortia, however, explicitly acknowledge that such consortia can be considered an organizational form in itself. For example, Sydow, Windeler, Schubert, and Möllering (2012) consider R&D consortia as "locales of collective agency" which should be consciously organized and managed in order to effectively govern the jointly created pool of resources. As explained in section 1.2, research on the effectiveness of complete networks has mostly considered public sector networks, yet the idea of focusing on the effectiveness of such networks can also be fruitfully applied to studying publicly funded consortium networks: such networks form as the result of the idea that collaboration stimulates innovation. Considering to what extent such networks deliver such innovative outcomes can be considered a litmus test for the fruitfulness of applying that idea. By focusing on many consortia as well as consortium networks, our study seeks to increase our knowledge about the general relation between networks and innovation.

Second, this dissertation addresses recent calls for more multi-level research in network studies (Contractor et al., 2006; Zappa & Lomi, 2015) in several ways. First, at the consortium level we consider antecedents of consortium innovative performance at both the consortium-level and the network-level. In addition, we consider the relative effects of the ego network position of a consortium with the position of this consortium in the complete network. Second, at the level of the network we consider these networks as being embedded in different technology fields. We propose that different technology fields have a different effect on the dynamics of such networks, as well as their effectiveness. By considering antecedents of innovation at different levels, we provide insight in the relative importance of antecedents at each level which allows for more targeted network management by both consortium managers as policy makers.

Our third contribution is that, although often a call for the specification of time in organizational research has been made (Albert & Bell, 2002; Ancona, Goodman, Lawrence, &

Tushman, 2001; George & Jones, 2000; Kavanagh & Araujo, 1995; Zaheer, Albert, & Zaheer, 1999), studies that incorporate the role of time in the relation between networks and innovation are scarce. Scholars have suggested that ties between actors and therefore simultaneously networks change over time. Consequently, the impact of certain network positions and structures on innovative outcomes might also change over time. Ahuja, Soda, and Zaheer (2012) illustrate this using structural hole theory, which posits that actors that bridge a structural hole have an advantage compared to actors who do not bridge such a structural hole (Burt, 1992). The moment one takes into account network dynamics, however, it could happen that structural holes disappear over time, and with that the advantages associated with such holes (Buskens & van de Rijt, 2008). Hence, the salience of such network effects depends on for example the extent to which a network is subject to structural and population dynamics (Ahuja et al., 2012). In addition, time must pass for relationships to develop, strengthen and deepen. It therefore can be expected that not all network effects are present instantly but need some time before becoming manifest. Lastly, several authors have suggested different knowledge gestation times for different technology fields (Gilbert & Campbell, 2015; Park & Zhou, 2005; Rothaermel & Hill, 2005), industries (Becker & Lillemark, 2006; Fabrizio & Thomas, 2012; Hameri, 1996; Henisz & Macher, 2004; Hyytinen & Toivanen, 2005; Nishimura & Okada, 2014; Spithoven, Frantzen, & Clarysse, 2010), and types of innovative activity (Ahuja, Lampert, & Tandon, 2014; Flammer & Bansal, 2017; Maine, Probert, & Ashby, 2005; O'Connor & DeMartino, 2006; Prettner & Werner, 2016; Souder, 1983). By considering the role of time in the general relation between networks and innovation we provide more insight in the timing of network effects at both the consortium and the network level.

1.5 Research approach and data collection

Answering our research questions requires the inclusion of as many consortia and consortium networks in our study as possible. We do dare to say that we do have a unique data-repository available that does cater for our purposes. Each chapter in this dissertation applies a quantitative research approach, while drawing on a dataset that contains secondary data on 1,928 Dutch R&D consortia, starting somewhere between 1981-2004.

After the post-WWII economic expansion, the economic downturn in the 1970s, with less financial resources for technological innovation, forced Dutch policy makers to think about how to create synergies between industry and universities, while preventing a technology push, and how to facilitate a demand driven innovation approach. Driven by in particular a remark made by one of the individuals involved (*"We all know what useful research is: useful research is research that others need"*), the decision was made that funding needed to take place based on an equal weighting of academic excellence and user interest (STW, 2005, 2016). This exercise coalesced with the growing concern of the Ministry of Economic affairs that there was too little interaction between academia and industry (resulting in the so-called "knowledge paradox" where, despite the country's strong science base, firms display a relatively weak R&D performance (Tijssen & van Wijk, 1999)). As a result, a technology foundation was established with the aim of prioritization of research funding for the technical sciences, and enhancing knowledge transfer between industry and excellent technical-scientific research. The assumption that has driven this foundation throughout the years is that even though generating innovative outcomes by any research focusing on R&D is inherently uncertain, collaboration between multiple agents increases the chance of succes.

Ever since its inception, the foundation has granted research funds to a broad variety of consortia, focusing on technologies such as improved donor organs, cleaner waste water, lighter airplanes (the foundation supported several consortia that were focused on the development of

GLARE), more reliable bridges, better treatment of heart attacks, faster communication and more efficient solar panels (STW, 2016). Two requirement for eligibility of project funding are: (1) the research institution that applies for the consortium and the foundation jointly own the research results and (2) potential users of the research results have to demonstrate their commitment upfront by participating in a user committee. These committee members can originate from industry, but public organizations and other research institutions are likely participants as well. The minimum amount of meetings committee members should have is twice a year, but usually contacts take place outside these meetings (STW, 2016). Knowledge transfer with the purpose of mutual allignment, steering of the research project and in the end knowledge valorization is key during all these interactions.

The approach of this funding organization is a clear reflection of the von Hippel-agenda, in which a prominent role in the process of R&D and innovation is reserved for users (von Hippel, 1988). The benefit of doing so is twofold: for researchers, involving users is a test of the viability of their research programme, and for industrial participants it is a relatively accessible way to keep up to date with the most recent scientific developments. The funding programme is one of the few programmes in the Netherlands that organizes research in this way (Velzing, 2013), and as indicated earlier, leads to network formation: joint membership by consortium participants in multiple consortia simultaneously leads to the forging of joint member ties between consortia and with that, the emergence of consortium networks.

The foundation is held accountable for providing consortium funds, and has to issue an annual publicly available report in which consortia that were funded 5 and 10 years ago are evaluated. In total, we used the information drawn from 23 annual reports to build our dataset. For the purpose of this introductory chapter, it would go too far to share specific details regarding the design of this dataset, as well as the decisions made while constructing it. Instead, we decided to report this in appendices to each empirical chapter in this dissertation. In each appendix, the focus will be on one of the key topics regarding the construction of this dataset, especially in the context of interorganizational network studies. The topics that we will cover in this light are (1) data sources and database construction (Chapter 2), (2) node specification (Chapter 3), (3) tie and network specification (Chapter 4) and (4) network boundary specification (Chapter 5).

1.6 Dissertation layout

Subsequent empirical chapters focus on the research questions formulated in this introductory chapter. In Chapter 2, we explain the likelihood of generating innovative outcomes by R&D consortia. Our research question in this chapter is twofold, and reads as follows: to what extent do the level of geographical proximity and technological diversity of consortium members as well as the level of network integration influence the likelihood of generating innovative outcomes of an R&D consortium, and to what extent is the relation between geographical proximity and technological diversity and the likelihood of a consortium generating innovative outcomes moderated by the level of network integration? We consider consortium-level features (i.e. geographical proximity and technological diversity) and features of the network in which consortia are embedded (i.e. network integration). The goal of this chapter is to provide levers for the design of R&D consortia and the design of consortium networks. In the literature on R&D consortia the focus hitherto has been mainly on either establishing R&D consortia as a new phenomenon of interest, or on motivations of members to enter, stay or leave an R&D consortium, as well as the effect of participating in R&D consortia on the performance of these members. We consider the R&D consortium in Chapter 2 as an organizational form in its own capacity and propose that the innovative outcomes of consortia are partly determined by aspects that are in the control of the consortium managers (consortium-level features), and partly determined by aspects that are not in the control of consortium managers yet can be steered by managing the overall network (network-level features).

A key insight in the literature on inter-organizational networks and innovation is that the network position of an organization influences its innovative outcomes. Yet, there is mixed evidence regarding the exact nature of this relation. Chapter 3 offers a model to decompose this relation by disentangling the temporality and topological effects of network position on outcomes along two dimensions. First, we make a distinction between the position of an R&D consortium in the local network (i.e. a consortium's ego network) and its position in the global network (i.e. the full consortium network). Second, we map both the local and global network position of R&D consortia over time. By investigating the effect of a consortium's network position on its likelihood of generating innovative outcomes across time and network order, we answer the research questions to what extent the innovative outcomes of R&D consortia are affected by a consortium's position in the local and global network, and to what extent said relationship is moderated by time. Our goal with this chapter is to provide insights for consortium managers regarding the relation between network positional dynamics of R&D consortia and the generation of innovative outcomes. The insights generated in this chapter complement the insights obtained in Chapter 2: whereas Chapter 2 provides levers for the design of R&D consortia, the insights in Chapter 3 suggest which layers of a consortium's network are important, and when. This enables consortium managers to develop a targeted strategy regarding the joint member ties of a consortium and its resulting network position.

Whereas the focus in Chapter 2 and Chapter 3 is on the R&D consortium, our attention in Chapter 4 and Chapter 5 moves to the level of the complete network. We explore the validity of one important starting point of existing innovation policy: network formation and development need to be stimulated regardless of differences in the organization of innovative activities within sectors and the subsequent differences in the pace and nature with which these networks develop. Chapter 4 addresses the issue whether technology field networks are homogeneous in their development. We do indeed find that field network development is rather heterogeneous. Focusing on consortium networks, where nodes are consortia and ties are joint member links between these consortia, we develop a descriptive state change model that uses node entry, stayers, node exit, network degree centralization and density as key parameters for describing network change. The resulting insight in the predictability with which field networks develop and the duration of different developmental stages is needed to develop are more targeted and differentiated approach towards steering such networks.

The insights regarding the developmental nature of different technology field networks are used as one of the inputs for Chapter 5. In this chapter, we answer the research questions to what extent network innovative performance is explained by node entry, stayers, node exit and network integration and to what extent the relation between said predictors and network innovative performance is moderated by the level of technology field stability. In this chapter, we suggest that networks between R&D consortia are worth organizing themselves, and we offer several levers for policy regarding the top-down management of such networks by public funding agencies.

Based on the findings in each of these empirical chapters, we will formulate an answer to the overarching research question in Chapter 6 and consider the implications of our findings in a broader academic and practical context.

2. The Structural Context of Innovation in Government-sponsored R&D Consortia: Effects of Network and Consortium Features[1]

Abstract

Existing research on organizational innovation has yielded many insights in possible antecedents, both at the organizational and the network level. Yet, what the antecedents of innovation are in multi-partner R&D consortia is a question that is still open to further exploration, especially when it concerns the role of the complete consortium network structure in the relationship between consortium features and the likelihood of a consortium generating innovative outcomes. This chapter addresses this question. Based on an analysis of 1,263 Dutch R&D consortia over the time frame 1989-2004, we test hypotheses regarding the role of network integration, geographical proximity between consortium members and their technological diversity, and the likelihood of a consortium generating innovative outcomes. Our results suggest that consortia embedded in networks that are characterized by mutual awareness of consortium members of what members in other consortia are doing (i.e. density-based network integration), are more likely to generate innovative outcomes compared to consortia in networks characterized by other types of integration. In addition, we find that especially in this condition of density-based network integration, an inverted U-shaped pattern exists between a consortium's level of technological diversity and the likelihood of this consortium generating innovative outcomes. Next to shedding light on the question regarding predictors of the innovativeness of R&D consortia, our study results have important implications for both top-down and bottom-up management of consortium networks and R&D consortia.

2.1 Introduction

The past four decades have been marked by a burgeoning academic interest in interorganizational relationships (IORs) (Cropper, Ebers, Huxham, & Ring, 2009). Combining the flexibility of markets with the predictability of hierarchies (Powell, 1990; Thorelli, 1986), IORs are formed by organizations to gain benefits such as access to critical resources (Gulati & Gargiulo, 1999), overcoming competency limitations (Mitchell & Singh, 1996) or support of innovative activities (Teece, 1992). Consequently, IORs are considered to be a critical determinant of organizational survival and growth, which has sparked the growth of a considerable body of research (Oliver, 1990; Parmigiani & Rivera-Santos, 2011).

Being manifested in simple dyadic arrangements initially, IORs have evolved over time into more complex structures that include multiple partners (Das & Teng, 2002; Zeng & Chen, 2003). These collaborations often do not only involve firms, but also include universities, research centres and governmental bodies (Kale & Singh, 2009; Mindruta, 2013). In comparison with dyadic relationships, collaborations involving three or more partners differ, for example because the interests of individual members can be suppressed for the interests of the majority of members (Krackhardt, 1999), social exchange mechanisms are based on different logics (Das & Teng, 2002), or individual members can, at times, let their self-interest prevail over the common interest (Zeng & Chen, 2003). This can have a profound impact on the dynamics of collaboration and requires a much more complex governance structure (Lavie, Lechner, & Singh, 2007). Hence, even though

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both dyadic and multi-partner collaborations tend to have the same value creation logic, the design and management of the latter is often more complicated (Das & Teng, 2002).

Research and development (R&D) consortia are marked examples of such multi-partner collaborations (Das & Teng, 2002). Their conduciveness to knowledge transfer, problem solving and joint learning through collaboration among firms and research institutions make them a common form of organizing, especially in fields characterized by knowledge production and technological development (Fonti, Maoret, & Whitbred, 2015; Foray et al., 2012; Sydow et al., 2012). The earliest attempt to form an R&D consortium has been credited to Josiah Wedgewood, who tried to bring together a group of Staffordshire potters around 1775. As an illustration of the complexities of designing and managing multi-partner collaborations, this consortium failed because of disagreements on priorities and financing (Alic, 1990). Even though R&D consortia were formed already in the 18th century, scholarly interest came to fruition no earlier than the 1980s. This resulted in the accumulation of three distinct bodies of knowledge on the topic: the first body of research focused at establishing R&D consortia as a new phenomenon, the second focuses on consortium members and the third considers R&D consortia as an organizational form in its own capacity.

As from the late 1980s, the focus was on establishing and justifying the R&D consortium as a new phenomenon. Back then, the R&D consortium was considered a relatively new form of organization. In the U.S., for example, joint R&D between organizations was illegal throughout most of the 20th century. Due to increased competition from foreign markets, however, the National Cooperative Research Act (NCRA) was established in 1984, which legalized conducting joint R&D activities between firms (Evan & Olk, 1990; Ouchi & Bolton, 1988). In Europe, the design of industrial research policy used to follow the American example, where the success of large firms was believed to result from taking advantage of multinational markets and economies of scale (Watkins, 1991). However, the success of cooperative industrial research in Japan motivated Europe to switch its policy in such a way that this mode of collaboration was emulated (Sakakibara, 1997; Watkins, 1991).

The subsequent wave of consortium formation (Adler, 2001) invited various researchers to perform descriptive studies with a clear geographical scope, such as Europe (Watkins, 1991), Japan (Aldrich & Sasaki, 1995; Odagiri, Nakamura, & Shibuya, 1997), and later also Taiwan (Mathews, 2002). The main objective was to describe the prevalence of R&D consortia, as well as to provide insight in their key descriptives. Also, comparisons between countries were made, especially between the United States and Japan (Ham, Linden, & Appleyard, 1998; Ouchi & Bolton, 1988). Mostly based on case studies, these papers focused on motivations for consortium formation (Ham et al., 1998; Mathews, 2002; Ouchi & Bolton, 1988), modes of organization, goal setting and managerial challenges (Corey, 1997; Evan & Olk, 1990; Ham et al., 1998; Ouchi & Bolton, 1988) and the (dis)advantages of a governmental role in the formation of these consortia (Odagiri et al., 1997; Watkins, 1991).

Scholarly attention shifted from establishing the consortium as a new organizational phenomenon to a focus on consortium members as from the late 1990s. Studies conducted in this realm were explanatory instead of descriptive: questions as to the motivations of member organizations to enter (Sakakibara, 2002), stay, or leave (Olk & Young, 1997) consortia became relevant to answer for both policy makers (do these consortia attract suitable members?) and consortium managers (how to deal with variation in composition over time, especially in relation to consortium performance?). Also addressed in this context were questions about the process of consortium formation by its members, and predictors for member involvement levels (Doz, Olk, & Ring, 2000; Fonti et al., 2015). A distinct topic in relation to studying consortia at the member-level was that of knowledge spill-overs: do spill-overs -as a core function of R&D consortia- actually occur (Watanabe, Kishioka, & Nagamatsu, 2004), and what are the antecedents of successful knowledge spill-overs between consortium members (Lin, Fang, Fang, & Tsai, 2009)? Lastly, the effects of consortium participation on the performance of individual members has been a topic of interest, both in the short (Sakakibara, 1997) and the long (Kaiser & Kuhn, 2012) run.

Only recently, the field has moved to a consideration of R&D consortia as an organizational form in its own capacity. This field has yet to come to full fruition, as only few scholars have addressed the topic, but the common theme that holds the field together is that of generating innovative outcomes by a collectivity of organizations. Contrary to research that has provided insight in the benefits for individual members of being member of an R&D consortium (Sakakibara, 1997), the key question here is how to organize R&D consortia in such a way that they are conducive to generating innovation at the collective level. In one of the early works in this realm, Browning, Beyer, and Shetler (1995) sought to derive understanding of factors that give rise or impede cooperative relations among actors in the SEMATECH consortium. They found that three sets of social conditions enabled the development and sustained viability of such relationships: early disorder and ambiguity, emergence of a moral community, and structuring of activities. Based on a case-study in the Dutch context, Roelofsen, Boon, Kloet, and Broerse (2011), for example, present an approach for facilitating and analysing learning processes in R&D consortia. In the view of these authors, R&D consortia can only develop technologies that meet social needs if the inputs of different stakeholders are adequately addressed. In another case-study, Allarakhia and Walsh (2012) present a model that aids our understanding of the way consortium members organize themselves in order to effectively govern the jointly created pool of resources. Only when consortia are managed effectively, the preconditions for generating innovative outcomes are set. The most clear example of work that considers R&D consortia as an organizational form is the study conducted by Sydow et al. (2012). This work considers R&D consortia as "locales of collective agency". Using a longitudinal, industry-based study, the authors aim at capturing how this collective agency extends existing and creates new technological paths in the field of semiconductor manufacturing. The underlying goal of this path extension and creation is to enable the innovative activities by consortia with the goal to generate innovation.

Although scholarly work conducted on R&D consortia hitherto has shed light on the different aspects related to their functioning, there is yet a considerable amount of work to be done before we can fully grasp the complexities of organizing R&D consortia in such a way that they are conducive to innovation. We seek to contribute to this debate by focusing on the moderating role of the complete consortium network (i.e. the structure of the full network rather than network position) in the relation between the geographical proximity of consortium members and their technological diversity on the one hand, and the likelihood of an R&D consortium generating innovation on the other. In short, this paper attempts to predict the innovative outcomes of R&D consortia by proposing that these consortia are positioned in a technology landscape. Network structural organization determines to what extent search in this landscape is guided. Not only does network structure directly affect the likelihood of an R&D consortium generating innovative outcomes, it also moderates the relation between geographical proximity and technological diversity of consortium members on the one hand, and the likelihood of generating innovative outcomes by the consortium on the other.

In contemporary organizational research, questions regarding the antecedents of innovation have been explored by and large, taking into account organizational (Damanpour, 1991) as well as networking (Meeus et al., 2008; Pittaway et al., 2004) antecedents. Yet, in as far as this work considers relational antecedents, the focus is mostly on dyadic collaborations rather than multi-partner collaborations. Consequently, despite the insights provided by the three studies described earlier, the limited availability of studies and their mainly case-based approach make that existing insights in the generation of innovative outcomes by R&D consortia are difficult to generalize. In addition, an ongoing debate in the field of organization studies revolves around investigating the relative effect of organization and network features on the generation of organizational outcomes (Ibarra, Kilduff, & Tsai, 2005). This debate is driven by the reality that many organizational phenomena are nested (Lusher et al., 2013). As an example, the performance of individual organizations depends on both features at the organizational level and features of their complete collaboration networks at the industry level (Brass et al., 2004; Schilling & Phelps, 2007). Yet, capturing multi-level effects has shown to be elusive for network researchers (Zappa & Lomi, 2015), who have been criticized for transforming multi-level data to a single level of analysis (Contractor et al., 2006). Hence, the current state of the literature is that only a few studies have taken into account both organizational and complete network antecedents[2] in explaining organizational innovation (see Schilling and Phelps (2007) and Uzzi and Spiro (2005) for examples). Consequently, not much is known about whether features of this complete network affect R&D consortia.

We aim to address these two issues in this chapter. By combining insights from the literature on whole networks, university-industry interaction, new product development teams and alliance portfolios, we aim to provide managers of R&D consortia with an insight in the antecedents of the likelihood of an R&D consortium generating innovative outcomes. In predicting this likelihood, we are especially interested in the extent to which different types of network integration moderate the relationship between geographical proximity of members and their technological diversity on the one hand, and the likelihood of generating innovative outcomes on the other. Given the path-dependence of technological development (Dosi, 1982), we suggest that R&D consortia are positioned in a technology landscape. All conceivable positions in such a technology landscape, regardless of whether they are realized, can be interpreted as accumulated bodies of knowledge that prescribe the technological (im)possibilities and viable future research directions. We conceptualize network integration as a network-level feature that guides search in this landscape: the clearer the overall picture that consortium members have of this landscape, the more likely this consortium is to effectively search the space of possible solutions, and with that generate innovative outcomes.

Networks channel the flow of information and knowledge among actors (Podolny, 2001). The concept of network integration reflects the mutual awareness among different consortium members of what members in other consortia are doing, and the extent to which the consortium network is characterized by a limited amount of common thematic foci. Thus, depending on the type of network integration, consortia embedded in these networks are guided in their search through the technology landscape. In addition to the complete network-level concept of network integration, members within R&D consortia need to be able to communicate knowledge effectively, and to create an innovative climate conducive to knowledge recombination. These elements are embodied in the concepts of geographical proximity and technological diversity, and are expected to create a process in which research findings and proposed implementations go

[2] With this term, we refer to network-level properties, such as density and centralization rather than network positions of individual nodes, such as centrality or structural equivalence.

through a maze of tests in order to determine whether they can be implemented in a technological innovation (Drazin & Schoonhoven, 1996). We propose that these aspects directly affect the likelihood of a consortium generating innovative outcomes, but that the extent to which this is the case depends on the extent that network integration allows for guided search in the technology landscape. Hence, network integration either amplifies or diminishes knowledge transfer and recombination at the consortium-level.

The empirical value of our theoretical ideas is assessed by performing a multi-level analysis of 1,263 R&D consortia, each of which started in the Netherlands in the time frame 1989-2004. These consortia received governmental funding, based on the philosophy that even though generating innovative outcomes by any research project that focuses on R&D is inherently uncertain, chances of success are increased when technology developers and potential users of the technology are brought together as early as possible in the developmental process. The consortia studied are dispersed across 7 different technology fields. Through determining consortium networks based on joint member ties within technology fields, we operationalize our concept of network integration. In turn, we estimate multilevel binary logistic regression models that predict the likelihood of an R&D consortium generating innovative outcomes as a function of network integration, geographical proximity and technological diversity. In addition, cross-level interactions between network integration and consortium-level features are included. Our results suggest that consortia embedded in networks characterized by mutual awareness of what members in other consortia are doing are more likely to generate innovative outcomes. In addition, even though our findings are opposite to what we expected, we find that especially in the condition of density-based network integration, an inverted-U shaped pattern exists between the level of technological diversity and the likelihood of a consortium generating innovative outcomes.

This study advances our understanding of innovation in R&D consortia in two important ways. First, by including both the consortium and the complete network-level of analysis in our model, we take on the challenge to improve the explanation of innovative outcomes in the context of multi-partner collaborations as a function of both nodal and complete network features. As indicated earlier, an abundance of previous studies has addressed questions related to antecedents of innovation using organizational (Damanpour, 1991) as well as networking (Meeus et al., 2008; Pittaway et al., 2004) antecedents. Studies that combine both dimensions, especially when it concerns complete network features, are rare. By combining both levels of analysis, we show that complete network structures matter for consortium innovation and provide insight in the comparative effects of features specified at both levels. Hence, not only being embedded in networks is important, also the complete network effect matters for the likelihood a consortium will generate innovative outcomes. Second, by employing a large dataset on R&D consortia across multiple technology fields, we aim to increase the generalizability of knowledge about antecedents of innovation in R&D consortia.

In addition to these theoretical contributions, our study offers useful insights for both policy makers focussing at stimulating consortium formation, and consortium managers. A useful distinction that can be made here is that between top-down and bottom-up management (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013) of networks. With top-down management of networks, we refer to the influence of policy in shaping consortium networks. Even though R&D consortia are an important vehicle for generating innovation, their formation is not self-evident. (Odagiri et al., 1997; Ouchi & Bolton, 1988; Watanabe, Asgari, & Nagamatsu, 2003; Watkins, 1991). Because the nature and range of potential applications is uncertain, and the ability to capture the returns of one's investment is likely to be limited, even if the research is successful (Foray et al., 2012), the willingness to invest at this early stage of basic research is low. Hence, it is often argued that government programs that aim at forging relationships between organizations in order to develop and deploy the relevant technologies are needed (Foray et al., 2012; Spencer, Murtha, & Lenway, 2005). To be able to develop effective programs, it is important to have knowledge about possible hampering or amplifying effects of complete networks on the likelihood of generating innovative outcomes by R&D consortia, and to be knowledgeable about levers that can be used to influence these structures. To do this, integration of structural and consortium-level theories is needed.

With bottom-up network management, we refer to designing consortia by consortium managers in such a way that effects at the complete network level are considered as well. Especially in situations where networks are created unconsciously, awareness of the structural context of an R&D consortium and ways in which this context alleviates or strengthens the effect of consortium features on the generation of innovative outcomes helps consortium managers to choose a consortium design that fits a certain structural context, or maybe even choosing a design that can actually change that structural context (Short, Ketchen Jr., Bennett, & Toit, 2006).

2.2 Theoretical framework

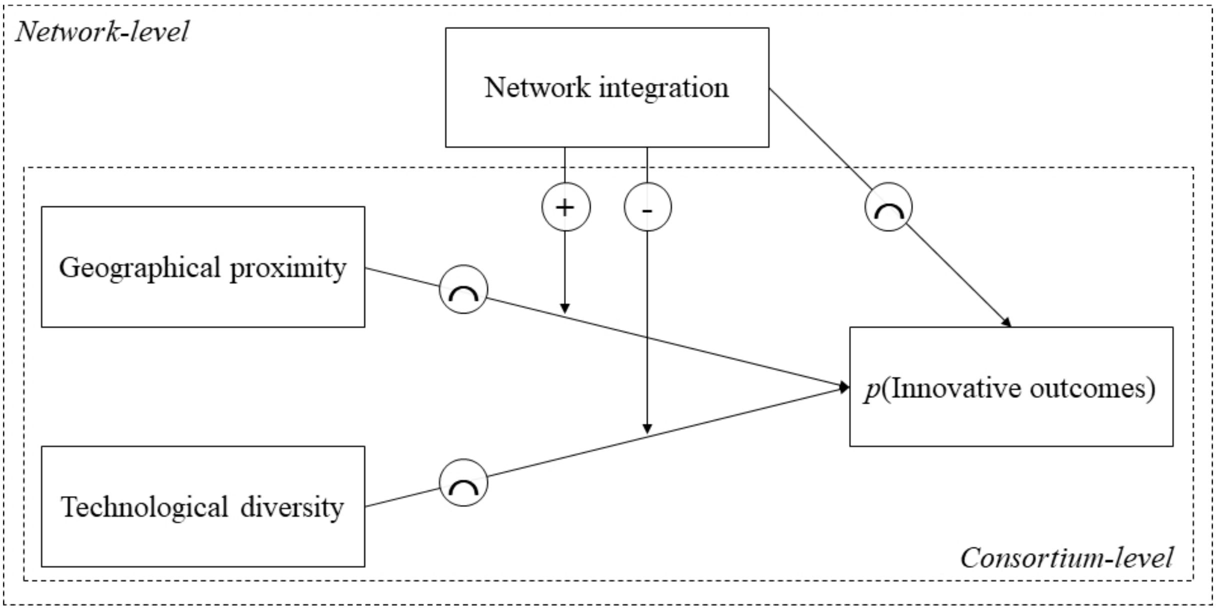
R&D consortia are collective structures among multiple organizations that focus on carrying out research and development activities, and that are typically dissolved after a pre-defined innovative goal is reached (Doz et al., 2000; Sakakibara, 2002; Sydow et al., 2012). The focus is on developing technologies, based on a certain task or need such as transporting commodities and passengers, producing chemical compounds with certain properties, or switching and amplifying electrical signals (Van Wyk, 2002). Although marked differences exist between countries (Aldrich & Sasaki, 1995; Mathews, 2002; Sakakibara & Cho, 2002), R&D consortia are generally initiated with the goal to develop products or processes that have the potential to be patented or commercialized (Aldrich & Sasaki, 1995). Typical activities conducted by consortium members include -but are not limited to- the generation of ideas, exploring technological feasibility, theoretical analysis, experimentation, analysis of research data, testing, prototyping, and product development (Aldrich & Sasaki, 1995; Ouchi & Bolton, 1988).

The aim of the model that we present in this chapter is to predict the likelihood of R&D consortia accomplishing their innovative goals. An important assumption that underlies this model is that activities conducted in R&D consortia are not totally ‘blind’, and unrelated with those conducted in other consortia (Frenken, 2006; Silverberg & Verspagen, 2005). Instead, research and development activities take place against the backdrop of an existing ‘technology landscape’ (Aharonson & Schilling, 2016; Fleming & Sorenson, 2001; Katila & Ahuja, 2002). As will be explained in this section, technology landscapes offer a useful heuristic for thinking about the space that consortium members search in their attempt to develop, or build forth on, useful new technologies (Fleming & Sorenson, 2004).

The conceptual model that reflects our theorizing is depicted in Figure 1. The general thrust of this model is as follows. Members of R&D consortia engage in search procedures within a technology landscape. This entails improving on an already existing product or process or filling up an empty position that has developmental potential. In either case, engaging in search activities and building forth on existing knowledge combinations or making new ones are key activities (Katila, 2002; Katila & Ahuja, 2002). The likelihood of a consortium generating innovative outcomes depends, on the one hand, on configurational properties of this consortium that (1) enable the effective transfer of knowledge between consortium members and (2) the existence of a collaborative climate that is conducive to knowledge recombination. We conceptualize these features as geographical proximity and technological diversity. Because an incomplete picture of the technology landscape restricts search in other directions once members succeeded in finding a technological improvement or solution (Kauffman, Lobo, & Macready, 2000), the presence of the 'right' mix of these consortium-level features is necessary, yet not sufficient for maximizing search within the technology landscape. For that, the complete network in which an R&D consortium is embedded needs to provide guidance to consortium members in such a way that it creates an overall picture of the interrelated knowledge components within the technology landscape (Macher, 2006). As such, it creates a structural context that guides search in the direction of the most promising rather than the firstly encountered feasible technological avenue (Fleming & Sorenson, 2004). Through, for example, creating a broader and better understanding of available knowledge components and knowledge interdependencies among consortia (Macher, 2006) or improved problem structuring (Shore, Bernstein, & Lazer, 2015), network integration enables members of R&D consortia to fully use the innovative potential created through geographical proximity and technological diversity by providing insight in the full range of the technology search space.

FIGURE 1

Conceptual model linking network and consortium-level features to innovative outcomes generated by R&D consortia



The remainder of this section will revolve around the elaboration on our conceptual model. The section is organized as follows. First, the concept of innovative outcomes in the context of R&D consortia is explained. It is outlined that innovation can be considered as a multifaceted process, and we focus in this chapter on three distinct outcome categories. Second, the key concept of network integration is introduced and a hypothesis for its direct effect on the likelihood of generating innovative outcomes is developed. Then, after having developed the baseline hypotheses regarding the direct effects of the selected consortium-level antecedents, hypotheses for the moderating role of network integration in these relations will be developed.

Innovative outcomes. Innovation is a term that encompasses a broad variety of activities (e.g. generation or adoption (Rogers, 2003)), foci of interest (e.g. diffusion of innovations through a population or organizational innovation (Damanpour, 1991)), degrees of newness (e.g. radical or incremental innovation (Tidd, Bessant, & Pavitt, 2005)) and perspectives (e.g. innovation as either an outcome or a process (Crossan & Apaydin, 2010; Gopalakrishnan & Damanpour, 1997)). An important dimension of innovation relates to the different stages of the innovation process. One can either interpret innovation as a process, consisting of stages such as idea generation, project definition, problem-solving, prototyping and commercialization (Gopalakrishnan & Damanpour, 1997), or innovation can be considered as a discrete outcome.

In this chapter, we use the heuristic of a technology landscape. Such a landscape can be defined as the overall space of technological possibilities within a technology field (Kauffman et al., 2000). Numerous positions can be delineated in such a space, with each position corresponding to an invention or innovation. Depending on technological feasibility and economic value, a targeted position can be occupied to a varying extent after a given period of time (Fleming & Sorenson, 2004; Kauffman et al., 2000). In line with this heuristic, we consider innovation as a categorical outcome. More specifically, an R&D consortium can generate an outcome that needs to be further developed (i.e. the targeted position in the technology landscape has not been reached yet), an outcome that can be considered a prototype (i.e. the targeted position in the technology has been reached yet is not fully functional yet) or an outcome that is fully realized (i.e. a position has been occupied in the technology landscape that fits in terms of performing the task or fulfilling the initial need as specified by its members). As the innovation process is fraught with uncertainties, we are especially interested in the probability of generating innovative outcomes by consortia.

Numerous antecedents of innovation have been identified in the organizational literature, taking into account organizational (Damanpour, 1991) and network (Pittaway et al., 2004) antecedents. Few studies have considered the effect of both features in concert, especially involving features of the complete network (Schilling & Phelps, 2007; Uzzi & Spiro, 2005). In addition, only recently R&D consortia are considered as a distinct organizational form, opening the discussion what explains the likelihood of consortia generating innovative outcomes. We contribute to this discussion by combining insights from the literature on whole networks, university-industry interaction, new product development teams and alliance portfolios. Based on two frequently discussed antecedents of innovation in these literatures, geographical proximity and technological diversity, we hypothesize a direct relation between network integration and the likelihood of generating innovative outcomes by a consortium. In addition, we develop cross-level hypotheses regarding the role of complete network integration in the relation between technological diversity and geographical proximity on the one hand, and innovative outcomes on the other. To this end, we will first elaborate on the latter concept.

Network integration. Integration is a well-established theme in organization and social theory. Yet, it has played a much more implicit role in interorganizational network research (Raab, 1998). Authors that have reflected on organizational integration consider it as one of the approaches to settling differences in organizations. This can be achieved through a system of cross-functioning and a sense of collective responsibility which entails both coordination and cooperation (Ettlie & Reza, 1992). At the network level, integration has been stated to be ill-defined (Provan & Milward, 1995; Provan & Sebastian, 1998). Our review of the literature that uses the term, however, suggested that similar dimensions to the ones discussed with respect to organizational integration can be identified. For example, in the work on whole networks (i.e. consciously created groups of three or more autonomous but interdependent organizations that strive to achieve a common goal and jointly produce an output (Raab & Kenis, 2009)), the focus is consistently on both interconnectedness between organizations (cooperation) and the extent to which these organizations are integrated and coordinated through a central authority (coordination) (Human & Provan, 1997; Provan & Milward, 1995; Sydow & Windeler, 1998; Turrini et al., 2009). This literature, however, makes strong assumptions about the extent to which network members acknowledge the network as a distinct organizational form that is goal-directed and needs steering. Many other types of networks, such as alliance networks or the consortium networks that we study in this chapter, are much more emergent and the goals are less specified. This means that the dimensions cooperation and coordination cannot be translated directly to these settings. Hence, a translation of these dimensions is needed. We will do this by using the technology landscape metaphor that was introduced earlier.

R&D consortia are positioned in an existing technology landscape in which numerous positions can be delineated and, possibly, occupied. Occupation of positions in a technology landscape is unlikely to be random. Instead, depending on the extent to which a technological trajectory for a given technology has been articulated (Abernathy & Utterback, 1978; Dosi, 1982), positions tend to cluster (Aharonson & Schilling, 2016). All conceivable positions in a technology landscape, regardless of whether they are realized, therefore can be interpreted as accumulated bodies of knowledge that prescribe the technological (im)possibilities and viable future research directions. Clusters of positions represent the interrelatedness between such bodies of knowledge. Thus, the technology landscape specifies the search space in which R&D consortia are positioned and operate (Nelson & Winter, 1982). Research and development activities -such as the examples given earlier- can be considered as search procedures within this landscape (Landini, Lee, & Malerba, 2017). This search can be suboptimal as a limited overview of the full technology landscape might lead consortium members to select technological improvements closest to them, rather than searching in other, more broad and possibly more fruitful directions (Kauffman et al., 2000).

Several studies have focused on mapping the technology landscape, often using Kauffman's (1993) NK-model. Landscapes are generally conceptualised as links between different knowledge components (Wang, Rodan, Fruin, & Xu, 2013). The shape of a technology landscape is influenced by different aspects of the technologies present in it (Kauffman et al., 2000), such as technological interdependencies (Fleming & Sorenson, 2004), complexity (Mihm, Sting, & Wang, 2015; Ziedonis, 2004) and range (Granstrand & Holgersson, 2013). Yet, most of a technology landscape is generally unknown to actors searching in it (Sorenson & Fleming, 2004; Stuart & Podolny, 1996). As a consequence, once a technological improvement has been found, actors tend to restrict search in other directions (Kauffman et al., 2000).

Instead of focusing on the shape of technology landscapes, we are interested in the extent to which search by R&D consortium members in a technology landscape is guided. With this, we mean that members are aware of the search space beyond the local search space resulting from the knowledge components focused on in the consortium, and hence are in the position to optimise search activities across the technology landscape. We propose that this guidance is provided by the complete network structure that emerges because of joint member linkages that form between R&D consortia[3]. Those linkages create a complete network that forms the structural context in

[3] Several authors have debated the relation between a technology landscape and the relational structure of the actors searching in this landscape. Some authors suggest that networks emerging as a consequence of links between different knowledge components approximate patterns of connections among researchers (Yayavaram & Ahuja, 2008). Other

which consortia operate. Different forms of integration of this context affect the extent to which consortium members can form a more complete overview of the technology landscape, guiding search in the direction of the most promising rather than the firstly encountered feasible technological avenue (Fleming & Sorenson, 2004).

This guidance can be considered an integrative mechanism in serendipitous networks. This integration can have two sources, which can be considered equivalent to cooperation and coordination in organizations and whole networks. First, network integration can be achieved through mutual awareness between network members of what others are doing (Erikson & Bearman, 2006; Fagerberg, Fosaas, & Sapprasert, 2012; Fagerberg & Verspagen, 2009). This mutual awareness is created through joint consortium members that are sources of identification and help to cement consortia in the network (Hollenstein, 2003; Koza & Lewin, 1999; Oh & Jeon, 2007). The more inter-consortium ties are formed through joint members, the more understanding members obtain of the available knowledge components and knowledge interdependencies among these components in the technology landscape. Second, network integration can be achieved through a small amount of common thematic foci (Fagerberg et al., 2012) and continuous efforts by prominent nodes to integrate the knowledge available in the network (Ata & Van Mieghem, 2009; Burt, 2007; Fagerberg et al., 2012; Fagerberg & Verspagen, 2009). This enhances the collective perception of consortium members of viable technological alternatives and possible future developments. A network that is integrated this way indicates a general commitment of members to a limited amount of core technologies (Afuah, 2013; Gay & Dousset, 2005; Soh, 2010), which are usually developed by consortia occupying more central network positions (Gay & Dousset, 2005; Powell et al., 2005).

An integrated network allows for the exchange of knowledge and information across consortia (Gulati & Gargiulo, 1999; Reagans, Zuckerman, McEvily, & Stuart, 2004). This results in a joint knowledge base, which facilitates both flexibility and efficient search for additional information (Shore et al., 2015; Staber, 1998). Consequently, the widest possible exploration of the search space takes place. In addition, it allows for specialization of individual consortia (Sydow & Windeler, 1998) by avoiding duplicate search activities (Shore et al., 2015) and allows for mutual technological adjustment (Soh, 2010). On the other hand, it has been argued that integrated networks make it more difficult for network members to look beyond the collective perception (de Vries & Verhagen, 2016; Ferriani, Cattani, & Baden-Fuller, 2009) which might lead to inertia (Staber, 1998). This reduces search scope, perceptions of alternatives and the diversity of both information and the interpretation of this information (Rowley, Behrens, & Krackhardt, 2000; Shore et al., 2015). As a consequence, consortium members might prematurely converge on a technological solution (Shore et al., 2015).

We bring the benefits and drawbacks of network integration for individual R&D consortia together through suggesting a curvilinear relationship. In lowly integrated networks, the lack of mutual awareness and thematic foci specifies a search space that offers no clear guidance as to which research avenues are fruitful to pursue. As a consequence, once succeeded in finding a technological improvement, actors tend to restrict search in other directions (Kauffman et al., 2000) which might lead them to miss more viable search directions. Under conditions of moderate

authors oppose this view, and argue that both networks are decoupled (Wang et al., 2013). This latter view is echoed by authors that suggest coevolution between technology landscapes and relational structures (Gulati, Sytch, & Tatarynowicz, 2012; Waguespack & Fleming, 2009). In this chapter, we view both networks as decoupled. We are especially interested in ways in which joint member relations across consortia guide search through a technology landscape.

network integration, either through mutual awareness or common thematic foci, a clearer picture of viable research directions emerges, having a beneficial effect on the likelihood of generating innovative outcomes by consortia. At high levels of network integration, however, consortia might become trapped in premature convergence (Shore et al., 2015), decreasing the likelihood of generating innovative outcomes. Thus, consortia benefit most from networks that are integrated to such an extent that viable research avenues are revealed and search in the technological landscape can be efficient, but not so much as to prevent sufficient exploration of viable options. We therefore argue that the likelihood of generating innovative outcomes by R&D consortia is the highest under moderate conditions of network integration:

Hypothesis 1: R&D consortia embedded in moderately integrated networks will be more likely to generate innovative outcomes compared to R&D consortia embedded in lowly or highly integrated networks.

Geographical proximity. This concept reflects the extent to which consortium members are spatially concentrated (Laursen, Masciarelli, & Prencipe, 2012; Silvestre & Dalcol, 2009; Whittington, Owen-Smith, & Powell, 2009). A vast literature -often with a focus on clusters of firms- points at the "lubricating effects" (Marchington & Vincent, 2004) of geographical proximity. It should be noted, however, that the positive effect of geographical proximity often is contingent on other factors, such as consortium composition (Dornbusch & Neuhäusler, 2015), duration (Broström, 2010), nature of the research (fundamental versus applied) (Autant-Bernard, 2001), the co-existence of other forms of proximity (Boschma, 2005; Schwartz & Hornych, 2008), or a cluster's developmental stage (Bodas Freitas, Marques, & Silva, 2013; Pouder & John, 1996). In this light, especially the work that has considered geographical proximity in the context of pre-competitive university-industry interactions, and inventor teams is of relevance to our model.

Most studies that considered geographical proximity in this context have underlined its enabling role for interactions among consortium members (Bercovitz & Feldman, 2011; Dornbusch & Neuhäusler, 2015; Ham & Mowery, 1998; Maietta, 2015). The underlying knowledge possessed by academic inventors is often not fully codified (Agrawal, 2006) and tacit in nature (Bishop, D'Este, & Neely, 2011; Geerts, Leten, Belderbos, & Van Looy, 2017). This type of knowledge therefore is difficult to transfer and has a high risk of integrity loss. Consequently, it requires specific means of communication. In addition, it is also more easily communicated incrementally through time instead of in large batches (Bartmess & Cerny, 1993; Lanzolla & Suarez, 2012; Sammarra & Biggiero, 2008). Geographic proximity of member firms is particularly useful for transferring non-codified, tacit knowledge as it increases the likelihood of informal, face-to-face interaction (Boardman & Corley, 2008; Kato & Odagiri, 2012). In turn, this increases the likelihood of actual knowledge exchange, both in terms of quantity as quality (Audia, Freeman, & Reynolds, 2006; Pouder & John, 1996; Vásquez-Urriago, Barge-Gil, & Modrego Rico, 2016). Lab visits, for example, allow academic faculty to advice other consortium members (Kato & Odagiri, 2012) and these members, in turn, can more effectively communicate possible issues, for example during a prototype test.

Fewer studies have pointed at the association between geographical proximity and consortium member local embeddedness. When members in close proximity collaborate, they do not only bring their own experience and knowledge to the table, but also their own social capital (Bercovitz & Feldman, 2011). This social capital has been demonstrated to be geographically determined (Laursen et al., 2012) and provides access to, for example, providers of financial capital (Bercovitz & Feldman, 2011) or other research teams (Kuemmerle, 1998). This, in turn could promote synergies between members (Vedovello, 1997) through increased opportunities for making new valuable combinations of resources (Molina-Morales, Martínez-Fernández, & Torlò, 2011). All in all, both increased levels of quantity and quality of knowledge transfer and opportunities provided through member's social capital lead to successful exchange of tacit knowledge, clearer problem articulation, more efficient project management, mutual understanding and resource access. These factors create a favourable innovative climate (Bramwell & Wolfe, 2008; Laursen et al., 2012), increasing the likelihood of a consortium generating innovative outcomes.

As opposed to the arguments provided for a positive association between geographical proximity and the generation of innovative outcomes, authors have pointed at several downsides of being spatially close to one another. One of these downsides is that the anticipated ease of future interaction might lead to consortia being formed without thorough consideration of the consortium's promises (Bercovitz & Feldman, 2011). Another downside is that the generally higher levels of trust associated with spatially close consortium members alleviate the risk of a "knowledge lock-in" (Crescenzi, Nathan, & Rodríguez-Pose, 2016; Schoenmakers & Duysters, 2010; Todo, Matous, & Inoue, 2016): given the limits to the amount of knowledge consortium members can process (Pouder & John, 1996), the amount of information fed to the consortium through trusting relationships between its members could inhibit access to knowledge outside the consortium (Molina-Morales et al., 2011) and make the consortium suffer from inertia and member bounded rationality (Pouder & John, 1996).

The contrasting arguments provided for the relation between geographical proximity and innovative outcomes of R&D consortia are brought together in this chapter as follows. First, at low levels of geographical proximity, effective transfer of especially sparsely codified, tacit knowledge is hampered, and the consortium suffers from inefficient problem articulation and project management. This creates an unfavorable innovative climate. This climate improves, however, as the level of geographical proximity increases. Here, the opportunity for in-depth, face-to-face interactions stimulates the transfer of more, higher-quality knowledge. Also, opportunities provided through member's social capital become more salient. After a certain level, however, a higher possibility of unthoughtful consortium formation and higher risks of knowledge lock-ins lead to inertia and member bounded rationality. This outweighs the before-mentioned benefits of geographical proximity, which again creates an unfavorable innovative climate. Hence, consortia benefit most from geographically proximate members when proximity enables higher quality knowledge transfer, but not so much as to prevent consortium members from becoming inert:

Hypothesis 2: R&D consortia with moderate levels of geographical proximity will be more likely to generate innovative outcomes compared to R&D consortia with very low or very high levels of geographical proximity.

The moderating role of network integration

We already made the remark that the effect of geographical proximity is often contingent on other factors. We propose network integration to be one of these factors. Network integration (1) provides consortium members with an enhanced understanding of the available knowledge components in a technology landscape and the corresponding knowledge interdependencies and (2) creates a joint perception of consortium members across the complete network of viable technological alternatives and possible future developments. It is especially the second aspect of network integration that affects two mechanisms underlying the relation between geographical proximity and the likelihood of generating innovative outcomes. The first is the mechanism related to the transfer of tacit knowledge. Under conditions of moderate network integration, consortium members create a more fundamental understanding of the technology landscape, and their developmental activities will be guided in the most promising technological avenues (Fleming & Sorenson, 2004; Rosenberg, 1990). Consequently, the likelihood of moving forward in the process of innovation and generating innovative outcomes increases. It is especially in these later R&D stages that transfer of tacit knowledge becomes key, as the developed technology needs to be transferred to the end users. At the same time, moderate network integration reduces the tendency for following opportunistic strategies (Koza & Lewin, 1999). Therefore, the likelihood that collaborations are formed without thorough consideration of the consortium's promises reduces. The net effect of both changes in mechanisms is that, under conditions of moderate network integration, the need for tacit knowledge transfer leads to a steeper relation between geographical proximity and the likelihood of generating innovative outcomes. Simultaneously, more thorough consideration of a consortium's purpose leads to a less steep decline in this relation. Hence, we hypothesize that:

Hypothesis 3: The inverted-u shaped relationship between geographical proximity of consortium members and the generation of innovative outcomes is amplified by network integration in such a way that the peak of the shape is higher in situations of moderate network integration compared to situations of high or low network integration.

Technological diversity. Different types of diversity have been identified in the past (Harrison & Klein, 2007), and technological diversity is defined in this chapter as the variety in the range of knowledge, expertise and experience between members of an R&D consortium (Bunderson & Sutcliffe, 2002; Hinds & Bailey, 2003; Reagans et al., 2004). This variety stems from the different sectoral backgrounds of members, leading to different routines and processes (Jiang, Tao, & Santoro, 2010) and different logics related to the production and valorization of knowledge (Swan, Bresnen, Robertson, Newell, & Dopson, 2010). Two streams of literature offer insight in the relation between the technological diversity of R&D consortia and the generation of innovative outcomes. These are the literature on new product development teams and the literature on alliance portfolio diversity. First, arguments for a positive association between technological diversity and innovative outcomes are given.

Various authors have pointed at the role of technological diversity in providing access to resources (Jiang et al., 2010), especially knowledge resources (Brown & Eisenhardt, 1995; Lee, Kirkpatrick-Husk, & Madhavan, 2014; van Beers & Zand, 2014). The variety of knowledge available to members of an R&D consortium has been argued to increase as technological diversity increases (Brown & Eisenhardt, 1995; Faems & Subramanian, 2013; Sakakibara, 2003; van Beers & Zand, 2014). As a consequence, the development of collaborative capabilities of consortium members is stimulated (Lovelace, Shapiro, & Weingart, 2001; Sivasubramaniam, Liebowitz, & Lackman, 2012). One of the key capabilities in this context is that of understanding the developmental process in the consortium more quickly and from a variety of perspectives (Brown & Eisenhardt, 1995). Not only does this facilitate the developmental process in general (Lovelace et al., 2001), it also leads to a higher potential for creating knowledge complementarities (Jiang et al., 2010; Lee et al., 2014; van Beers & Zand, 2014). In addition, improved mutual understanding activates a "gatekeeping"-function, as it allows members to catch possible developmental problems in an early stage, when these problems are generally smaller and easier to solve (Brown & Eisenhardt, 1995; Cohen & Bailey, 1997; Gemser & Leenders, 2011). Against this backdrop, the flexibility and range of value creating activities in the R&D consortium increases (Jiang et al., 2010), as well as member creativity (Lovelace et al., 2001; Sivasubramaniam et al., 2012) and the potential for knowledge recombination and subsequent technology development (Faems & Subramanian, 2013; van Beers & Zand, 2014). As such, technological diversity of an R&D consortium can be expected to lead to an increased likelihood of a consortium generating innovative outcomes.

Contrary to the positive effect of technological diversity on the likelihood of generating innovative outcomes, authors have argued that technological diversity has a detrimental effect on this likelihood. These authors challenge the assumption that consortium members display an unconditional willingness to share information. The variation in the range of knowledge, expertise and experience between members of an R&D consortium signals different functional areas, and with that different routines and logics. This can trigger social categorization and stereotyping amongst members (Bunderson & Sutcliffe, 2002; Dahlin, Weingart, & Hinds, 2005). Social categorization theory suggests that members seek to maintain high self-esteem through defining themselves in ways that lead to favorable social comparisons (Bunderson & Sutcliffe, 2002). When consortium members place themselves and other members into social groups based on functional background, and in turn attribute positive characteristics to their own group and negative characteristics to other groups, psychological safety can be diminished and stressful relationships initiated (Edmondson & Nembhard, 2009; Keller, 2001). As a consequence, social integration and member cohesion is hampered (Cohen & Bailey, 1997; Keller, 2001) and knowledge sharing is reduced (Bunderson & Sutcliffe, 2002; Edmondson & Nembhard, 2009; Mathieu, Maynard, Rapp, & Gilson, 2008).

When members refrain from sharing knowledge, a joint understanding of the developmental process is not created. Instead, different perceptions and interpretations will linger (Cronin & Weingart, 2007; Mooney, Holahan, & Amason, 2007), leading to issues in generating consensus (Lee & Chen, 2007; Lovelace et al., 2001; Montoya-Weiss, Massey, & Song, 2001) as well as an increased potential for conflict (Cronin & Weingart, 2007; Mathieu et al., 2008; Mohr & Puck, 2005; Mooney et al., 2007; Song & Montoya-Weiss, 2001). This, in turn, further attenuates the tendency of sharing knowledge by individual members, as the likelihood of understanding the value of doing so to the whole task decreases (Gardner, Gino, & Staats, 2011). Additionaly, from a desire to retain harmony members could get the tendency to minimize arguments and conform to majority views. As a consequence, the consortium will be less open to adverse information (Gemser & Leenders, 2011). Against this backdrop, the innovative potential of the consortium might be stiffled due to the process and efficiency losses and increased coordination costs associated with the consequences of a lack of joint understanding (Ancona & Caldwell, 1992; Kotha, George, & Srikanth, 2012; Mathieu et al., 2008; Milliken & Martins, 1996; Mohr & Puck, 2005; Sivasubramaniam et al., 2012).

We reconcile both views on the relation between technological diversity and the likelihood of generating innovative outcomes by R&D consortia as follows. First, low levels of technological diversity offer meagre opportunity for building a large and varied body of knowledge in the consortium, as members essentially draw upon the same knowledge base. This opportunity increases when the level of technological diversity increases. As the quantity and variety of knowledge available to the consortium increases, opportunities for creating new combinations are created. After a certain level of fuctional diversity, however, social categorization is triggered, and the development of a joint understanding of the development process is hampered. Here, the costs associated with getting all members at the same page outweigh the benefits of a large and diverse body of knowledge because the development process now is characterized by process and efficiency losses. Hence, consortia benefit most from technologically diverse members when diversity creates opportunities for new combinations but not so much as to prevent efficient joint understanding. We therefore argue that technological diversity bears a nonlinear relationship with the innovative outcomes of R&D consortia:

Hypothesis 4: R&D consortia with moderate levels of technological diversity will be more likely to generate innovative outcomes compared to R&D consortia with very low or very high levels of technological diversity.

The moderating role of network integration

As indicated earlier, network integration provides consortium members with an enhanced understanding of (1) the available knowledge components in a technology landscape and the corresponding knowledge interdependencies and (2) the joint perception of consortium members across the complete network of viable technological alternatives and possible future developments. It is especially the first aspect of network integration that affects the mechanism relating to the variety of knowledge available and that underlies the relation between technological diversity and the likelihood of generating innovative outcomes. Previous research has shown that when networks are included, the impact of technological diversity drops significantly. Hence, networks substitute for technological diversity of consortium members (Reagans et al., 2004): the joint and fast understanding of the development process by consortium members no longer arises from their varying backgrounds, but instead stems from the enhanced understanding of the technology landscape. This is especially salient when networks are integrated in such a way that a clearer picture of knowledge interdependencies within the technology landscape emerges. Therefore, knowledge recombination is shaped less by the different knowledge resources brought in by consortium members, and more by the available knowledge components in the technology landscape. In addition, problems in generating consensus will be mitigated, as search directions in the technology landscape are more clearly outlined (Song & Montoya-Weiss, 2001). Hence, we hypothesize that:

Hypothesis 5: The inverted-u shaped relationship between technological diversity of R&D consortia and the generation of innovative outcomes is mitigated by network integration in such a way that the curve is smoothened in situations of moderate network integration compared to situations of high or low network integration.

2.3 Data and methods

Research setting and data

To test the hypotheses developed in this chapter, we drew upon a larger data collection endeavour intended to generate data for multiple research projects. This involved collecting secondary data on 1,928 Dutch R&D consortia, each of which started in one of the years in the time frame 1981-2004. These consortia are funded by a technology foundation that was established with the aim of realizing knowledge transfer from excellent technical-scientific research. The assumption that has driven this foundation throughout the years is that even though generating innovative outcomes by any research focusing on R&D is inherently uncertain, collaboration between mutliple agents increases the chance of succes.

Ever since its conception, the foundation has provided research funds to a broad variety of consortia, focusing on technologies such as improved donor organs, cleaner waste water, lighter airplanes, more reliable bridges, better treatment of heart attacks, faster communication and more efficient solar panels (STW, 2016). Two main conditions under which funds are provided are (1) the research institution that applies for the consortium and the foundation jointly own the research results and (2) potential users of the research results have to demonstrate their commitment upfront by participating in a users committee. These committee members can originate from industry, but public organizations and other research institutions are likely participants as well. The minimum amount of meetings committee members should have is twice a year, but usually contacts take place outside these meetings (STW, 2016). Knowledge transfer with the purpose of mutual allignment, steering of the research project and in the end knowledge valorization is key during all these interactions. The technology foundation is held accountable for providing consortium funds, and hence issues a report on a yearly basis in which consortia that were funded 5 and 10 years ago are evaluated. In Appendix I of this chapter, we provide an example of such a consortium evaluation, as well as our approach towards converting the information from all evaluations into a relational database.

Our research interest is in predicting the likelihood of generating innovative outcomes by R&D consortia, using a model that considers features of the structural context in which these consortia are positioned and consortium features that represent the potential for knowledge transfer and knowledge recombination. The consortia funded by the technology foundation provide a suitable context for our research purpose for several reasons. The first reason is the geographical context. Although the Netherlands is a relatively small country, it is large enough to create enough variation in spatial concentration among consortium members. Consequently, the different contrasting mechanisms described with respect to the relation between geographical proximity and the generation of innovative outcomes are likely to be covered. Second, the spatial boundedness of our sample facilitates the formation of inter-consortium linkages. Relative to the number of consortia started and operated each year, the pool of potential committee members is limited. This implies that at any point in time, one or more members create links with other consortia through participation in more than one consortium. As a result, a consortium network emerges that acts as the representation of the structural context in our model. Third, a variety of partners can participate in the consortia, creating a technological diversity range that covers the contrasting mechanisms described with respect to that concept. Fourth, the pre-competitive nature of the R&D consortia keeps consortium members from claiming positions in the technology landscape through patenting, therewith putting a fence around that set of knowledge components (Mihm et al., 2015). Fifth, the innovative outcomes of consortia are measured five years after the start of a consortium, ensuring a causal relationship between the predictors and the outcome measure used. In addition, although the consortium information is provided by the consortium leader, the outcome is evaluated by a committee external to the consortium, taking away concerns of common method bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Lastly, the strong emphasis on knowledge transfer and utilization create the basic conditions for an innovative atmosphere.

We use the heuristic of a technology landscape in which members of R&D consortia engage in search procedures. Earlier research reports that the propensity to collaborate varies between sectors because of differences in the reliance on scientific knowledge among technologies (Hagedoorn, 2002; Peri, 2005; Tamada, Naito, Kodama, Gemba, & Suzuki, 2006). In addition, our theoretical arguments with respect to network integration draw on the exchange and integration of technological knowledge and information between consortia. We therefore considered only those inter-consortium ties as being relevant when both consortia were active in the same technology field. This network boundary specification step was accomplished through assigning each of the 1,928 consortia to a technology field, based on a classification scheme proposed by both Engelsman and van Raan (1994) and Schmoch (2008). Both authors developed a comparable classification scheme based on a translation from International Patent Classification (IPC) codes to more generic technology fields. Since a considerable amount of evaluation reports mentioned one or more patents as one of the consortium outcomes, we looked up the IPC codes of these patents via Espacenet. These codes were used for assigning consortia to one of the following subfields within the generic technology fields: Electrical engineering, Instruments, Medical technology, Chemistry, Life Sciences, Mechanical engineering or Civil engineering. When patent information was unavailable, we assigned projects to subfields based on an analysis of consortium description in the evaluation. Two researchers first coded all 1,928 consortia independently, and then compared results. In the event classification of a consortium differed, this difference was resolved through discussion between the coders. Appendices I and II in Chapter 5 provide more information as to the boundary specification procedure followed.

To operationalize network integration, networks were constructed based on technology field similarity: a joint member tie between consortia was considered only when both consortia belonged to the same technology field and had a joint membership tie in the first year of their existence. Because of this, and because of data incompleteness, not all 1,928 consortia were included in our final sample. First, 153 consortia did not contain information on committee members. These consortia were excluded from the dataset. Second, 141 consortia ended up as isolates in our network, and 40 consortia appeared in the network as dyads that were not connected to the main component. Because these consortia were not embedded in a technology landscape and to come to a fair calculation of complete network measures, these 181 consortia were excluded from the data set as well. Lastly, 331 consortia did not receive an explicit evaluation. The reason for this was that the technology foundation started using a structured evaluation approach as from the early 1990s. This means that consortia reported before could not be compared systematically. These consortia were excluded as well from the analysis, resulting in a total of 1,263 R&D consortia in our sample.

Measurements

Innovative outcomes. In this chapter, we consider an innovative outcome as a categorical outcome. As indicated earlier, an R&D consortium can generate an outcome that needs to be further developed, an outcome that can be considered a prototype, or an outcome that is fully realized. As the innovation process is fraught with uncertainties, we are especially interested in the likelihood of generating innovative outcomes by consortia. For each R&D consortium in our dataset, an evaluation of the technological outcomes is available. The evaluation is performed five years after a consortium's start and carried out by a committee of specialists. This committee is external to the consortium and appointed by the funding agency. In the original evaluations (see the three-letter code provided in the first block in Table 6), four distinct scores could be assigned to three dimensions, the second[4] of which refers to the technological outcome: 0 (failure), A (further research is necessary), B (a prototype has been developed) and C (substantial results were generated). We created a categorical outcome variable from the described outcome classification scheme. Because very few consortia were assigned the outcome score of 0, these scores were lumped with outcome category A. The other two categories (i.e. B and C) were left unchanged.

Network integration. Network integration in this chapter is defined as the extent to which search by members of R&D consortia in the technology landscape is targeted. We have identified two sources of network integration in serendipitous networks, which can be considered as equivalent to the two sources identified in research on whole networks. First, network integration can be achieved through mutual awareness between network members of what others are doing. Second, network integration can be achieved through a small amount of common thematic foci and efforts by prominent nodes to integrate knowledge. Following Provan and Milward (1995), these sources

[4] The first letter in this three-letter code refers to the involvement of members during the consortium, and as such can be considered an evaluation of the collaboration process. The last letter refers to a consortium's economic outcome. As the three dimensions are strongly correlated, we only focus on the evaluation of technological outcomes.

were captured by using two complementary measures: network density and network centralization. Whereas network density is an expression of the "connectedness" of consortia through joint members (indicating mutual awareness), network centralization expresses the extent to which these joint member ties are organized around one or more central consortia (indicating common thematic foci).

Both measures were calculated for the first year in which a consortium was embedded in the complete network. Network density was calculated by dividing the actual number of ties present in a network by the total number of theoretically possible ties in that network (Scott, 2000). Ties in the consortium networks studied in this chapter were undirected. For calculating network centralization, we selected network degree centralization: out of the three centralization measures delineated by Freeman (1978), this measure is closest to reflecting transmission of knowledge and information, as opposed to betweenness centralization (focus on control) or closeness centralization (capturing independence). We normalized all degree centrality scores that were used as an input for calculating degree centralization, to account for differences in network size. When a network consisted of multiple components, we first calculated degree centralization for each component individually, and then a weighted average based on component size was calculated. When performing these calculations, use was made of the functionality available in the statnet suite (Goodreau, Handcock, Hunter, Butts, & Morris, 2008) available in the R statistical environment (R Development Core team, 2016). Table 1 displays the basic descriptive statistics per technology field for the resulting centralization and density scores.

TABLE 1

Network descriptives per technology field

Technology field	Density				Centralization			
	Mean	s.d.	Min	Max	Mean	s.d.	Min	Max
Chemistry………………....	.23	.05	.17	.32	.38	.06	.29	.47
Civil engineering………......	.32	.04	.26	.43	.31	.08	.18	.42
Electrical engineering……..	.36	.06	.28	.47	.32	.03	.27	.36
Instruments……………….	.16	.03	.13	.21	.24	.04	.17	.34
Life sciences………………	.12	.03	.09	.20	.20	.04	.15	.29
Mechanical engineering…...	.27	.11	.16	.57	.36	.13	.17	.72
Medical technology……….	.21	.04	.15	.27	.34	.07	.24	.45

As a last step, we used the continuous centralization and density variables to create network integration dummies. Even though this implies loss of detailed information about the variation in values on both variables, we believe that dummies are a fairer representation of network integration. One of the reasons for this is that -as earlier indicated- network integration is an ill-defined concept. Not only does this make interpretation of absolute density and centralization scores difficult, another consequence is that the narrative surrounding the concept is characterized by rather binary distinctions. One of the dimensions that we identified, for example, was that integration is reached when there is mutual awareness between network members of what others are doing. This implies that a network does not get integrated when, relative to its size, only few members recognize what others are doing, no matter how small ‘few’ exactly is. Instead, a network becomes integrated when this ‘few’ turns into the majority of, or even all network members. Therefore, even though nuances might exist, we consider differences between networks within certain states of integration as less meaningful compared to differences between networks in different integration states. Another reason is that by constructing dummies, we can explicitly consider the effect of different types of integration: integration can be either density-based, centralization-based or both. By using a continuous interaction term in the analysis, especially the distinction between the first two types of integration would be lost.

Table 2 shows our approach to determining network integration dummies. Based on means and standard deviations of both centralization and network density, five distinct categories were created. For example, when within a field network both centralization and density scores of a network were lower than the mean minus the standard deviation of that field network, the label ‘low integration’ was assigned. Based on all other possible combinations, dummies were constructed that represented ‘average integration’, ‘high integration’, ‘density-based integration’ and centralization-based integration’. The reference category was the ‘average integration’ category. Whereas ‘low integration’ and ‘high integration’ form the extreme categories, ‘density-based integration’ and ‘centralization-based integration’ represent network integration based on one of the two dimensions identified. Lastly, the ‘average’ category represents networks that are not pronouncedly integrated. Network integration dummies represent the type of network integration in the first year a consortium is embedded in the network.

TABLE 2

Determination of network integration types

<table>
<tr><th></th><th></th><th colspan="3">Density</th></tr>
<tr><th></th><th></th><th>< Mean - s.d.</th><th>Mean ± s.d.</th><th>> Mean + s.d.</th></tr>
<tr><td rowspan="3">Centralization</td><td>< Mean - s.d.</td><td>low integration</td><td></td><td rowspan="2">density-based integration</td></tr>
<tr><td>Mean ± s.d.</td><td rowspan="2">centralization-based integration</td><td>average</td></tr>
<tr><td>> Mean + s.d.</td><td></td><td>high integration</td></tr>
</table>

Geographical proximity. This measure captures the extent to which consortium members are spatially concentrated. To calculate it we followed the approach by Gibson and Gibbs (2006) and van Beers and Zand (2014). First, for all consortia information was available about the member’s residences. Using this information, each member was in turn assigned to one of the 12 Dutch provinces. In the rare event one of the members originated from another country, this member was assigned to the category ‘other’. Geographical proximity in turn was calculated using the formula $1 - \sum_{ij}(PA_{ij})^2$, where PA_{ij} is the proportion of members that belong to province *j*. Because more different provinces lead to a higher score of the index (the second term in the formula), this index is subtracted from 1 to cover similarity between members. Due to differences in consortium size, the obtained proximity scores could not be directly compared with one another (Biemann & Kearney, 2009). To account for these differences, we applied the rescaling procedure outlined by (Solanas, Selvam, Navarro, & Leiva, 2012). The resulting measure reflects member geographical proximity during the consortium.

Technological diversity. We defined technological diversity as the variety in the range of knowledge, expertise and experience between consortium members. As a first step in constructing the corresponding measure, we assigned SIC-codes to all members. This is an often followed approach in alliance research (Lavie et al., 2007; Schilling, 2009). An issue with the resulting classification was that it led to a rather fine-grained classification. This hampered making a meaningful distinction between members. As a second step, we therefore translated each industry that is covered by one of the SIC-codes to one of the five Pavitt sectors (Pavitt, 1984): supplier-dominated, specialised suppliers, science-based, scale-intensive or information intensive firms. Pavitt's taxonomy is devoted to classifying firms on the grounds of their technological competence (Archibugi, 2006), and considers the nature, sources and patterns of innovation (Bogliacino & Pianta, 2016). As such, it is a useful representation of consortium members' different technological backgrounds. Using the resulting Pavitt classification, an index equivalent to geographical proximity was calculated, using the formula $\sum_{ij}(PA_{ij})^2$, where PA_{ij} is the proportion of members that belongs to Pavitt sector *j*. Here, the term is not subtracted from 1 to cover differences between members instead of similarity (as is the case for geographical proximity). The resulting index has been claimed to be one of the most accepted measures of diversity in the economic literature (Baum, Calabrese, & Silverman, 2000; van Beers & Zand, 2014). We followed a similar procedure as outlined for geographical proximity for normalizing this measure. The resulting measure reflects member technological diversity during the consortium.

Control variables. Several controls were included in our analysis. First, we included *size* of the consortium as a control. Size is associated with the level of resources available to a consortium (de Vaan, Vedres, & Stark, 2015; Kotabe & Scott Swan, 1995; van Beers & Zand, 2014), and hence can be expected to have a positive effect on the generation of innovative outcomes. This control variable was determined by counting 1 (the research institution with which the project leader was affiliated with) plus the number of user committee member organizations. Second, we included *duration* in years as a control variable. Even though time is not of specific interest in this chapter, especially the limited availability of it has been argued to play a key role in multi-partner collaborations such as R&D consortia (Bakker, DeFillippi, Schwab, & Sydow, 2016). Duration was measured in years. Especially in early years, detailed information was given on project's start and end dates. For more recent projects, the website of the funding agency proved to be a valuable resource. In cases where no information about the start and end date was given, the start date was deducted from the year in which the report was issued, and the end year was estimated using the average project duration of all project for which this information was available. Third, the level of *financial resources* was included as a control. This variable captures the funds provided by the technology foundation and -being an indication of general commitment to the consortium (Sakakibara, 2002)- controls for the likelihood to affect the consortium's output (Vaarst Andersen, 2013). Financial resources were measured in 2012 euro's (*1,000). The fourth control variable is *consortium leader experience.* This variable captures the learning effect that is at play when a consortium leader gets more efficient in organizing and executing activities in R&D consortia (Faems, Van Looy, & Debackere, 2005; Goerzen, 2007; Hoang & Rothaermel, 2005; Pangarkar, 2009), as well as more experienced in technology utilisation (Hoye & Pries, 2009). The variable is determined by counting the total number of R&D consortia a consortium leader has executed in the five preceding years. The fifth control variable is that of *member relational experience.* Members who have interacted with one another repeatedly are less prone to opportunistic behaviour (Goerzen, 2007; Sakakibara, 2002), build trust (Gulati, 1995) and shared routines (Goerzen, 2007) and get embedded in a network that they can tap from (Lin, Fang, et al., 2009; Mannak, 2015; Sakakibara, 2002). This variable is determined by counting the total number of members a consortium leader has collaborated with in the five preceding years. The last control variable included in our analysis is that of *multiple consortium membership*. Lavie et al. (2007) outline two distinct advantages of being involved in multiple multi-partner alliances for individual members that also can be argued to reflect on the consortium. First, by having members that are exposed to R&D activities conducted in other consortia, multiple consortium membership can lead to a better grasp of overall technological challenges and their possible solutions. Second, by creating awareness of technological developments in other consortia, multiple consortium membership offers opportunities for technological integration, for example in terms of complementarity (combining a core technology with peripheral components, or vice versa) and interoperability (ensuring that a technology works well with other technologies). Both advantages are value enhancing, as they increase the chance of a technology becoming (part of) a dominant design (Lavie et al., 2007). In addition to these two technological advantages, the literature on multiple team membership suggests advantages in terms of collaboration efficiency as well. Involvement in multiple consortia prompts members to adopt more efficient collective work practices, as the time and availability of individual members is limited. This has been argued to result in a more effective use of inputs and gains in processing time, implying a higher potential for generating innovative outcomes (Kolodny, 1979; O'Leary, Mortensen, & Woolley, 2011). Multiple consortium membership was determined as the number of links to different consortia, therewith ignoring the number of joint members responsible for these links. Based on the earlier discussed consortium networks, degree centrality for each consortium in the first year of its embeddedness in the consortium network was determined. This was calculated using the statnet suite (Goodreau et al., 2008) available in the R statistical environment (R Development Core team, 2016). The first three controls (i.e. size, duration and financial resources) reflect the respective consortium features during the consortium. The controls consortium leader experience, member relational experience and multiple consortium membership were determined for the first year of the consortium.

Data analysis

Two characteristics of the dataset determined the selection of our analytical method. First, based on earlier observations that collaboration propensity varies between sectors as a consequence of differences in reliance on scientifc knowledge among technologies (Hagedoorn, 2002; Peri, 2005; Tamada et al., 2006), we specified 7 distinct technology fields and constructed consortium networks for each of these fields. Indeed, as can be seen in Table 1, marked differences in network organization exist between technology fields. This reflects differences between fields in, for example, common primary motivations (Martin, 2003), institutional contexts (Dimaggio & Powell, 1983), or innovation speed. Hence, by delineating different fields, we account for the fact that consortium outcomes might vary simply because search activities are conducted in different technology landscapes. Because of the resulting "nestedness" of consortia within technology fields, a multi-level modelling approach is advisable: although consortia will vary in terms of geographical proximity and technological diversity, network integration is the same for all consortia embedded in a certain network in a certain year. As a consequence, information about the effect of the network in which consortium A resides, for example, also provides meaningful insights about the effect of this network on consortium B (Holcomb, Combs, Sirmon, & Sexton, 2009). Multi-level analysis accounts for these resulting interdependencies between observations, which would violate the assumption of, for example, ordinary least square regression (Gelman & Hill, 2007; Gujarati &

Porter, 2009; Hox, 2010). The second characteristic of our data is that the dependent variable is categorical. Hence, an OLS-based analytical method is not justified here (Pampel, 2000). Taking both aspects into account, we have selected a multilevel binary logistic regression to test our hypotheses.

The general modelling approach consisted of two components: first, an ordinal logistic regression with 1,263 data points was conducted for the dependent variable of interest, predicting the outcome at *t+5* using both consortium and network-level predictors, either at *t*, or relating to the whole duration of the consortium. Intercepts could vary[5] by technology field and year. This intercept was estimated for each field and year combination by the second component of the model, which is an ordinal logistic regression with 112 data points (7 technology fields × 16 years) using network and year-level predictors. Five distinct models were estimated. Model 1 only models the intercepts across technology fields and years. Next to functioning as the baseline model for assessing improvement in the fit of more elaborate models, it also provides insight in the proportion of variance in the data that can be explained by consortia simply being grouped in different technology fields and years. Models 2-5 gradually build up to the complete model, where Model 2 includes all control variables, Model 3 adds the network-level predictors, Model 4 includes the consortium-level predictors and Model 5 includes all interactions. Based on this latter model, inferences about our hypotheses were made. We used the 'ordinal'-package (Christensen, 2011) for estimating our models. To aid model interpretation, effect plots were created for all significant effects in the full model, as well as significant cross-level interactions using the ´effects´-package developed by Fox (2003). This package calculates marginal effects of a predictor of interest at the average of all other predictors. Both packages were implemented in the R statistical environment (R Development Core team, 2016). For interpretation and comparison purposes and to aid model convergence, all predictor variables were scaled using the default scale function available in R (default settings were used). All pictures in this chapter were made using the 'ggplot2'-package (Wickham, 2009) available in R.

2.4 Results

Descriptives and correlations

Means, standard deviations and the minimum and maximum observation per variable are shown in Table 3 for the consortium-level variables, and Table 4 for the network-level variables. It should be noted that correlations at the consortium level do not consider non-independence within the data, and therefore should be interpreted with caution. Of special interest are predictors that are highly associated with one another (if this is the case, multicollinearity could lead to difficulties in estimating precise standard errors for the regression coefficients (Gujarati & Porter, 2009)), large standard deviations (indicating the presence of outliers that might mainly drive significant results in the regression analysis) and peculiarities with respect to the distribution of variables (Zhang & Shaw, 2012).

[5] A plethora of interpretations has emerged over the years with respect to the terms 'fixed' and 'random' effects. In an illustrative overview, Gelman and Hill (2007) identify 5 distinct interpretations that have been used in different research fields, and advise to abandon the terms at all in order to not further exacerbate confusion. We give follow-up to this advice in this chapter and indicate for our analyses which of the two main elements in the model that is to be estimated (i.e. intercept and slope) can vary across time and technology fields.

TABLE 3

Descriptives and correlations among consortium-level variables[6]

Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8
1. Innovative outcomes$_{t+5}$………………	1.99	.78	1	3	-							
2. Size…………………………………..	4.61	2.50	1	24	.11**	-						
3. Duration……………………………..	4.28	1.04	1	15	.04	.03	-					
4. Financial resources…………………...	535.32	340.92	1.14	3,738.36	.08**	.21**	.28**	-				
5. Consortium leader experience$_t$………..	1.13	1.78	0	11	.06*	.05	.02	.01	-			
6. Member relational experience$_t$………..	1.14	2.35	0	16	.03	.17**	-.02	.02	.68**	-		
7. Multiple consortium membership$_t$……	.22	.18	.01	1	-.05	.24**	.01	.08**	-.00	.07*	-	
8. Geographical proximity……………...	.26	.28	0	1	-.04	-.29**	.03	-.06*	-.04	-.07*	-.07*	-
9. Technological diversity………………	.64	.30	0	1	.02	.34**	-.00	.03	-.02	.06*	.13**	-.31**

[6] n = 1,263. $^{**}p < .01$; $^{*}p < .05$.

TABLE 4

Descriptives and correlations among network-level variables[7]

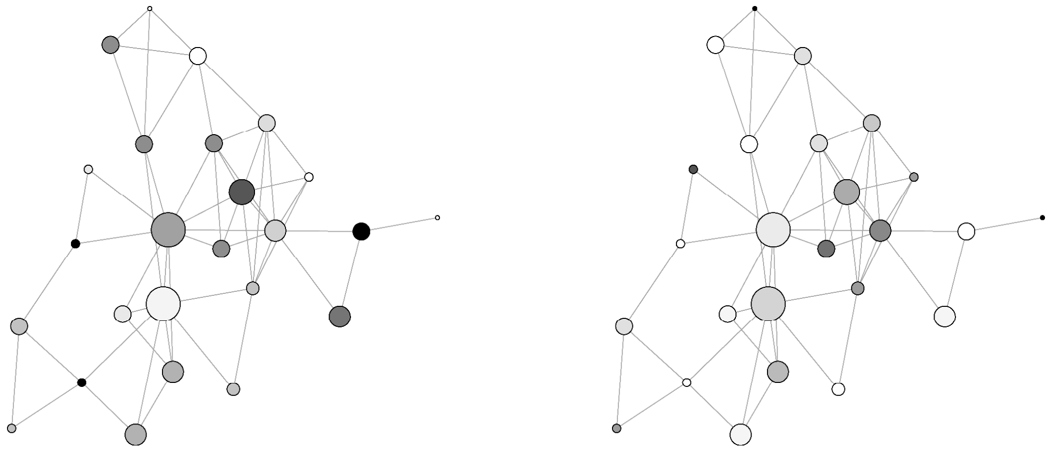
Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1. Chemistry……………………………	.19	.40	0	1	-										
2. Civil engineering……………………..	.06	.24	0	1	-.13**	-									
3. Electrical engineering………………...	.18	.38	0	1	-.23**	-.12**	-								
4. Instruments…………………………	.18	.39	0	1	-.23**	-.12**	-.22**	-							
5. Life sciences………………………..	.24	.43	0	1	-.28**	-.15**	-.26**	-.27**	-						
6. Mechanical engineering………………	.04	.20	0	1	-.10**	-.05	-.10**	-.10**	-.12**	-					
7. Medical technology…………………..	.10	.29	0	1	-.16**	-.08**	-.15**	-.15**	-.18**	-.07*	-				
8. Year…………………………………	1996.98	4.47	1989	2004	-.00	-.07*	.05	-.07*	-.03	.04	.01	-			
9. Low integration$_t$……………………...	.08	.27	0	1	.11**	-.00	-.14**	.18**	-.17**	-.01	.04	.17**	-		
10. Density-based integration$_t$…………..	.18	.39	0	1	.07**	.06*	.13**	-.07*	-.16**	.06*	-.03	-.21**	-.14**	-	
11. Centralization-based integration$_t$……	.17	.38	0	1	.11**	.09**	.23**	-.16**	-.26**	.00	.07**	.04	-.13**	-.22**	-
12. High integration$_t$……………………	.10	.30	0	1	.03	-.09**	-.16**	.04	.16**	-.06*	-.00	-.28**	-.10**	-.16**	-.15**

7 $n = 112$. $^{**}p < .01$; $^{*}p < .05$. The reference category for the integration dummies is 'Average integration'.

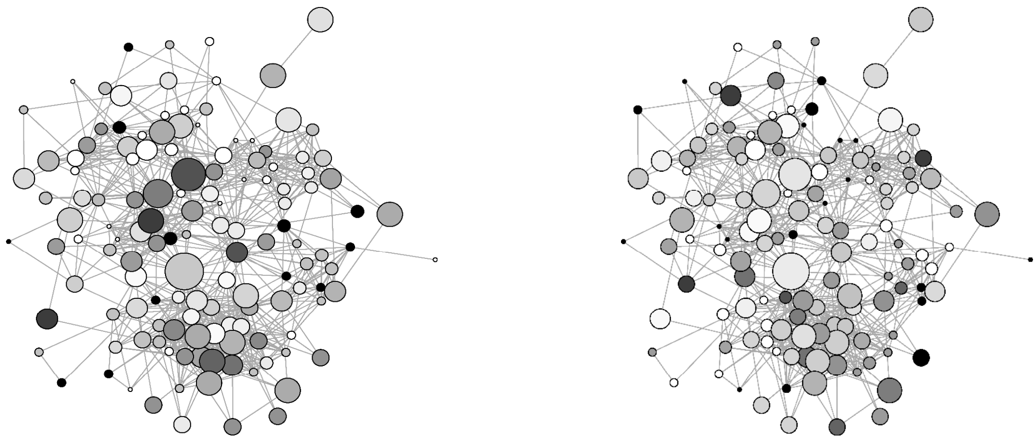
FIGURE 2

Examples of different forms of network integration[8]

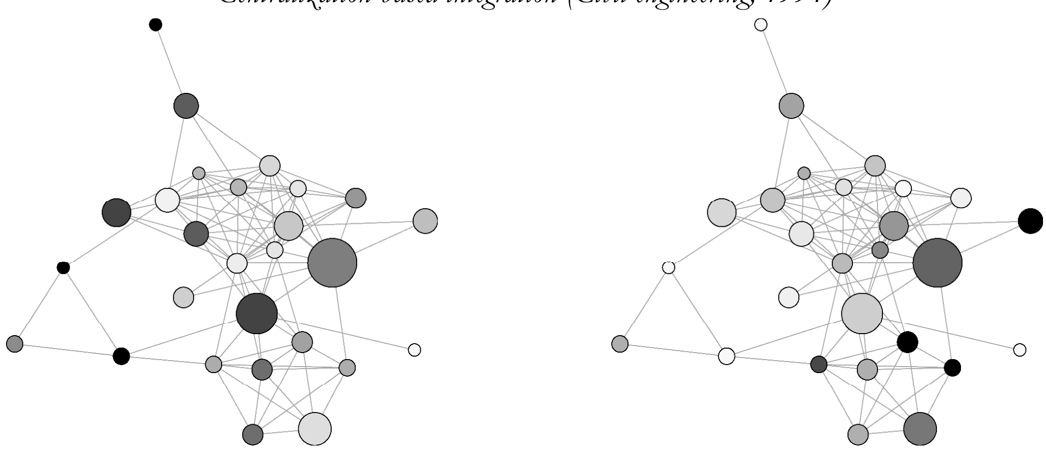
Low network integration (Medical Technology network, 1990)



Density-based integration (Life Sciences network, 1998)



Centralization-based integration (Civil engineering, 1994)

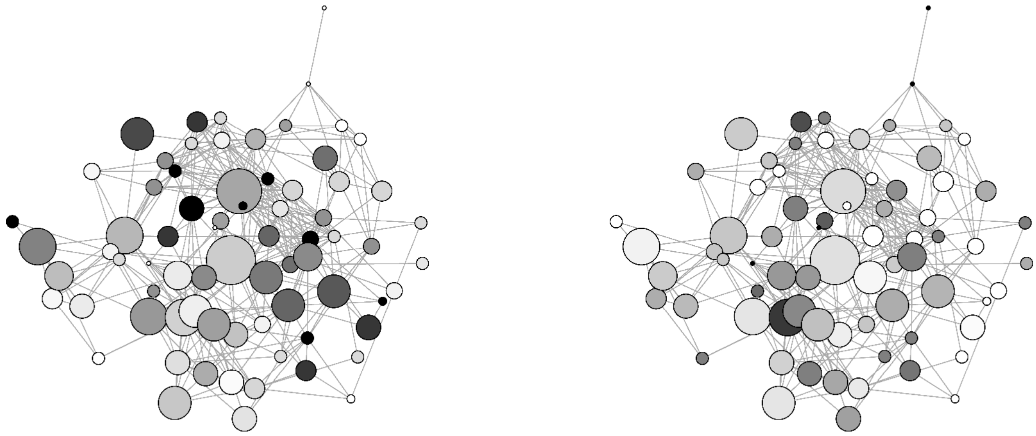


[8] Key to all examples: node size indicates consortium size, node colours (darker is higher) indicate levels of technological diversity (left) and geographical proximity (right).

FIGURE 2 (CONTINUED)

Examples of different forms of network integration[8]

High network integration (Instruments, 2000)



Except for a positive correlation with size ($r = .06$, $p < .05$). and financial resources ($r = .06$, $p < .05$), the dependent variable 'technological outcomes' does not show any significant associations with the consortium-level variables. Especially interesting are the zero correlations between technological outcomes and geographical proximity and technological diversity respectively, indicating an absence of a linear relationship but not excluding the possibility of the hypothesized non-monotonic associations. As mentioned in earlier studies (Hinds & Bailey, 2003), the correlation between geographical proximity and technological diversity ($r = -.31$, $p < .01$) reflects the phenomenon that higher technological diversity often goes hand in hand with spatial distribution. With respect to the control variables, especially the associations between the size of the consortium and technological diversity ($r = .34$, $p < .01$) and geographical proximity ($r = -.29$, $p < .01$) catch the eye. Intuitively, however, it makes sense that larger consortia are more likely to be diverse both in terms of functional background and geographical distribution. This is also illustrated by the already mentioned high correlation between technological diversity and geographical proximity. Salient is the correlation between member relational experience and consortium leader experience ($r = .68$, $p < .01$): over time, members tend to cluster around consortium leaders that are more experienced. Both variables have relatively large standard deviations indicating substantial variation in terms of both types of experiences in our dataset.

From Table 4 we infer from the mean values of the first 7 variables that the different technology field networks differ in size. Also, many significant correlations exist between technology fields and the network integration dummies. The correlation coefficient between the technology field 'Electrical engineering' and the dummy for 'Centralization-based integration' ($r = .23$, $p < .01$) is an example of this: relative to the 'Average integration' category, the centralization-based category of network integration is observed more often in the field of Electrical engineering. This suggests that the different forms of network integration are not equally distributed across technology fields. In addition, significant correlations can be found between the year variable and the integration dummies, with the exception of the dummy for 'Centralization-based integration'.

TABLE 5

Results of multilevel ordinal logistic regression models predicting *p*(technological outcomes$_{t+5}$)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
[Innovative outcome = prototype]…..	-.94*** (.19)	-.97*** (.20)	-.87*** (.21)	-.88*** (.21)	-.90*** (.22)
[Innovative outcome = product]……..	.83*** (.19)	.84*** (.20)	.94*** (.21)	.94*** (.21)	.96*** (.22)
Controls					
1. Size………………………………....		.20*** (.06)	.21*** (.06)	.23*** (.07)	.24*** (.07)
2. Duration…………………………...		.02 (.06)	.02 (.06)	.03 (.06)	.04 (.06)
3. Financial resources……………….....		.16** (.06)	.15* (.06)	.15* (.06)	.14* (.06)
4. Consortium leader experience$_t$……..		.08 (.07)	.08 (.07)	.07 (.07)	.06 (.08)
5. Member relational experience$_t$……...		-.06 (.07)	-.05 (.07)	-.05 (.07)	-.04 (.07)
6. Multiple consortium membership$_t$…		-.22*** (.06)	-.24*** (.06)	-.23*** (.06)	-.24*** (.07)
Network-level predictors[9]					
7. Low integration$_t$…………………....			-.00 (.22)	-.00 (.22)	-.10 (.25)
8. Density-based integration$_t$…………			.35* (.17)	.35* (.17)	.36* (.18)
9. Centralization-based integration$_t$…..			.18 (.16)	.19 (.16)	.20 (.16)
10. High integration$_t$………………….			.02 (.22)	.03 (.22)	.02 (.22)
Consortium-level predictors					
11. Geographical proximity…………..				-.30 (.19)	-.54† (.28)
12. Geographical proximity^2…………				.28 (.20)	.42 (.30)
13. Technological diversity…………...				.11 (.20)	-.07 (.29)
14. Technological diversity^2…………..				-.17 (.20)	.13 (.29)
Cross-level interactions					
15. 7 × 11…………………………….					1.11 (.72)
16. 7 × 12…………………………….					-.79 (.79)
17. 7 × 13…………………………….					.58 (.97)
18. 7 × 14…………………………….					-.20 (.83)
19. 8 × 11…………………………….					-.16 (.58)
20. 8 × 12…………………………….					.26 (.61)
21. 8 × 13…………………………….					1.68** (.65)
22. 8 × 14…………………………….					-2.03*** (.61)
23. 9 × 11…………………………….					.45 (.49)
24. 9 × 12…………………………….					.00 (.53)
25. 9 × 13…………………………….					-.14 (.53)
26. 9 × 14…………………………….					.00 (.51)
27. 10 × 11…………………………...					-.06 (.73)
28. 10 × 12…………………………...					-.12 (.71)
29. 10 × 13…………………………...					-.27 (.73)
30. 10 × 14…………………………...					-.27 (.72)
Deviance	2,690	2,656	2,651	2,647	2,609
Δdf	-	6	10	14	30
p (> χ^2)	-	.00***	.00***	.00***	.00***
Year variance	.14	.15	.16	.16	.20
Technology field variance	.16	.16	.17	.17	.19

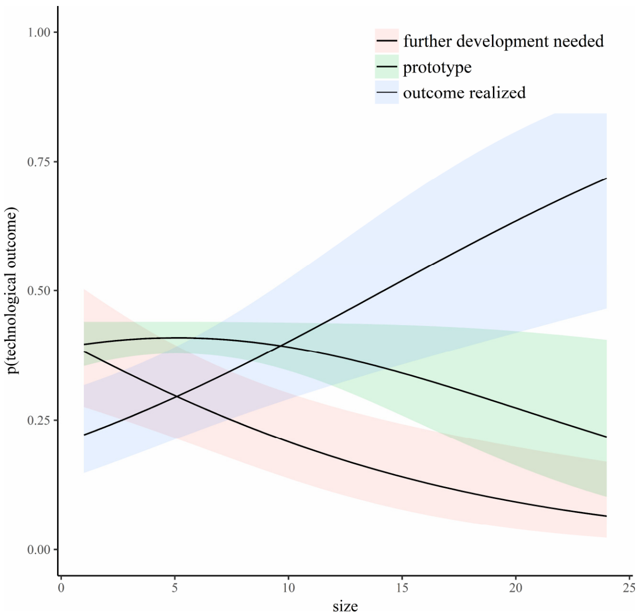
note: n = 1,263. Multilevel specification used in all models accounting for the levels *years* (*n* = 16*)* and *technology fields* (*n* = 7*)*. Standard errors displayed between parentheses. ***p < .001; **p < .01; *p < .05; †p < .1

[9] The reference category is 'Average network integration'.

FIGURE 3

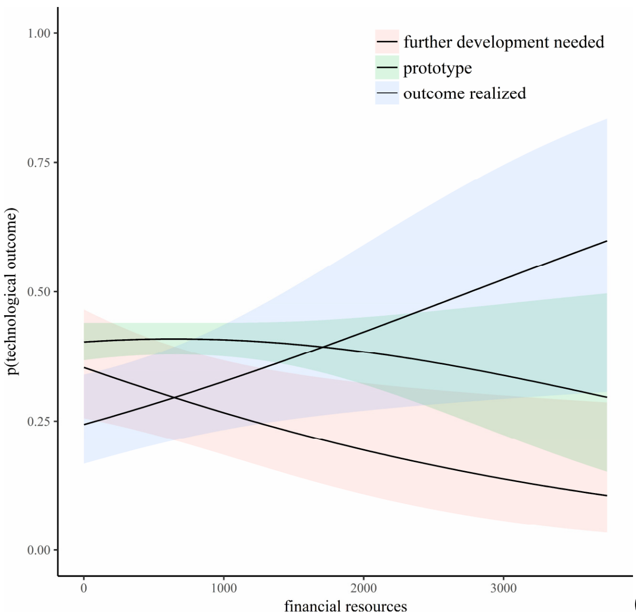
Marginal effects for significant coefficients

Size



(a)

Financial resources

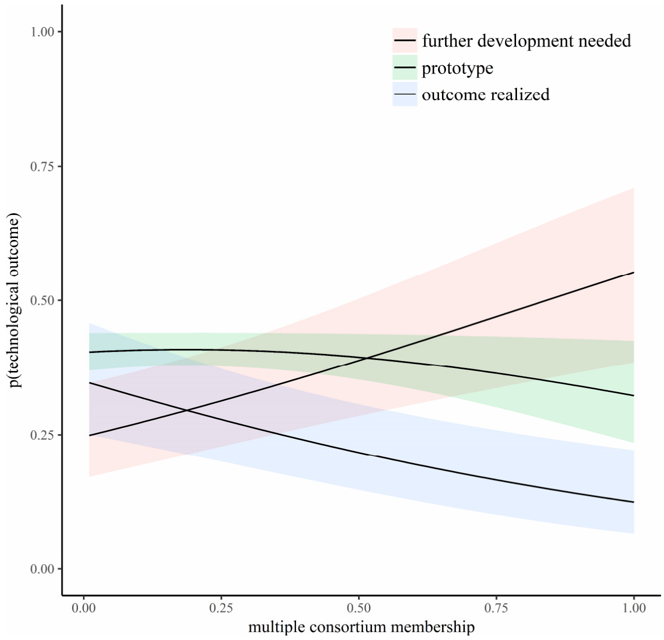


(b)

FIGURE 3 (CONTINUED)

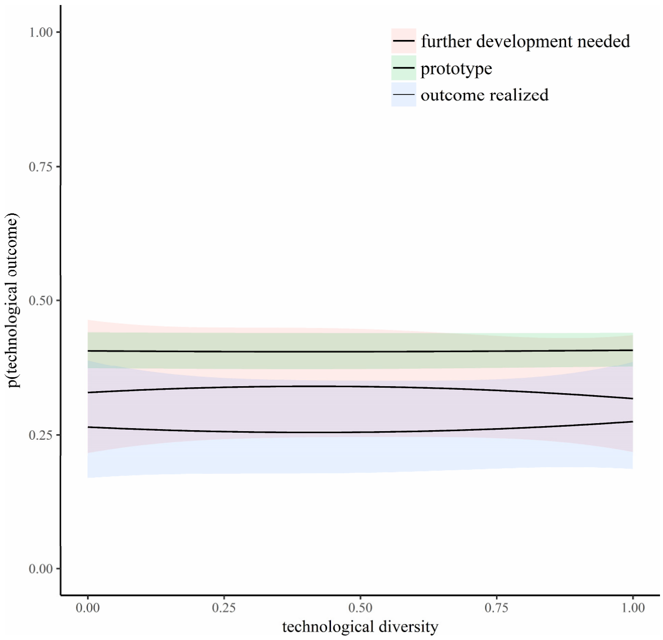
Marginal effects for significant coefficients

Multiple consortium membership



(c)

Technological diversity, average network integration

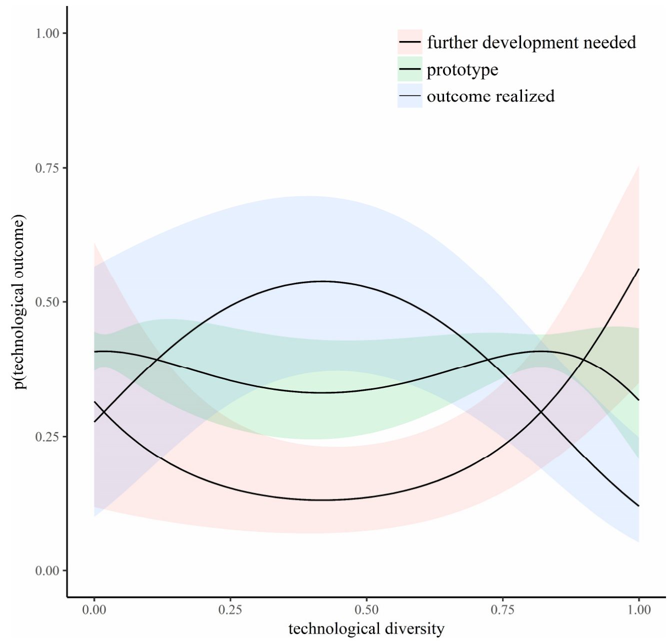


(d)

FIGURE 3 (CONTINUED)

Marginal effects for significant coefficients

Technological diversity, density-based network integration



(e)

This implies that network integration forms either come into existence over time, or instead disappear as time progresses. To provide the reader with a sense of what the different types of network integration look like, Figure 2 presents examples per network integration type.

Ordinal logistic regression results

The results of the multilevel logistic regression analysis are reported in Table 5. Complementary to this table, we display marginal effect plots in Figure 3 based on Model 5. These plots show the marginal effects for significant variables in this model. All predictor variables were standardized to aid model convergence. Hence, variables are standardized to have a mean of 0 and a standard deviation of 1. Consequently, each coefficient in Table 5 represents the change in log odds when the corresponding predictor changes one unit, holding all other explanatory variables at their average value. For each significant predictor, Figure 3 displays the probabilities derived from these coefficients for the full ranges of these predictors, holding all other predictors at their average. Before the results of the hypotheses tests are presented, we first consider (1) intraclass correlations and model variance, and (2) model fit.

A useful property of Model 1 is that it provides an estimate of the intraclass correlation (ICC) (Hox, 2010). This ICC indicates the proportion of the variance explained by the grouping structure in the population and can be interpreted as the expected correlation between two randomly drawn consortia in the same technology field or same year. As such, it is sometimes used to 'justify' the additional cost of using multilevel modelling. Because the network integration dummies are the same for consortia in the same technology field and year, a multilevel model is needed in any case, because the assumption of independence between observations when estimating a classical OLS regression model is violated. Hence, our aim is not to justify the choice of a multilevel model, but instead to provide insight in the extent of variation in the generation of innovative outcomes that can be explained by a consortium being grouped in a technology field or year. The ICC is calculated by dividing the variance of one of the groups by the total variance, which is the sum of the group variance and the residual variance. This residual variance in multilevel logistic regression models is fixed to approximately $\pi^2/3$ (Hox, 2010). Hence, the ICC for technology fields is (.16/3.45) 4.64% and the ICC for years is (.14/3.43) 4.08%. Although seemingly small, especially the ICC for technology fields is in the usual ICC range observed in other studies that apply multilevel models (Aguinis, Gottfredson, & Culpepper, 2013; Hox, 2010).

Additional insight in the extent of variation between groups in the generation of innovative outcomes can be obtained by examining the technology field and year intercepts. By doing so, we can see how consortia in different fields compare to one another with respect to the average likelihood for generating innovative outcomes. Recalculating these field intercepts to probabilities, this comparison results in (from largest to smallest probability): 67% (Medical technology), 54% (Instruments), 53% (Civil engineering), 53% (Electrical engineering), 48% (Mechanical engineering), 39% (Life sciences), and 37% (Chemistry). Hence, consortia in fields in which the focus is on developing instruments generally are more innovative compared to engineering-based consortia. In their turn, engineering-based consortia are more innovative compared to science-based consortia. With respect to year intercepts (1989-2004), the maximum probability is 63% (1994), the minimum probability is 23% (2000), and the standard deviation is 9%. When plotted (not displayed), probabilities gradually increase during the time frame 1989-1995, then decline between 1996 and 2000. From 2000 to 2001 a steep increase is observed, after which the value of the intercept stabilizes from 2001-2004. From this pattern, we deduce that temporality in the likelihood of innovative outcomes occurs.

Contrary to what one would expect based on classical regression models, adding predictors actually increases the variance terms. This is considered non-problematic in multi-level models (Gelman & Hill, 2007). The phenomenon can be best understood when one focuses on the intercept-only model (Model 1) in Table 5. This model predicts the threshold coefficients that denote where the (latent) dependent variable is cut to delineate the three groups that are observed in the dependent variable. In addition, the model decomposes the variance in three independent components: the variances at the technology field and year level, and the variance at the consortium level (labeled 'residual variance') (Hox, 2010). Because of the lack of predictors in the model, offsetting between variation across levels is possible (Gelman & Hill, 2007). The more predictors are added, the more the 'true' variance at each level might be revealed, causing one or more variance terms to increase. This behaviour of variance terms across models is problematic for assessing model fit (Hox, 2010; Snijders & Bosker, 1999). For this purpose, we therefore focus at the model deviances. Reported in Table 5 are the results of model χ^2 tests that compare the difference in the deviance of Models 2-5 vis-à-vis Model 1. From these tests, it can be deducted that each of the models fits the data significantly better than the baseline model. We will now discuss the outcomes of our hypotheses tests using the results of Model 5.

In general, the results suggest that both features of the technology field and R&D consortium features, as well as interactions between both predict the likelihood of a consortium generating innovative outcomes. Our results are not conclusive, however, and offer several insights that were not expected based on our theorizing. Our first hypothesis predicted that R&D consortia embedded in moderately integrated networks will be more likely to generate innovative outcomes compared to R&D consortia embedded in lowly or highly integrated networks. An indication of a curvilinear relationship would be if the dummies representing density-based integration and centralization-based integration would be higher compared to the reference category, which represents networks that are not pronouncedly integrated. In addition, the dummies for low and high integration should not be significant either, as then networks that fall in both categories have a similar effect on consortia compared to the average category. We deduct from Table 5 that the latter is indeed the case. In addition, consortia embedded in networks characterized by density-based network integration are more likely to generate innovative outcomes. The positive coefficient ($.36^*$ (.08)) means that, compared to the reference category, R&D consortia embedded in networks integrated through mutual awareness between network members on average have a 59% higher probability ($e^{.36}/(1+ e^{.36})$) to generate innovative outcomes. The dummy for centralization-based network integration is not significant. All in all, under conditions of moderate network integration, especially because of mutual awareness across consortia, a clearer picture of viable research directions in the technology landscape emerges, having a beneficial effect on the likelihood of generating innovative outcomes by consortia. Hence, hypothesis 1 is supported in as far as density-based network integration is concerned. For centralization-based network integration, it is rejected.

We expected that consortia benefit most from geographically proximate members when proximity enables higher quality knowledge transfer, but not so much as to prevent consortium members from becoming inert. We therefore hypothesized an inverted u-shaped relationship between geographical proximity and the probability of an R&D consortium generating innovative outcomes. None of the coefficients for geographical proximity are significant at the 5%-level, which suggests the absence of a salient non-linear relationship. Even though a weakly significant negative relationship between geographical proximity and the probability of an R&D consortium generating innovative outcomes is suggested by our analysis, we do not find support for hypothesis 2.

Hypothesis 3 predicts that the curvilinear effect of geographical proximity on the likelihood of generating innovative outcomes would be amplified under conditions of moderate network integration. Even though our test of hypothesis 2 did not provide evidence of a curvilinear association between proximity and innovation at all, it could still be the case that under conditions of moderate network integration this curvilinear association appears. The relevant cross-level interactions that shed light on this question are the interactions numbered 19, 20, 23 and 24. None of these interactions is significant at the 5% level, hence we do not find support for our third hypothesis.

We expected that consortia benefit most from technologically diverse members when diversity creates opportunities for new combinations but not so much as to prevent efficient joint understanding. Our fourth hypothesis therefore predicts an inverted u-shaped relationship between technological diversity and the probabilty of a consortium generating innovative outcomes. However, the corresponding coefficients in Table 5 are not significant at the 5% level (.-.07 (.29) and .13 (.29)). Hence, we do not find support for hypothesis 4.

Hypothesis 5 predicts that the inverted-u shaped relationship between technological diversity and the probability of a consortium generating innovative outcomes is smoothened by network integration in such a way that the effect of technological diversity dissapears under conditions of moderate network integration. Our results suggest the opposite: the hypothesized relationship actually appears under the condition of density-based network integration and is absent when other forms of integration are considered: panels (d) and (e) in Figure 3 suggest that under the condition of average network integration, no association between technological diversity and the probability of generating innovative outcomes exists (panel (d)). An association appears, however, under the condition of density-based network integration: at both low and high levels of technological diversity, a low likelihood of an R&D consortium generating innovative outcomes is observed. However, at intermediate levels of technological diversity, we observe the highest likelihood of an R&D consortium generating innovative outcomes (panel (e)). The corresponding coefficients in Table 5 suggest the existence of this inverted u-shaped relationship under the condition of density-based network integration as well (1.68^{**} (.65) and -2.03^{**} (.61)). Following Haans, Pieters, and He (2016), we modelled this non-linearity using a multilevel ordinal logistic spline regression model. The results of this regression are that the slope in the low range of technological diversity is positive and significant at the 5% level, the slope in the range of the turning point is non-significant, and the slope in the high range of technological diversity is negative but significant at the 10% level. Hence, hypothesis 5 is not supported and our results suggest that an inverted-u shaped relationship between technological diversity of R&D consortia and the generation of innovative outcomes exists under the condition of density-based network integration, with the understanding that one of the slope tests using a spline regression is significant at an alpha of 10%.

With respect to the included control variables, both the effects of consortium size ($.24^{**}$ (.07) and panel (a) in Figure 3) and financial resources ($.14^{*}$ (.06) panel (b) in Figure 3) are as expected. Contrary to what we did expect, however, the effect of multiple consortium membership on the probability of a consortium generating innovative outcomes is negative ($-.24^{***}$ (.07)). This interesting by-catch of our analysis will be explored further in our discussion.

Robustness tests

One of the concerns with the analysis reported in this chapter is that the specification of the network integration dummies could affect our results. We therefore estimated two models with alternative dummy specifications. Both specifications varied in the approach outlined in Table 6: following approach 1, any combination that involved a group 'Mean ± s.d.' was classified as 'average network integration' instead of being assigned to either centralization- or density-based network integration. In approach 2, these combinations were assigned to their adjacent more extreme form of integration (i.e. either 'low integration' or 'high integration'). With respect to the direct effects of both network-level as consortium-level predictors, analysis results using the 1st alternative dummy specifications were the same. The effect of density-based network integration disappeared when dummies were specified according to approach 2. With respect to this approach, however, one could question how sensible it is to assign a middle group to the lowest or highest category. Depending on how large or small the reference category 'average network integration' was made, cross-level interactions tended to disappear or shift across terms 15 – 30 in Table 5: following approach 1, the significant interaction between density-based network integration and technological diversity dissapeared, whereas following approach 2 both significant cross-level interactions dissapeared and were replaced by an interaction between high network integration and technological diversity that was significant at the 10%-level. The issue with approach 1, however, is that it lumps the majority of the networks in one group, making it difficult to detect nuances in the data set. All, in all, we believe that the coding approach to network integration followed in this chapter gives the most fair grouping of network integration based on the underlying scores on network density and centralization.

The second concern with the analysis reported in this chapter that we address is that a model that only allows intercepts to vary by year and technology field might be insufficient to capture all effects. The longitudinal nature of our data, for example, invites the possibility that relations of interest might change over time. It has, for example, been suggested that the significance of geographic proximity should wane as time progresses, because of the expansion of the geographic reach of actors resulting from a more institutionalized technology field (Stuart & Sorenson, 2003). More insight in this could be obtained by estimating a model that allows for varying slopes across fields. However, estimating such models is plagued by computation and convergence issues. Splitting the sample multiple times in different time frames (e.g. 1989-1996 and 1997-2004; 1989-1995 and 1996-2004, and so on), however, did shed some light on the issue. We observed no changes over time with respect to the effect of the control variables used in the model. The effects of both network density and technological diversity seemed especially salient in earlier years. The interaction between density-based network integration and technological diversity was most salient in early years as well. As our focus in this chapter is on the bigger picture, this is not of much concern to the current analysis. The matter of time-dependency of some of the relations, however, is considered by us to be of such great interest, that it will be further explored in the next chapter.

2.5 Discussion and conclusion

Especially in fields characterized by knowledge production and technological development, R&D consortia become a more prevalent form of organizing, due to their conduciveness to knowledge transfer, problem solving and joint learning through collaboration among firms and research institutions (Fonti et al., 2015; Foray et al., 2012; Sydow et al., 2012). This chapter was motivated by two observations: (1) relatively few studies focus on antecedents of the generation of innovative outcomes by R&D consortia and (2) generally, the literature on interorganizational networks and innovation lacks studies that account for both organizational features *and* features of the complete network.

This study addressed these two issues by focusing on the extent to which different types of network integration moderate the relationship between geographical proximity of members and their technological diversity on the one hand, and the likelihood of generating innovative outcomes on the other. We envisioned members of R&D consortia as engaging in search procedures within an existing technology landscape. One of the determinants of the likelihood of a consortium generating innovative outcomes in this model was the extent to which member search through the technology landscape was guided. This was reflected in the network-level concept of network integration. In addition, we proposed that configurational properties at the consortium-level (1) enable the effective transfer of knowledge between consortium members (geographical proximity) and (2) create a collaborative climate that is conducive to knowledge recombination (technological diversity) are important predictors of the likelihood of generating innovative outcomes as well. Lastly, we proposed that interactions between network-level and consortium-level features existed: the relationship between geographical proximity and the likelihood of generating innovative outcomes could only come to full fruition under conditions of moderate network integration, whereas this same condition of network integration would dampen the relationship between technological diversity and innovation.

We found that embeddedness in consortium networks in which consortium members are mutually aware of what members of other consortia are doing, increases the likelihood of these consortia generating innovative outcomes. Hence, the first key finding of this research is that when a certain critical mass of joint membership ties between consortia is reached in a network, serendipitous joint members between consortia transform to important conduits for information both to, and from the consortium. As a result, the available knowledge components as well as knowledge interdependencies in the technology landscape are clearer across consortia, leading to a higher probability of any of these consortia to be innovative. This finding resonates well with the literature on interorganizational networks, in which the legitimacy of partnerships is positively associated with the level of density (Gulati & Gargiulo, 1999), as well as research on team boundary spanners, which states that the benefits of team boundary spanning can extend well beyond a focal team itself to the performance of other interdependent parties and the organization as a whole (Mathieu, Marks, & Zaccaro, 2001). The finding also is in line with the work of Schilling and Phelps (2007), who find that firms embedded in networks characterized by both clustering and reach - both are associated with high levels of density- have higher levels of patent performance.

The second key finding of our study relates to the role of technological diversity, especially in combination with the condition of density-based network integration. Contrary to our expectations, we found that, in dense networks, an inverted u-shaped relation exists between a consortium's technological diversity and its innovative outcomes. Thus, contrary to what is suggested by our theoretical model, networks do not substitute technological diversity but instead enable it. Dense networks enable the joint understanding of the available knowledge components and interdependencies of these components in the technology landscape. Through technological diversity levels that allow for assimilating and recombining these different knowledge components (i.e. a neither too high nor too low level of technological diversity), members of R&D consortia are best suited to assess these knowledge components for their potential usability and integrate it in the artefact that is developed in the consortium.

The third and last key finding of this study relates to the role of geographical proximity. None of the hypotheses tests involving geographical proximity suggested a role of this concept in the generation of innovative outcomes by R&D consortia. Earlier, scholars have stated that the effect of geographical proximity is only salient in certain stages of the innovation process (Knoben & Oerlemans, 2006) and only facilitates innovation conjointly with other aspects of a collaboration (Boschma, 2005). A possible explanation for not finding empirical support for our hypotheses involving geographical proximity could be that in the early stages of the innovation process, aspects such as face-to-face interaction and the transfer of tacit knowledge -aspects that are facilitated by geographical proximity- are not yet opportune.

One interesting secondary finding is worth mentioning: contrary to contemporary insights regarding the relationship between centrality and innovation (Meeus et al., 2008), we found a negative relationship between multiple consortium membership (operationalized as a consortium's degree centrality) and the probability of this consortium generating innovative outcomes. Not only was this an unexpected finding, it is also slightly problematic given one of the primary insights of this study that networks characterized by high density increase the likelihood of an innovating consortium. Hence, even though from the network's perspective one wants consortia to have relatively many joint member ties with other consortia, this is exactly what hampers individual consortia in fulfilling their innovative potential. This suggests that it is most beneficial for individual consortia to be positioned in the periphery of a relatively dense consortium network. Possible explanations for this negative effect can be found in the team literature. Here, it is stated that membership of multiple teams increases the need of team members to switch between contexts, and members have multiple deadlines, interruptions and task switches. This leads to coordination issues, diluted attention and limited time to allocate to any of the consortia involved in (Bertolotti, Mattarelli, Vignoli, & Macrì, 2015). In addition, it decreases opportunities to work collectively

(O'Leary et al., 2011). Another explanation can be found in the alliance literature, where the direction of knowledge flows between organizations (inward or outward) has been suggested to determine whether or not a central network position is actually beneficial: when both flows are in balance, centrality benefits the innovative potential of firms, but when central firms have low levels of inward and high levels of outward knowledge transfer, this actually hampers innovation (Caner, Sun, & Prescott, 2014). In addition, besides being affected by its own joint members, a consortium is also affected by the joint members of consortia it is linked with (Vanhaverbeke et al., 2009). Hence, it might be that even though a consortium's global network position is detrimental to innovation, whereas its local centrality position is conducive to it. This is also reflected by the ideas regarding first- and second order networks by Uzzi (1997), who proposes differential performance effects of a node's position in its first-order network (i.e. its ego network) and its second-order network (i.e. its ego network and the relations that ego's alters have with others). The distinction between the local and global network position of consortia and the effect of both on the likelihood of generating innovative outcomes will be further elaborated on in the next chapter.

Theoretical and practical implications

All in all, and to the best of our knowledge, this chapter is one of the first works to report on a large-scale quantitative study on the innovative outcomes of R&D consortia, considering both consortium features and network features. It demonstrates the importance of complete network effects and shows that both network and consortium features play a role in explaining the generation of innovative outcomes by R&D consortia. As such, it provides novel insights to both the work that considers R&D consortia as an organizational form in its own capacity and the work that has stressed the importance of combining organization and network features as predictors of the generation of organizational outcomes. With respect to the first, we have demonstrated the importance of network integration and technological diversity, as well as the effect of multiple consortium membership. With respect to the second, we have shown that indeed both features matter, and that the effect size of network features can be like those related to consortium features.

Our findings bear implications for practice as well. Many governmental programs that focus on stimulating joint R&D are driven by the with to stimulate demand by potential users for the technologies being developed by involving users early in the process of R&D (Foray et al., 2012). Our results suggest that this homogeneous recipe should be refined, and the focus should not only be on funding consortia in isolation, but also on the overall network in which these consortia are, or will be, embedded. Even though these networks form in a serendipitous way, they do have important ramifications for the outcomes generated by the consortia embedded in them. A first step would be to map these networks for different technology fields and assess their levels of network integration. The goal then would not be to just increase their density, but to consider the state of the technology landscape. Based on this consideration, it could be decided to assign explicit leading roles to consortia, or to either stimulate or discourage the formation of joint member ties. We believe it is most important to become aware of these overarching network structures to more effectively initiate and design R&D consortia.

From a bottom-up management perspective, consortium managers and members should be focused on establishing a level of technological diversity that is neither too high nor too low to maximize the likelihood of generating innovative outcomes. In addition, network mapping and assessment is important for these actors as well, as being central in a network characterized by density-based integration does not necessarily has to lead to the largest possibility for generating innovation. Our results suggest that the number of joint members should be kept to a minimum.

In addition, consortium managers should consider the structure of the complete network they might get embedded in when involving members.

Strengths, limitations and suggestions for future research

One of the strengths of this chapter is that a large dataset is employed, focusing on 1,263 R&D consortia dispersed over 7 technology fields and 16 years. Although some of the measures used (e.g. geographical proximity and technological diversity) might be somewhat crude, we were still able to sketch a large, overall picture of the antecedents of innovation in R&D consortia across different fields and years. These findings particularly echo the call for including multiple levels of analysis in network research (Ibarra et al., 2005), and invite a closer consideration of the role of technological diversity in R&D consortia. This strength, however, also has the drawback that we could not go in more depth into single fields and years. For example, even though we observed that technology fields and network integration are correlated, our main research focus kept us from delving deeper into this. Another limitation is that, even though we have considered many R&D consortia, these consortia all have formed in a specific context and fell under a specific funding scheme. Although a large leap was made in terms of generalizability in as far as it concerns these specific consortia, future replication studies should demonstrate to what extent our findings hold for R&D consortia that have formed under different conditions. In addition, these studies should incorporate a comparison with consortia that do not have joint member ties with other consortia at all, to assess how being embedded in a larger structural context compares to not being embedded in such a context at all.

In addition, some of the correlations found as well as the results of our robustness tests showed that the role of time is rather pervasive in our study. For example, our correlation analysis suggested that some forms of integration emerge over time, whereas others dissolve as time progresses. In addition, from the robustness tests it appeared that both network density and technological diversity seemed especially salient in earlier years. We already suggested that this could have something to do with the developmental stages of the underlying technologies, and also want to echo here the suggestion made by Shore et al. (2015) that different structures might be needed for different phases of collective problem solving. This time-dependency would be a very interesting avenue to include in future research designs. We will focus on this in the next chapter.

Moreover, the role of joint consortium membership discussed in the above should be examined in more detail. As indicated earlier, existing literature suggests that differential performance effects of a node's position exist, depending on whether the first-order network or the second-order network is considered. Involving time here might prove fruitful as well: are consortia that are central in early years of their existence more innovative compared to central consortia in later years?

Furthermore, the question to what extent successful consortium members actually are aware of the structural context in which their consortium operates, how they navigate through the network and what the costs are associated with doing so (Reagans et al., 2004) are interesting ones to answer. Hitherto, only a handful of empirical studies into networks actually has connected such network strategies to outcome measures (de Man & Duysters, 2005). Insight in this, however, might deliver more tangible levers for individual consortium managers to influence their network position in a more targeted way.

All in all, both complete network and consortium features have direct and interacting effects on the likelihood of a consortium generating innovative outcomes. Given that both features matter in predicting innovative outcomes, both governments aimed at stimulating innovation and consortium managers should not only think about the design of individual consortia, but also consider the structural context in which consortia operate.

Appendix I: Data Sources and Database Construction

The technology foundation is held accountable for providing consortium funds, and hence issues a report on a yearly basis in which consortia that were funded 5 and 10 years ago are evaluated. We used the 5 year reports as the main source for our data collection throughout this dissertation. Although marked differences between different editions of the reports issued exist, a typical example of a 5-years consortium evaluation can be found in Table 6. This table consists of several blocks of information, the majority of which is self-explanatory. Of special interest is the three-letter code provided in the first block that also contains the project code. This code represents a multi-dimensional project evaluation and is used as the operationalization of the concept of innovative outcomes.

TABLE 6

Example of consortium evaluation

04671 **BAC**	**Aerobic Granular Sludge Reactors**
project leader: Prof.dr.ir. M.C.M. van Loosdrecht **allocated research grant in euro**: 201.023,50 **contracts**: Transfer Technische Universiteit Delft, DHV Water BV; **research collaboration:** TUD-TNW, STOWA **patents**: none **incomes in euro**: 136.134,00	
goal: The development of a simple, cost-efficient and compact wastewater treatment technology based on aerobic grain slurry.	
result after 5 year: This research has developed a first concept of growing aerobic grain slurry in the laboratory into a full-flegded technology based on SBR reactors. In a very compact reactor, high simultaneous removal of CZV (100%), nitrogen (94%) and phosphate (94%) can be accomplished. The design of a water purification plant based on aerobic grain sludge shows that 75% less space is needed compared to conventional active sludge installations. Also, energy consumption can be reduced up to 30% and investment costs are 15% to 20% lower. This technology -developed by TU Delft and DHV- is very interesting for purifying both domestic and industrial wastewater. The aerobic grain slurry is patented in two patents. DHV introduces the technology on the market under the name of Nereda™. There has been considerable interest from Dutch water boards and industry, where three installations already are implemented. Pilot research will lead to the first application for domestic wastewater, and (inter) national projects for the construction of Nereda™ installations are scheduled.	
user committee members: DHV Water BV, Amersfoort / Haskoning Nederland BV, Nijmegen / Paques BV, Balk / STOWA, Utrecht / Van der Pluijm Water- en Milieumanagement, Boxtel / Wageningen Universiteit & Researchcentrum, Wageningen / Waterschap AA en Maas, Den Bosch / Waterschap Hollandse Delta, Dordrecht / Waterschap Reest en Wieden, Meppel	

In total, the information from 23 evaluation reports was collected. Before entering this information, we conducted a pilot project in which the evaluations available in the three most recent reports were entered in a database. This pilot project served several purposes. The first purpose was to establish a basic database design. We followed general database design principles as outlined in Groh et al. (2007), as well as the principles tailored to designing a database that allows for generating network data as outlined in Appendix 1.3.3. in de Nooy, Mrvar, and Batagelj (2005). Second, we developed a set of queries that allowed for extracting the relevant data needed for variable construction. In addition, because data entry involved splitting up each project report in five separate tables, a set of queries was developed in order to reproduce the original reports to check for possible errors in data entry and database design. The last goal of this pilot project was to develop data entry heuristics. Especially the names of organizations involved in user commitees turned out to be prone to variation, in terms of both small semantic differences as well as more salient differences, for example as a consequence of reorganizations or mergers. Even though a subjective element in making data harmonizing decisions can never be ruled out completely, developing these heuristics allowed for a consistent data entry approach.

After the pilot stage, consortium evaluations from the remaining 20 reports were entered. As from 2001, these reports were available through the website of the technology foundation. Hardcopies from the 13 reports issued in earlier years were sought after in Dutch libaries and digitalized, after which applying OCR made them suitable as well for entering in the database. Data normalization principles (Groh et al., 2007) were applied as much as possible and five core tables were contructed: a table containing project information (1,928 projects, in total 3,186 distinct records), a table containing user information (2,634 unique users, 3,045 distinct records), a table containing consortium leader information (1,361 distinct records), a table linking consortium leaders with projects (3,883 links. Especially in early editions of the report multiple consortium leaders were reported) and a table linking users with projects (15,539 links). In the event a consortium report was incomplete, we resorted to the foundation's website and 10 year reports that in some cases contained additional project information.

3. From Pipes to Prisms: The Time-Varying Effects of Global Brokerage and Local Closure on the Generation of Innovative Outcomes by R&D Consortia[10]

Abstract

Existing research on organizational knowledge networks and innovation has yielded important insights regarding the relation between an organization's network position and its innovative performance. However, no consensus has emerged with respect to the question which network position is most advantageous. This is especially salient in the debate that focuses on the question whether network brokerage or closure provides the most efficient structure for innovation. This chapter addresses this issue by analysing the effect of both global and local network position on the likelihood of generating technological innovation, including the role of time in the salience of this effect. We test our theoretical predictions with a multi-level analysis of 814 Dutch R&D consortia, each of which was active somewhere in the time frame 1989-2004. Contrary to our expectations, we find that -although not salient across all years- global brokerage has a negative effect on the likelihood of generating technological innovation. We also find that local cohesion consistently enhances the likelihood of innovation over time. Lastly, a time-dependent effect is found for the interaction between both: especially in the early years, consortia that combine being in locally embedded networks with a brokerage position in the complete network are more innovative compared to consortia that have other combinations of these network positions. In addition to elucidating the direct effect of global brokerage and local closure on the innovative potential of R&D consortia, as well as the importance of the interaction between both in early stages of an R&D consortium, our study results provide valuable insights for both consortium managers and innovation policy.

3.1 Introduction

Existing research on organizational networks suggests that an organization's outcomes are affected by its network position. Well-positioned organizations augment their internal resources and capabilities through mechanisms such as access to external resources, trust, power and control, and signalling an organization's network position. These determine its access to diverse information, the cost-effective functioning of its collaborations, interdependencies with its partners and means to evaluate potential partners (Zaheer, Gozubuyuk, & Milanov, 2010) which all are determinants of its innovative performance, chances of firm survival, and overall performance (Borgatti & Foster, 2003; Brass et al., 2004; Gulati, 1999; Podolny & Page, 1998).

A specific body of research focuses on the role of interorganizational networks for innovation. Here, the focus is on the role of knowledge (see Meeus et al. (2008), Phelps, Heidl, and Wadhwa (2012) and Pittaway et al. (2004) for literature reviews on this topic). Given the increased emphasis on interaction in the literature on systems of innovation (Edquist & Hommen, 1999), user-producer interaction (Meeus et al., 2001; von Hippel, 1988) in science policy and innovation studies (Foray et al., 2012; Martin, 2012; Perkmann et al., 2013), this research has yielded important insights, enabling both organizations and policy makers to devise more targeted networking strategies and policy measures. However, even though the empirical evidence points at the

[10] Previous versions of this chapter were presented at the 28th EGOS Colloquium (Helsinki, July 2012) and the DRUID Academy 2014 Conference (Copenhagen, June 2014).

existence of a relation between network position and innovation, there is no consensus among researchers regarding which network position is most advantageous. In their review on inter-organizational networks and innovation, for example, Meeus et al. (2008) and Dagnino, Chiara Cantù, Levanti, Minà, and Picone (2015) observe that for several network features, research has provided a mixed bag of findings regarding their relation with innovation.

An important question in the literature on the topic of interorganizational networks and innovation is whether dense networks provide the most efficient structure for knowledge search (i.e. closure (Ahuja, 2000a; Coleman, 1988; Hung, 2017)), or if this search is facilitated by networks rich in ties that bridge distant, unconnected nodes (i.e. brokerage (Brass et al., 2004; Burt, 1992; Soda, Stea, & Pedersen, 2017; Vanhaverbeke et al., 2009)). According to the closure perspective, organizations embedded in cohesive networks have several advantages, such as building up trust and fine-grained information sharing (Coleman, 1988; Nahapiet & Ghoshal, 1998; Uzzi, 1996). Others have pointed at the downsides of being embedded in cohesive networks, and advocated the structural holes perspective, with its timely access to non-redundant information and control benefits (Burt, 1992). Although seemingly contradictory, attempts to unite these perspectives have been made by considering the boundary conditions of both (Burt, 2005; Perry-Smith & Mannucci, 2017) or, in other words, by considering the factors that determine whether an organization can adequately exploit either structural holes or closure. Indeed, recently authors have suggested environmental contingencies that might be at play here, especially focusing on industry context (Ahuja, 2000a; Dyer & Nobeoka, 2000; Hargadon & Sutton, 1997; Pollock, Porac, & Wade, 2004; Rowley et al., 2000).

Two important issues are rarely addressed in this literature. First, most of the studies that examine the effect of brokerage and closure on innovation focus on ego networks and examine the position of a focal organization in this ego network. Although the issue has been addressed by some authors (Everett & Borgatti, 2005; Pallotti, Tubaro, & Lomi, 2015; Reagans & Zuckerman, 2008; Salman & Saives, 2005; Sytch & Tatarynowicz, 2013a), scholars usually have overlooked the possibility that these effects might stem from an organization's position in the complete network (Guler & Nerkar, 2012; Kilduff & Brass, 2010; Provan, Fish, & Sydow, 2007). For example, in the nascent and scarce research on second-order social capital, it is emphasized that the performance effects of a node's first-order network location should be separated from its second-order network location (Burt, 2000; Sasson, 2008). The issue at stake here is control: whereas a focal organization can control its own direct ties, it is usually much harder to control the establishment of ties between its partner's ties, ties between the partners of its partners, and so on (Vanhaverbeke et al., 2009). In addition, even in relatively small organizational contexts, it is difficult to accurately perceive those ties that connect us to distant alters (Krackhardt & Kilduff, 1999). Hence, should higher order network effects be present, then the difficulties an individual organization has with affecting its position in this higher order network could be a reason for policy to aim at mitigating possible detrimental higher order network effects through top-down network interventions. Work in this area has shown inconsistent findings, ranging from non-relevance of second-order contacts (Burt, 2007) to a significant effect of this second-order network on employee influence (Galunic, Ertug, & Gargiulo, 2012; Sparrowe & Liden, 1997; Sparrowe & Liden, 2005). In a slightly different context, studies have shown that clusters of obese persons extended to three degrees of separation (Christakis & Fowler, 2007). Similar findings were reported in studies focusing on the spread of happiness in social networks (Fowler & Christakis, 2008) or smoking cessation behaviour (Christakis & Fowler, 2008). These studies suggest that both local as global network effects can be discerned, and extended consideration of both network dimensions -despite its relevance- is missing at present in most organizational network research (Kilduff & Brass, 2010).

The second issue is that, although often a call for the specification of time in organizational research has been made (Albert & Bell, 2002; Ancona et al., 2001; George & Jones, 2000; Kavanagh & Araujo, 1995; Zaheer et al., 1999), studies that incorporate the role of time in generating benefits from either a brokerage or closure position are scarce (Bidwell & Fernandez-Mateo, 2010). Scholars have suggested that relationships and with that networks are prone to development over time, which means that the significance of bridging structural holes is not unconditionally present. Instead, its salience depends on for example the extent to which a network is subject to structural and population dynamics (Ahuja et al., 2012). In addition, time must pass for relationships to develop, strengthen and deepen. Hence, it can be expected that the effect of closure is not present instantly but needs some time before becoming manifest. It also might retain its value longer compared to network brokerage (Soda, Usai, & Zaheer, 2004). Lastly, several authors have suggested different knowledge gestation times for different technology fields (Gilbert & Campbell, 2015; Park & Zhou, 2005; Rothaermel & Hill, 2005), industries (Becker & Lillemark, 2006; Fabrizio & Thomas, 2012; Hameri, 1996; Henisz & Macher, 2004; Hyytinen & Toivanen, 2005; Nishimura & Okada, 2014; Spithoven et al., 2010), and types of innovative activity (Ahuja et al., 2014; Flammer & Bansal, 2017; Maine et al., 2005; O'Connor & DeMartino, 2006; Prettner & Werner, 2016; Souder, 1983). This implies that not considering the role of time in the relation between brokerage and closure and innovation might be too simplistic.

In this chapter, we take on the challenge of incorporating (1) the effect of network position in networks of different orders on the likelihood of generating innovation and (2) the role of time in the salience of this effect. We focus on a specific form of collaboration for generating innovation that, due to the increased complexity of innovation problems (Foray et al., 2012), has become a prominent form of collaboration: the R&D consortium. Members in these consortia jointly develop product or process innovations that are new to the world, with the aim of innovation adoption by one or more end users. Through joint member ties with other consortia, a consortium network emerges in which each consortium is embedded. By characterizing R&D as a search process over a knowledge space that aims at refining or recombining existing knowledge components, we propose time-varying effects of a consortium's global brokerage and local closure. By doing so, we build forth on scholars that propose that brokerage and closure are complements rather than mutually exclusive (Burt, 2005). We argue that global brokerage (i.e. brokerage in the complete network of R&D consortia) provides access to distant information types about the distribution of knowledge elements or know-how in a certain technology field, as well as access to the latest developments and trends in this field. This helps consortium members in the initial problem-solving stage of the consortium. This function of networks as 'pipes' (Podolny, 2001) is especially important in early stages of the R&D consortium. As the artefact that is developed in a consortium matures, activation of members of neighbouring consortia becomes important, to embed the artefact in the existing technology base. Here, the function of local closure (i.e. an ego network characterized by a high level of density) is important, and for this the function of networks as 'prisms' (Podolny, 2001) is relevant, as it enables knowing who to activate in this stage.

We test the empirical value of these theoretical ideas by performing a multi-level analysis of 814 R&D consortia, each of which was active in the Netherlands somewhere in the time frame 1989-2004. Through constructing consortium networks based on joint member ties between consortia, we established both the global as the local network structure of each consortium over multiple years, and in turn estimated several multilevel ordinal logistic regression models that predict the likelihood of an R&D consortium generating innovative outcomes as a function of global brokerage and local closure. Contrary to our expectations, we find that global brokerage has a negative effect on this likelihood, which does not always occur as time goes by. In addition, we find that local cohesion consistently enhances the likelihood of innovation over time. Lastly, a time-dependent effect is found for the interaction between both: especially in the early years, consortia that combine being in locally embedded networks with a brokerage position in the complete network are more innovative compared to consortia that have other combinations of these network positions.

With this chapter, we contribute to the existing literature on organizational networks in two related ways. First, we add to the debate on brokerage and closure in networks that it is especially the combination of global brokerage and local closure in early stages of an R&D consortium that is beneficial for the innovative potential of this consortium. Whereas most studies on the relation between networks and innovation take into account using a network that consist of a mix of collaborations in only one sector (de Man & Duysters, 2005), we make this claim based on an analysis that focuses on one type of relation, taking into account seven different technology fields. Second, we show that the direct effects of brokerage and closure in this specific setting are time-invariant. With this insight, we contribute to the contingency view on brokerage and closure: for R&D consortia to come fully to fruition, these consortia need dense local networks and in general should avoid obtaining a brokerage position in the complete network of consortia.

In addition to the theoretical contributions of our study, we offer insights for practice. Our results show that positive network effects for R&D consortia occur at the first network order, which can be controlled by members of these consortia. This insight opens the door for actively managing this local environment by consortium members. This can, for example, be achieved by a targeted selection of members active in other consortia, to establish cross-consortium links and, with that, enhance the cohesion of the focal consortium's ego network. In addition, by focusing on the interaction between global brokerage and local cohesion and its associated time dimension, our results suggest that members of R&D consortia -in addition to building a dense local network- benefit from brokerage positions in the complete network in the consortium's early stages. This brokerage position, however, is difficult to manage by members of individual consortia. Instead, here lies a task for innovation policy. As indicated earlier, interorganizational knowledge networks are important for innovation. Although this insight has been adopted by innovation policy, most policy measures are relatively untargeted and happen out of the realm of control of those positioned in these networks (Meeus et al., 2008). Our results suggest that policy should more directly target these networks, through developing measures that aim at stimulating network brokerage for newly started R&D consortia, as well as stimulating enough structural dynamics in these networks for these consortia not to get trapped in their network position without being able to change this position.

3.2 Theoretical framework

We draw on two distinct but related streams of literature for building our theoretical arguments. We start from the literature on social and organizational networks, especially one of the important debates in that literature that focuses on the question whether dense networks provide the most efficient structure for knowledge search (i.e. closure (Coleman, 1988)), or if search is facilitated by networks rich in ties that bridge distant, unconnected nodes (i.e. brokerage (Brass et al., 2004; Burt, 1992; Soda, Stea, et al., 2017; Vanhaverbeke et al., 2009)). Both views are grounded in the assumption that network structure affects the flow of knowledge between actors, and as such determines the extent to which actors can use this knowledge to beneficial ends (Kajikawa, Takeda, Sakata, & Matsushima, 2010). We then combine arguments taken from this literature with the literature on organizational search (Fleming & Sorenson, 2004; Katila, 2002; Rosenkopf & Nerkar, 2001) to develop a theory of search in the context of interrelated R&D consortia. Especially the distinction between local and distant search in the strategic management literature has been fruitfully combined with the lenses of brokerage and closure that are employed in the network literature (Paruchuri & Awate, 2016). It is this distinction that forms the basis of our theoretical arguments. The basic arguments in both literatures are well known, and we do not aim in this chapter to make fundamental changes to these arguments. What we do aim for, however, is to make the role of time -often implicit in the arguments used- more explicit and develop hypotheses that include this role.

To set the stage of our theoretical framework, we will start with focusing on the debate that revolves around the distinction between brokerage and closure in relational structures. We then will characterize the process of research and development by members of an R&D consortium that is interconnected in a network of R&D consortia as a knowledge search process and explain the role of brokerage and closure in such a network. We especially focus on the role of *global* brokerage (i.e. access to a wide array of bodies of knowledge and the possibility of knowledge arbitrage) and *local* cohesion (i.e. the possibility to mobilize members of neighbouring consortia to deepen a specific body of knowledge). For each concept, a separate hypothesis is developed that includes the moderating effect of time on the concept's relation with the likelihood of generating innovative outcomes. Lastly, we develop a time-dependent hypothesis for the interaction effect between both concepts.

The brokerage perspective asserts that networks consist of multiple groups of interconnected nodes. The key assumption underlying this perspective is that knowledge, values and behaviour are homogeneous within groups, and heterogeneous between groups (Burt, 2004; Soda, Stea, et al., 2017). This homogeneity results from the specialization of members in each group by focusing on a limited set of problems and -in tandem with that- a shared focus on the immediate tasks resulting from solving these problems to the exclusion of adjacent tasks. Consequently, holes emerge in the organization of the network: nodes within groups lose track of what those in other groups are working on and become unaware of the benefits they could offer one another. Because ties within groups are likely to carry the same knowledge, they are called redundant. The abundance of redundant ties within the group and the lack of non-redundant ties across groups is argued to result in nodes within groups not fully realizing their potential (Burt, Hogarth, & Michaud, 2000). However, nodes that are connected across different groups through non-redundant ties gain exposure to a greater variety of knowledge and ways of thinking. Consequently, the likelihood to see connections between otherwise disparate knowledge elements increases, which increases the likelihood of creating new knowledge combinations (Burt, 2004; Lingo & O'Mahony, 2010; Vanhaverbeke et al., 2009). Hence, nodes that have a brokerage position in the network have more opportunities to obtain performance advantages from their position compared to nodes that are not in such a position (Kajikawa et al., 2010; Shipilov, 2006).

Different conceptions of what a brokerage position entails exist in the literature. In Burt's (1992) original explanation, brokers were presented as the *tertius gaudens*, or "the third who benefits". In this conception, a broker can obtain important performance advantages by exploiting relationships to partners that do not maintain direct ties to one another. The latter implies that these partners are connected to heterogeneous sources of information, and that their invitations to jointly exploit business prospects present the broker with access to diverse knowledge recombination opportunities (McEvily & Zaheer, 1999; Shipilov, 2006). This enables the broker to take advantage of opportunities that arise from bridging otherwise disconnected parts of a network (Vanhaverbeke et al., 2009). Hence, in the conception of brokerage as *tertius gaudens*, individual brokers gain advantages by employing a strategy of disunion through the preservation of unique ties to other nodes and keeping those other nodes apart from one another (Collins-Dogrul, 2012; Lingo & O'Mahony, 2010; Quintane & Carnabuci, 2016).

Scholars that use the conception of brokerage as *tertius gaudens* often study brokerage in competitive relationships found in markets or conflict mediation, in which reaping individual gains is key (Collins-Dogrul, 2012). Another conception of brokerage focuses at the collective advantages that can be obtained through bridging disconnected groups in a network (Ibarra et al., 2005). In this conception, brokers are present as the *tertius iungens*, or "the third who connects". By joining previously disconnected groups, this type of broker facilitates coordination, collaboration and the pursuit of common goals (Obstfeld, 2005). Next to this role as go-between, this type of broker can play a combinatorial role by assisting in bringing together previously disparate pieces of knowledge to, for example, create a novel technological approach (Hargadon & Sutton, 1997; Stuart, Ozdemir, & Ding, 2007). Both are achieved through balancing and eliminating possible incompatibilities between groups. As such, brokerage in this conception not only involves the structural position of a node, but also its relational practices by enabling direct knowledge exchange between brokered parties (Lingo & O'Mahony, 2010; Quintane & Carnabuci, 2016).

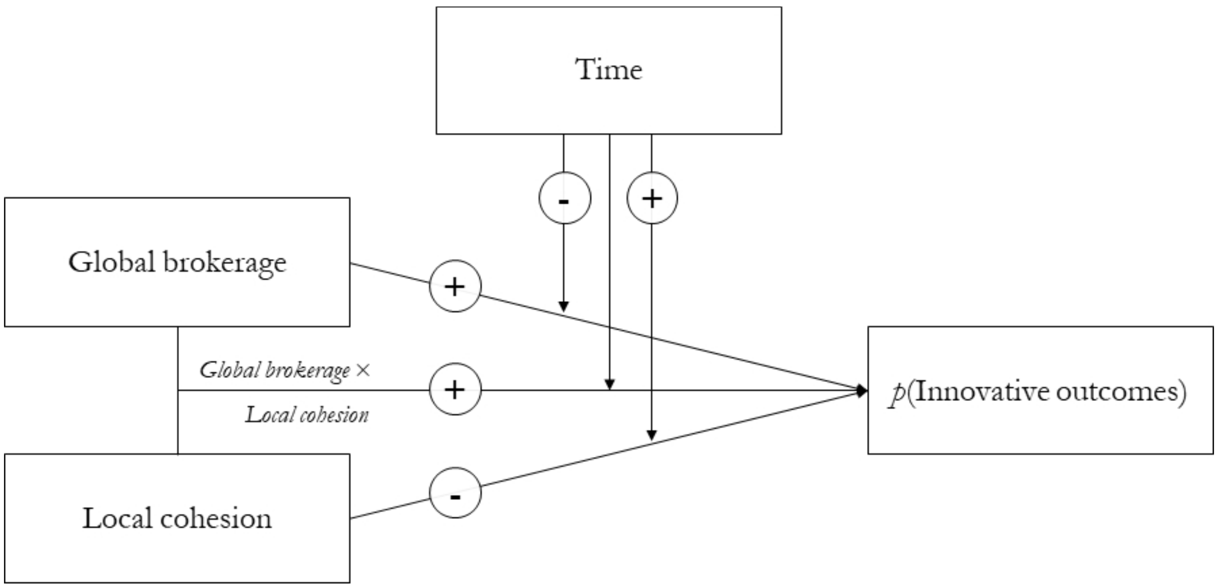
The conception of brokerage as *tertius iungens* implies that over time, nodes in a network become more connected. This brings us to the complementary perspective of brokerage, which is called the closure perspective. This perspective stresses the role of cohesive ties in fostering an environment that facilitates cooperation among nodes (Vanhaverbeke et al., 2009). When nodes in a network are connected through a closed network, each node has access to fine-grained and redundant but in-depth knowledge, for example about the capability and willingness of other nodes to join forces and share resources in cooperative ventures (Baum, Rowley, & Shipilov, 2005; Forti, Franzoni, & Sobrero, 2013; Walker, Kogut, & Shan, 1997), as well as their 'idiosyncratic' knowledge and particular knowledge domains (Morris & Snell, 2007). This eases the mobilization of nodes around new ideas, partly due to similarities in perspectives and interests (Obstfeld, 2005). In addition, network closure increases the likelihood of knowledge being up to date, accurate and reliable (Patzelt, Lechner, & Klaukien, 2011). These knowledge features are absent in networks characterized by structural holes, yet necessary to achieve synergies and share resources with network partners that enhance a node's ability to be innovative (Ahuja, 2000a; Shipilov & Li, 2008; Soda, Stea, et al., 2017). Closure also results in more shared partners and trust between nodes, which reduces their action autonomy because they take feedback from one another into consideration (Patzelt et al., 2011), and facilitates long-term relationships and learning (Forti et al., 2013). It has been suggested that it is especially local cohesion, i.e. cohesion in the immediate neighbourhood of nodes, that is beneficial (Guler & Nerkar, 2012).

Although initially the brokerage and closure perspective were competing perspectives, there is increasing consensus that the efficiency of a certain network structure depends on contingencies such as the environment in which a node operates, or the nature of the task. Hence, the key to creating value is to put the two together (Ahuja, 2000a; Baum, Cowan, & Jonard, 2014; Burt, 2005; Lee, 2007), meaning that a combination between both needs to be established in which a trade-off is made between getting knowledge access through structural holes and integration of knowledge through closure (Funk, 2013; Gilsing & Duysters, 2008; Michelfelder & Kratzer, 2013; Mors, 2010; Obstfeld, 2005).

The conceptual model that guides our theorizing is shown in Figure 4. We propose that innovative R&D consortia capitalize on their *tertius gaudens* position initially, accessing different bodies of knowledge and increasing the prominence of the artefact that it developed by disseminating its knowledge through the network. Then, as time progresses, a *tertius iungens* position is occupied: through mobilizing and activating members of neighbouring consortia around the artefact that is developed, its interoperability is ensured and valuable complementarities with artefacts in other consortia can be recognized. Somewhere over time, an amplifying effect of both network positions can be discerned (Perry-Smith & Mannucci, 2017).

FIGURE 4

Conceptual model linking local and global brokerage to innovative outcomes generated by R&D consortia



Innovative outcomes. Research and development, invention and innovation are terms that encompass a broad variety of activities, analytical levels, degrees of newness and perspectives (Gopalakrishnan & Damanpour, 1997). Many scholars have framed these activities as a search problem (Henderson & Clark, 1990; Rosenkopf & Nerkar, 2001; Schumpeter, 1934), sparked by idiosyncratic problems and opportunities that members of, for example, R&D consortia face (Ahuja & Katila, 2004; Nelson & Winter, 1982). R&D activities focus at searching, developing and recombining different types of knowledge that were previously non-associated, or refining previous knowledge combinations (Bercovitz & Feldman, 2011; Carnabuci & Operti, 2013; Fleming & Sorenson, 2001; Kogut & Zander, 1992). This eventually leads to invention (i.e. the creation of a new product, technology or process) which, once successfully adopted, can be classified as innovation (lo Storto, 2006).

The focus in this chapter is on the process of research and development in R&D consortia that are embedded in an emergent consortium network. Members in these consortia jointly develop product or process innovations that are new to the world, with the aim of innovation adoption by one or more end users. Multiple stages in this generation process have been identified. In an extensive review, Gopalakrishnan and Damanpour (1997) identified five stages: (1) idea generation, (2) project definition, (3) problem-solving, (4) design and development, and (5) marketing or commercialization. Our interest is especially in the last three stages: whereas marketing or commercialization of the artefact that is developed is the aim, problem solving and development into a final product are the main search activities members of R&D consortia engage in.

A key element in our current understanding of search in the context of innovation is that actors search over a knowledge space. Different conceptualizations of such a space exist (Kauffman et al., 2000; March, 1991), but the overarching argument is that knowledge that potentially can be further developed or recombined is sought after from a set of knowledge elements in an actor's environment (Katila, 2002; lo Storto, 2006). The implication of this is that search rarely starts ab initio, but instead builds forth on already existing knowledge elements and combinations (Yayavaram & Chen, 2015). The development of new technology by members of an R&D consortium concerns incorporating scientific knowledge into physical artefacts for the benefit of users (Ahuja & Katila, 2004). These artefacts must function reliably in a variety of usage circumstances and hence development involves experimentation and feedback-based, experiential learning by members (Ali & Gittelman, 2016). Consequently, search activities focus on both scientific knowledge and technology-related knowledge.

Several types of information have been suggested to be relevant to innovation. First, this information may focus on the distribution of knowledge elements or know-how within a technology field or, in other words, who knows what. Secondly, information about the latest developments and trends in a certain area can be sought after. This information can be about trends in methods, procedures and tools for solving technological problems, or contemporary technological issues. It is this type of information that is likely to be a guide to advancing the contents of existing knowledge elements, or the creation of new, or new combinations of knowledge elements. Lastly, characteristics of other agents active in the search space such as their current endeavours, capabilities and trustworthiness can be relevant (Wang et al., 2013).

Search activities for this type of information may be local (i.e. close to the current knowledge of consortium members), or distant (i.e. farther away from the existing knowledge of members) (Katila & Ahuja, 2002; Lopez-Vega, Tell, & Vanhaverbeke, 2016; Stuart & Podolny, 1996). Whereas both types of search are aimed at overcoming the limitations of a consortium's existing knowledge base (Ahuja & Katila, 2004), local search has been shown to result in convergence of search approaches (Stuart & Podolny, 1996). In contrast, distant search entails recombination of knowledge (Fleming & Sorenson, 2004; Rosenkopf & Nerkar, 2001), which provides more opportunities for the generation of innovation (Lopez-Vega et al., 2016). Given that R&D consortia often focus on problems at the interface between science and technology that is characterized by ill-structured problems, novelty creation and with that engaging in distant search is key for consortium members (Stokes, 2014).

By bringing together multiple partners, R&D consortia already are intended to be diversity-enabling platforms. Although sometimes hampered by issues stemming from joint search activities by multiple organizations (Knudsen & Srikanth, 2014), the range of recombination opportunities resulting from search indeed has often been argued to increase by bringing together organizations with complementary knowledge (Bonesso, Comacchio, & Pizzi, 2011; Garriga, von Krogh, & Spaeth, 2013; Laursen & Salter, 2006). Guided by its own perspectives, each member organization can trigger a process of deliberate exploration in which various areas of the search space can be considered (Knudsen & Srikanth, 2014; Olsen, Sofka, & Grimpe, 2016). However, we contend that even multiple members of an R&D consortium that are united by a joint problem still are limited in their potential for knowledge recombination. Because the potential for knowledge recombination in the knowledge space is essentially infinite, it is hard for individuals, groups or even communities to obtain an overall picture of all knowledge elements and opportunities for refinement or recombination (Fleming, 2001). So, relative to all possible improvements and potential for recombination in the knowledge space, consortium members still build on relatively local knowledge sources. Hence, we propose that in addition to the diversity generated by consortium members, the potential for accessing even more distant knowledge can be tapped from the complete network of R&D consortia, which acts as a vehicle for diffusing ideas through the knowledge space (Chang & Harrington, 2007). As a result, the position of R&D consortia in this network becomes of interest, as well as the question what type of search in this network (i.e. distant or close) is relevant, and when during the innovation process these types are most relevant.

We claim that access and activation are key elements in the answer to this question. Access to distant information types about the distribution of knowledge elements or know-how in a certain technology field, as well as access to the latest developments and trends in this field aids consortium members in the initial problem-solving stage of the consortium. In analogy with Podolny's metaphor, it is especially the role of networks as pipes (i.e. conduits through which knowledge flows (Podolny, 2001)) that is of importance here. Building on Burt's (1992) conception, we capture this aspect of networks with the concept 'global brokerage'. As time progresses, knowing which ties to other consortia to activate becomes of key importance to generate a bearing area for the artefact that is being developed in the focal consortium. Having insight in the characteristics of other consortia becomes relevant here, and it is the role of networks as prisms (i.e. optical elements that split out and induce differentiation among other consortia in the network (Podolny, 2001)) that becomes important. Here, we build forth on Coleman's (1988) ideas and capture this aspect of networks with the concept of 'local cohesion'.

Global brokerage. The arguments for network brokerage were initially developed for social networks (Burt, 1992). Both Leana and Van Buren (1999) and Gulati (1998), however, explained that the ideas stemming from research on social networks can be extended to organizations and their intra- and interorganizational networks. R&D consortia are especially suitable for studying the changing role of network brokerage over time in the generation of innovation: the initial focus on problem specification and goal setting (Corey, 1997; Doz et al., 2000; Evan & Olk, 1990), long exchange horizons between members (Das & Teng, 2002) and external knowledge inflows stemming from the involvement of members in multiple consortia simultaneously (Lavie et al., 2007) are three features of R&D consortia that are of importance here. They allow for changing information needs over time, a time horizon long enough to allow for these needs to change and various levels of network brokerage across consortia that allow for each consortium to be at various levels of risk of bumping into knowledge that provides the opportunity to be innovative (Burt, 2004).

Regarding this latter point, an orthodox interpretation of brokerage sets rather strict constraints to the networks being studied: these networks need to combine both clustered groups of nodes and bridging ties between those clusters for individual nodes to be the only bridge between two otherwise separated clusters. The existing research on organizational brokerage and its relationship with innovation, however, has been more lenient in its interpretation. Some scholars have constructed organizational ego networks and studied to what extent the ego organization in such networks brokered the relations between its alters, and its subsequent knowledge and innovation benefits (Aalbers, Dolfsma, & Leenders, 2016; Ahuja, 2000a; Lee, 2010; Vanhaverbeke et al., 2009; Zaheer & Bell, 2005). Other scholars have considered the question if the knowledge benefits stemming from structural holes are not only the product of an organization's primary ties, but also stem from its secondary ties (i.e. moving knowledge between partners of partners) (Burt, 2007; Galunic et al., 2012; Kajikawa et al., 2010). Lastly, authors have related the concept of brokerage to an organizations' position within the overall pattern of relationships between organizations (Meeus et al., 2008; Owen-Smith & Powell, 2004; Salman & Saives, 2005; van Wijk, Jansen, & Lyles, 2008).

This last conception of network brokerage is closest to our use of the term in the context of interconnected R&D consortia. With innovation in these consortia being the result of search activities across a broad knowledge space that is hard to comprehend by individuals, groups, or even communities (Fleming, 2001), having a broker position within the overall pattern of relationships between organizations rather than being a broker in the 1st or 2nd order network puts members of R&D consortia at the highest risk of encountering information or knowledge that has the potential to serve as the input for innovation. Hence, our label 'global brokerage'. This interpretation is also in line with Burt (2007), who outlines that whereas brokerage in the first order network is especially relevant for an ego being affected in his or her emotions, brokerage in the second order (and higher) networks is more salient for capturing information advantages. We will now start reviewing arguments for the innovative advantages of global brokerage in general before relating those arguments to the contingency of time.

The literature has proposed two main mechanisms along which global network brokerage leads to innovation that are relevant for the R&D consortia studied in this chapter: access to non-redundant knowledge and information, and knowledge arbitrage. With respect to the first mechanism, the reader should be reminded that R&D activities can be considered as search activities over a knowledge space, and innovation looms once knowledge is recombined. It is this latter feature of knowledge search that is enabled by global brokerage: joint member ties that allow a consortium to reach different parts of a network enable members of R&D consortia to move beyond local solutions and engage in broader search for non-redundant information and knowledge (Dahlander, O'Mahony, & Gann, 2016; Jung & Lee, 2015; Rosenkopf & Nerkar, 2001; Vanhaverbeke et al., 2009). Not only does the increased amount of new knowledge elements overcome pre-mature idea saturation (Guler & Nerkar, 2012), it allows consortium members to envision novel connections and elaborate syntheses between apparently disparate and unrelated knowledge elements. This, in turn, increases the likelihood of making novel combinations and a larger set of recombination opportunities, which increases the likelihood of finding a global optimum in the form of an invention (Carnabuci & Operti, 2013; Gruber, MacMillan, & Thompson, 2008; Kajikawa et al., 2010; Katila & Ahuja, 2002). Because a global brokerage position also allows for the timely access to these knowledge elements, consortium members can seize opportunities relatively early, therewith pre-empting others from doing so (Lee, 2010; Soh, 2010).

Another effect of having access to redundant knowledge and information is that the knowledge generated by consortia that have a brokering position is perceived to be rich by members of other consortia, for example because access to diverse knowledge sources helps members of such a consortium to reach a more accurate understanding of the search space (McEvily & Zaheer, 1999; Shipilov, 2006). This might attract members of other consortia to seek out this knowledge for recombination in their own activities, with the result that the brokering consortium's knowledge is also used in the recombinant activities of other consortia (Nerkar & Paruchuri, 2005).

With respect to the second advantage of global brokerage, knowledge arbitrage, a brokerage position may enable the consortium to act as an information gateway that disseminates and receives information and knowledge through its joint member ties. For example, through disseminating knowledge about the design of the artefact that is being developed and affecting the flow of information and knowledge, consortia can improve their own chances on generating innovation by shaping the expectations of other consortia with respect to preferred standards and with that, the possibility to develop complementary products (Jones et al., 1998; Lee, 2010; Nerkar & Paruchuri, 2005; Soh, 2010). In addition, by virtue of an accurate understanding of the knowledge search space, consortium members might recognize potential collaboration opportunities with other consortia faster (Burt et al., 2000). Through increasing its knowledge and product prominence, a consortium increases its likelihood to successfully diffuse its innovation.

Contrary to these positive effects of brokerage, the literature has identified two effects of brokerage that are detrimental to the innovative outcomes generated by R&D consortia. First, even though a brokerage position allows for searching the broader knowledge space, excessive search of this space can be counterproductive as it demands time and resources. When search takes place excessively, this reduces the time devoted to further integrating the obtained knowledge (Ahuja & Katila, 2004; Vanhaverbeke et al., 2009). Second, brokerage might lead to random drift (i.e. the consortium's knowledge base is altered frequently in uncertain directions) (Ahuja & Katila, 2004; Lounamaa & March, 1987; Vanhaverbeke et al., 2009). Not only does this cause the accessed novel knowledge to be difficult and costly to integrate, it also decreases the reliability of the artefact that is developed (Hsu & Lim, 2014; Katila & Ahuja, 2002). Hence, both from a search costs as knowledge integration point of view, having many non-redundant ties decreases the potential for effective knowledge recombination (Vanhaverbeke et al., 2009).

We integrate the benefits and drawbacks of global brokerage by introducing the role of time. That the value of network brokerage changes over time has been suggested by several authors in the management literature (Adler & Kwon, 2002; Soda et al., 2004; Vanhaverbeke et al., 2009; Walker et al., 1997). In addition, recent research on social networks, creativity and innovation has suggested that in each phase of the innovation process, innovators have distinct primary needs: whereas flexibility and an environment that enables remote and uncommon associations between conceptually distant ideas are needed initially, a more unifying climate is needed once the developmental stage is reached. Features of the initial stage might even be detrimental for this later stage (Perry-Smith & Mannucci, 2017). This implies that, whereas initially members of R&D consortia benefit from exploring the larger search space which enables them to envision new connections and syntheses between apparently disparate and unrelated knowledge elements, it is exactly the broadness of this search space that leads to the overflow of information that has been suggested to lead to drift in later stages (Vanhaverbeke et al., 2009). We therefore argue that the positive effect of global network brokerage on the likelihood of generating innovative outcomes by R&D consortia is eroded over time, and turns negative as the consortium comes closer to its end:

Hypothesis 1: Time negatively moderates the positive effect of complete network brokerage on the likelihood of an R&D consortium generating innovative outcomes.

Local cohesion. Similar to the arguments for network brokerage, the arguments for network closure can be extended to organizations and organizational networks (Gulati, 1998; Leana & Van Buren, 1999). In addition, the interconnectedness of R&D consortia through joint members, and the relatively long duration of R&D consortia allows for applying the brokerage perspective to the changing knowledge and information needs of these consortia over time. When a consortium is embedded in a cohesive network, this means that joint membership ties between consortia are configured in such a way that the pattern of inter-consortium linkages is dense. Features of cohesive ties are their ability to circulate fine-grained and redundant but in-depth knowledge (Baum et al., 2005; Forti et al., 2013; Morris & Snell, 2007; Uzzi, 1997; Walker et al., 1997), and that they foster trust (Patzelt et al., 2011). Contrary to the broad knowledge and information benefits stemming from global brokerage, cohesion has often been suggested to be especially salient for innovative outcomes in the local context (i.e. a consortium's ego network) (Guler & Nerkar, 2012; Soh, 2010). Hence, we use the label 'local cohesion' for this concept.

Local cohesion provides an environment that facilitates the collective circulation of fine-grained information and knowledge, which has the tendency to be in-depth, complex and tacit (Fleming, Mingo, & Chen, 2007; Hung, 2017; Nahapiet & Ghoshal, 1998; Soh, 2010). For example, it enhances in-depth understanding of product complementarities, and standards ensuring interoperability (Lavie, 2007; Soh, 2010). In addition, network closure increases the likelihood of knowledge being up to date, accurate and reliable (Patzelt et al., 2011). These knowledge features are absent in networks characterized by structural holes, yet necessary to achieve synergies and share resources with network partners that enhance a node's ability to be innovative (Ahuja, 2000a; Shipilov & Li, 2008; Soda, Stea, et al., 2017). As a result, more in-depth search can take place, which positively affects product innovation as it enhances creativity, reduces the likelihood of errors and false starts and facilitates the development of routines, which makes search more reliable (Fleming, 2001; Fleming et al., 2007; Katila & Ahuja, 2002). In addition, it makes search more predictable and deepens the understanding of already familiar concepts (Katila & Ahuja, 2002).

Next to the knowledge benefits of local cohesion, cohesive ties generate trust, which facilitates exchange and stimulates flexibility and risk-taking (Nahapiet & Ghoshal, 1998). Even though it reduces the action autonomy of consortium members, as they take feedback received from other consortia into consideration (Patzelt et al., 2011), it facilitates long-term relationships and learning (Forti et al., 2013). In addition, increased trust eases the mobilization of suitable nodes around new ideas, also partly due to similarities in perspectives and interests (Leana & Van Buren, 1999; Obstfeld, 2005). Finally, inter-consortium trust facilitates positive affect, learning, and risk taking, all considered to be crucial components of creativity (Fleming et al., 2007).

Contrary to the positive effects of local cohesion on innovation, authors have proposed several potential detrimental consequences. First, local cohesion incurs costs, for example costs due to the maintenance of ongoing joint member ties (Nahapiet & Ghoshal, 1998). Second, although knowledge depth increases the understanding of members between consortia, excessive depth can have the negative consequence that members become too rigid in their search activities and search a part of the knowledge landscape that is already close to exhaustion (Katila & Ahuja, 2002). In addition, the continuous in-depth knowledge sharing between the same consortia over time might become without value, as knowledge redundancy looms at the horizon. This reduces the potential for new combinations between knowledge elements, and with that innovation (Battilana & Casciaro, 2012; Forti et al., 2013; Guan, Zuo, Chen, & Yam, 2016; Leiponen & Helfat, 2010). It also may reduce the openness of consortium members to alternative information and ways of doing things, which decreases the consortium's innovative potential (Guler & Nerkar, 2012). Consequently, costs of foregone innovation are incurred, due to members being stifled in embedded practices and procedures which hampers new information from entering the system, and causing members to have a preference for the most close solutions (Dornbusch & Neuhäusler, 2015; Nahapiet & Ghoshal, 1998).

Analogous with the changing value of global brokerage over time, some scholars have suggested that the effect of local cohesion on the likelihood of generating innovative outcomes by members of an R&D consortium is subject to the influence of time (Adler & Kwon, 2002; Soda et al., 2004; Vanhaverbeke et al., 2009; Walker et al., 1997). First, the effects of closure take time to fully come to fruition: no closed network delivers results right away (Walker et al., 1997). Kogut (2000), for example, stresses the longer time horizons that are needed for local cohesion to deliver benefits compared to brokerage. In addition, Bidwell and Fernandez-Mateo (2010) argue that as ties last longer, it is easier for actors to gain access to private information. Lastly, the distinction between brokerage as *tertius gaudens* and brokerage as *tertius iungens* implies that local cohesion needs time to develop: one first needs to have a structural brokerage position before one can act upon this position and bring disparate parties together and close the network (Obstfeld, 2005).

In addition to the time that is needed for local cohesion to develop, the needs of consortium members also change over time. In early stages, too much closure can lead members to become trapped in local search activities (Yu, Gilbert, & Oviatt, 2011). Perry-Smith and Mannucci (2017), in their work on social networks, creativity and innovation, argue that especially in later stages of the developmental process, legitimacy, shared vision and understanding are critical, which underlines the need for closure in later stages. Closure in later stages also has been argued to be beneficial as it shields consortia from possible knowledge spill-overs to consortia beyond a consortium's ego network, who by that time might be more at competition with the focal consortium (Hernandez, Sanders, & Tuschke, 2014). Hence, we argue that initially, local closure has a negative effect on the likelihood of generating innovative outcomes by R&D consortia, but this effect becomes smaller over time and turns positive once the consortium reaches its final stages:

Hypothesis 2: Time positively moderates the negative effect of local cohesion on the likelihood of an R&D consortium generating innovative outcomes.

Interaction between global brokerage and local closure

Besides the direct effect of global brokerage and local cohesion on the likelihood that an R&D consortium generates innovative outcomes, we propose a time-dependent interaction effect between both. Various authors already have proposed an interaction effect between brokerage and closure, or related concepts (Burt, 2005; Uzzi, 1997). In short, these authors contend that combining both features makes that the negative effects of global brokerage (i.e. difficulty in knowledge integration and risk of random drift) are offset by the positive effects of local cohesion (i.e. in-depth, tacit and up-to-date knowledge and flexibility), and the negative effects of local cohesion (i.e. costly and risk of over-search) are offset by the positive effects of global brokerage (i.e. access to non-redundant knowledge and information and knowledge arbitrage).

For example, authors that used Granovetter's (1973) distinction between strong and weak ties -comparable to local cohesion and global closure- have shown that strong ties with key partners and weak ties with peripheral partners results in an organization's highest innovative capability (Capaldo, 2007). In the context of innovation projects, it has been shown that a combination of bridging ties and strong ties results in the highest level of knowledge integration (Tiwana, 2008). Lastly, in the German car industry, a combination between embedded strong ties and a weak network architecture has the most beneficial consequence for innovation (Rost, 2011). The arguments used here all combine the need for access to a diverse array of knowledge stemming from distant search through bridging ties that in turn needs to be integrated through the activation of strong local ties in order for this knowledge to be applied instead of being lost (Rost, 2011; Tiwana, 2008).

This productive combination between local cohesion and global brokerage also resonates in the literature that focuses at network brokerage and closure and innovation. Nerkar and Paruchuri (2005), for example, argue that global brokerage can help to amplify the quality of the knowledge circulated through local cohesion. In addition, it has been argued that the potential information overflow stemming from spanning structural holes can be mitigated by the focus that results from having a close, local network (Baumann & Siggelkow, 2013; Caner, Cohen, & Pil, 2016; Paruchuri & Awate, 2016; Puranam, Alexy, & Reitzig, 2013). Diverse knowledge acquired through global brokerage can be received with more support in a dense ego network (i.e. local closure) as here mobilization around this new knowledge can be expected to be easier (Soh, 2010).

Although the studies reported in the above make fruitful claims about the positive effects of combining global brokerage with local closure, none of them explicitly address the role of time. In line with the arguments we provided for the effect of time on global brokerage and local cohesion, we argue that the interaction between both features is especially salient when the needs of consortium members switch from non-redundant knowledge and information to tacit and up-to-date knowledge. According to the developmental stages proposed by Perry-Smith and Mannucci (2017), this would be in the switch from the idea elaboration stage -with an emphasis on making uncommon associations between conceptually distant ideas to the idea championing stage, where the emphasis is more on gaining legitimacy. This is the point where a switch takes place from idea generation to acting on the idea (Obstfeld, 2005; Tiwana, 2008). Even though it is the exact timing of this switch cannot be specified, we can at least hypothesize that the interaction effect is not salient at either the start or end period of the R&D consortium:

Hypothesis 3: A positive interaction effect between an R&D consortium's local cohesion and global brokerage on the likelihood of an R&D consortium generating innovative outcomes exists in-between the consortium's initial stage and end stage.

3.3 Data and methods

Research setting and data

The empirical value of our hypothesis is assessed with a dataset that was developed for multiple research projects (see, for example, the other chapters in this dissertation and Mannak (2015)). This dataset[11] contains secondary data on 1,928 Dutch R&D consortia that were funded by a technology foundation aiming at realizing knowledge transfer between science and industry. Each consortium consists of one project leader -usually an academic researcher- and one or more interested organizations. These organizations form the so-called 'users committee', which is involved already in the early stages of the resarch. Its main tasks are taking note of and discussing the research progress and results, reflecting on the applicability of research findings to practice, and steering the research where and when necessary. Also, organizations involved can act as a testing-ground for the artefact being developed in the consortium in order to further aid its development. All in all,

[11] As indicated in the general introduction of this dissertation, several topics regarding the construction of this dataset are elaborated on in the different appendices to the different empirical chapters in this dissertation. The topics covered are (1) data sources and database construction (Chapter 2), (2) node specification (Chapter 3), (3) tie and network specification (Chapter 4) and (4) network boundary specification (Chapter 5).

the committee's explicit task is to provide an environment in which the chance of knowledge utilisation is maximized.

The first consortia started in the spring of 1981, and the most recent starting year that is included in the dataset is the year 2004. On average, 80 new consortia started each year, which means that at any point in time as from the year 1985, about 400 consortia were active, dispersed over 7 technology fields (see Appendix I and II of chapter 5 for the classification approach taken). Although no data are available on the exact relational structure amongst members within consortia, the occurrence of many organizations that participate in multiple consortia provides ample information on ties between consortia. This information was used to construct the consortium networks that form the basis of our analysis. The procedure followed with respect to tie and network specification is explained in Appendix I of Chapter 4.

The selection of the consortia included in our analysis was based on several considerations. First, out of all 1,928 consortia of which data was available, 153 consortia did not contain information about members of the users committee. In addition, 141 consortia did have members reported, but none of these members were involved in one or more of the other consortia. Also, 40 consortia did have joint members with other consortia, but the resulting dyad was not part of the main component of the network. Of another 331 consortia, no outcome evaluation was available. Consequently, these consortia (totalling 665) were excluded from the dataset, resulting in 1,263 consortia that were eligible for analysis. Since in this chapter we are interested in the effect of global brokerage and local closure over time, it was key that the consortia being analysed were embedded in the consortium network for at least 5 years without any interruptions. This was not the case for 449 consortia. These consortia either were embedded in the consortium network for less than 5 years (445 consortia[12]) or were not embedded in the consortium network for 5 subsequent years (4 consortia). After removing these consortia, a dataset resulted with 814 consortia that were suitable for analysis.

Our research interest in this chapter is in examining the role of time in the relationship between global brokerage and local closure on the one hand and the likelihood of an R&D consortium generating innovative outcomes on the other. We consider the consortia funded by the technology foundation that are analyzed in this chapter suitable for characterizing this relationship for several reasons. First, activities in each consortium are conducted in the context of highly knowledge-intensive and innovation driven technology fields (i.e. Chemistry, Civil engineering, Electrical engineering, Instruments, Life sciences, Mechanical engineering, and Medical technology) and focuses at pre-competitive research and development. This means that overcoming the limitations of a consortium's existing knowledge base through distant search and recombining existing knowledge elements as well as integrating these elements are pivotal for these consortia to be succesful. Second, the interconnectedness of consortia through joint members or consortium leaders allows for examining the resulting consortium network structure. Especially the long time period over which the funding agency has reported the results of funded consortia allows for the determination of both global and local network positions of consortia over time. These positions can be assumed to vary over time, due to the yearly new inflow of newly started consortia,

[12] Although the number of 445 consortia might seem alarmingly large, one should realize that most of these consortia started after the year 1999. Given that the most recent year of observing consortia is 2004, these consortia simply were not observed long enough to allow for measuring global brokerage and local cohesion for 5 subsequent years. In addition, it should be noted that none of the consortia that started in the technology field 'Mechanical engineering' in 1991 nor the technology field 'Civil engineering' in 1992 fulfilled the selection criteria outlined above. Hence, the consortia studied in this chapter are dispersed across 82 unique technology field – year combinations.

and outflow of consortia that have finished. Collecting network data over longer time periods is an exception more than the rule, given the daunting task of collecting longitudinal data for multiple networks (Provan et al., 2007). Hence, our dataset provides an excellent opportunity for studying the time-varying effects of networks on innovation. This is enabled by the clear time lag that exists between the moment of measuring for example a consortium's global brokerage and the moment of measuring its innovative outcomes. Depending on the specific structure chosen, this lag is always at least one year, which suppresses concerns of reversed-causality between the independent and dependent variables in our model (Antonakis, Bendahan, Jacquart, & Lalive, 2010).

Measurements

Innovative outcomes. We consider innovative outcomes in this chapter as the result of R&D activities that focus at searching, developing and recombining different knowledge components that are sought after in a knowledge landscape. Our interest is in three stages of these search activities (Gopalakrishnan & Damanpour, 1997), namely problem-solving activities, design and development and commercialization. Given a fixed duration between the start of an R&D consortium and the moment of its evaluation (i.e. 5 years after its start), the results of any consortium can be categorized into one of these three outcomes when evaluated. Indeed, the evaluation score of the technological outcomes of a consortium that is assigned by the funding agency (see the three-letter code provided in the first block in Table 6 in Chapter 2) resembles this categorization: four distinct scores can be assigned, which ranges from 0 (failure), A (further development needed), B (prototype) and C (outcome realized). As consortium outcomes rarely get assigned a score of 0, this category was lumped with category A. As a result, three ordinal classes were created, each representing a unique stage in the knowledge search and recombination process.

Global brokerage. This concept is operationalized using Freeman's (1978) betweenness centrality measure. A host of centrality measures for network analysis are available, yet Freeman's three measures (degree, betweenness and closeness centrality) can be considered to be the bedrock measures based on which further refinements have been made (Friedkin, 1991). Out of these three measures, betweenness centrality captures global brokerage best, as it considers the frequency with which a focal consortium falls between pairs of other consortia on the shortest paths connecting them. As such, it captures the extent to which an R&D consortium occupies a brokerage position in the complete network. It has been used to capture network brokerage -either implicitly or explicitly- by many other authors (see, for example, (Allatta & Singh, 2011; Bekkers, Duysters, & Verspagen, 2002; Bond, Walker, Hutt, & Reingen, 2004; Breschi & Catalini, 2010; Dess & Shaw, 2001; Díez-Vial & Montoro-Sánchez, 2016; Geletkanycz, Boyd, & Finkelstein, 2001; Gilsing, Nooteboom, Vanhaverbeke, Duysters, & van den Oord, 2008; Hansen, 2002; Mehra, Dixon, Brass, & Robertson, 2006; Owen-Smith & Powell, 2004; Salman & Saives, 2005; Thieme, 2007)).

The betweenness centrality C_B of a consortium *k* reflects the frequency with which this consortium falls between pairs of other consortia on the shortest or geodesic paths connecting them[13] (Freeman, 1978). The obtained value for betweenness centrality can be made independent of network size by employing the following formula:

$$C'_{\mathrm{B}}(p_k) = \frac{2C_{\mathrm{B}}(p_k)}{n^2 - 3n + 2}$$

[13] In the event of multiple possible shortest or geodesic paths, one must work with probabilities in the calculation of a point's betweenness centrality. For the sake of simplicity, this situation is not being considered in this example.

The result of this formula yields a score that ranges from 0 (representing a case in which a consortium does not fall on the shortest path between any pair of other consortia) to 1 (representing a case in which a consortium falls on the shortest path between all pairs of other consortia). Consortium I in panel (c) of Figure 10, for example, lies on two shortest paths between other pairs of consortia: the path between consortium II and III and the path between consortium II and IV. Hence, the absolute betweenness centrality score of consortium I is 2. The betweenness centrality score of the other consortia in this figure is 0, as none of them is bridging the path between any other pair of consortia. Given that n = 4, normalizing the betweenness score of consortium I using the formula in the above yields ⅔ (2×2 / 6).

Calculations of betweenness centrality for each consortium were supported using the statnet suite (Goodreau et al., 2008) that is available in the R environment for statistical computing (R Development Core team, 2016). These calculations did not include tie strength (e.g. one joint member link to another consortium is formed by multiple members of the focal consortium). In addition, when a network consisted of multiple components, the normalization of the betweenness centrality score took place using the size of the component a consortium was part of, and not using the size of the total network.

Local cohesion. We use Burt's constraint measure (Burt, 1992) to determine the connectedness of a consortium at the ego network level. Together with the measures for effective network size and number of bridges, constraint is one of the three measures that expresses the extent to which the ego-network -or local network- of a consortium acts like a 'straight jacket' for that consortium, in the sense that opportunities for receiving non-redundant knowledge and information are limited. Whereas the first two measures rely on counts (Borgatti, 1997; Burt, 1992), constraint is a measure that provides a normalized measure of the extent to which an ego-network is clustered, making it conveniently comparable with our measure for global brokerage, betweenness centrality. In addition, it can be considered a more refined measure of the multiple consortium membership control variable that was used in the previous chapter.

Being calculated using a consortium's ego network, the constraint index varies with three conditions: (i) ego network size (larger networks are less constraining), (ii) density (networks of more strongly interconnected contacts are more constraining), and (iii) hierarchy (networks in which all contacts are exclusively tied to a single contact are more constraining) (Burt, 1992). Local cohesion, or the constraint of a consortium i was calculated with the following formula (Burt, 1992):

$$C_i = \left(p_{ij} + \sum_q p_{iq} p_{qj} \right)^2, q \neq i, j$$

In this formula, p_{ij} denotes the proportional strength of consortium i with consortium j. This proportional strength is based on the degree (i.e. the total number of joint member links with other consortia, regardless of the number of members that forge that link) of consortium i. Consortium I in panel (c) of Figure 10, for example, has a total degree of 3. Hence, the proportional strength of the link that consortium I has with any of the other consortia is ⅓. The product $p_{iq}p_{qj}$ expresses the extent to which one of the other consortia to which consortium i is linked, q, is also linked with consortium j. The higher this product term, the more augmented a direct link between i and j becomes through the pathway from p_{iq} to p_{qj}, and the less likely it is that i receives novel information and knowledge from j.

The squared product represents the constraint of *i* from a lack of primary holes around consortium *j*. If, for example, one would be interested in the constraint of consortium I with respect to consortium III in panel (c) of Figure 10, we do not only have to consider the link between both consortia, but also the link between consortium III and IV as the latter consortium too is linked to consortium I (with proportional strength of ½). Hence, the constraint of consortium *i* with respect to a lack of primary holes around consortium III is 0.25 $(⅓ + (⅓\times½))^2$. Aggregated across all contacts *q* (excluding *i*), this yields the aggregated constraint of *i*. In the example given, the aggregated constraint of consortium I equals .61, the aggregated constraint of consortium II is 1 and the aggregated constraints of consortia III and IV are 1.01.

Operationalizing local cohesion -or the lack of local brokerage opportunities- using constraint is consistent with a long research tradition (Battilana & Casciaro, 2012; Hernandez et al., 2014; Lee, 2010; Lin, Peng, Yang, & Sun, 2009; Shipilov, Li, & Greve, 2011; Soda, Stea, et al., 2017; Soda et al., 2004; Zaheer & Bell, 2005). Scores on constraint range from 0 (representing full brokerage) to 1 (representing full constraint). In special cases, this measure can exceed 1 (Bruggeman, 2008). In those cases, the score was normalized to 1 as this value is normally assigned to nodes that have a complete lack of structural holes (Foss, Frederiksen, & Rullani, 2015). We calculated constraint using the igraph package (Csárdi & Nepusz, 2006) that is implemented in R (R Development Core team, 2016). Similar to the calculation of betweenness centrality, these calculations ignored tie values.

Control variables. The control variables included in the previous chapter were used in this chapter's analysis as well. Hence, in addition to *technology field and year dummies*, *size*, *duration*, and the levels of *financial resources, consortium leader experience* and *member relational experience* all were included in the analysis. In addition, we controlled for the curvilinear effects of *geographical proximity* and *technological diversity* which were shown in the previous chapter to influence the likelihood of a consortium generating innovative outcomes as well. Variables examined in the previous chapter that were <u>not</u> included in our primary analyses were the variables that reflected the level of *network integration*. The main reason for not doing so stems from the difference between the lag structure used in previous chapter's model (independent variables at *t* were related to a dependent variable at *t+5*) and the model that is estimated in the current chapter (independent variables at various points in time, *t+i* (with *i* ranging from 0 to 4), are related to a dependent variable at *t+5*). The assumption underlying the first model is that network integration serves its role with respect to creating mutual awareness and common thematic foci among R&D consortium members especially in the consortium's maiden year, as at that point in time the search space is still fully unexplored. As we did not hypothesize any effects with respect to the time-dependent effect of network integration, including the variables in the current model -even though possible- would be especially problematic for the years that follow a consortium's first year, as no theoretical expectations have been formulated for these lags. In addition, the different size of the sample employed in this chapter compared to the sample used in the previous chapter would make a clear comparison between both analyses problematic. We will, however, address the issue in our robustness tests. In addition, we did not include the control variable *multiple consortium membership*, as we focus on the more refined network measures global brokerage and local cohesion instead and want to avoid multicollinearity issues if too many measures referring to a consortium's network position are included in the analysis.

Data analysis

The three hypothesized relationships all propose a moderating role of time on the relation between on the one hand global brokerage and local cohesion (including an interaction between both), and on the other hand the likelihood of generating innovative outcomes. In the dataset used, all variables are time-invariant, with the exception of global brokerage and local cohesion: due to new consortia entering the consortium network over time, and older consortia leaving this network, the betweenness centrality and constraint measures for a given consortium are prone to variation. For this reason, the direct effect of betweenness centrality and constraint on the likelihood of generating innovative outcomes will be tested in five sets of models, each of which includes the same variables, but differs in the time lag between the predictors and the outcome variable. This approach resembles the one taken by Ahuja & Katila (2004). Should there be a significant change in the effect of, for example, betweenness centrality as the time lag between observing the independent variable and the dependent variable decreases, then this would indicate a moderating effect of time.

Time lags in this chapter are denoted with the letter *i*. An *i* with score 5 means that 5 years needs to pass before the consortium is evaluated, i.e. the consortium is at its start. Other time lags are i=4, i=3, i=2 and i=1. Although the time lag is determined by the consortium evaluation procedure (a consortium is evaluated five years after its start), the current literature suggests that exploring a window of five years for assessing the technological impact of R&D is appropriate. Studies on R&D depreciation have shown that the value of knowledge depreciates over time, losing most of its economic value within five years (Griliches, 1979; Hall, Griliches, & Hausman, 1984; Pakes & Schankerman, 1984; Stuart, 2000; Vanhaverbeke et al., 2009).

The ordinal nature of the dependent variable implies that an ordinal logistic regression approach is required. The nature of the variable fits our research purposes well: say that over time, higher scores of betweenness centrality increase the likelihood of ending in the outcome category 'further development needed', this would suggest that global network brokerage causes consortia to dwell into the global search space. Similar to the previous chapter, we employ a multi-level framework. This choice stems from the nature of the control variables technology field and year, which are at the network level instead of at the consortium level. For each time lag, we first estimated an ordinal logistic regression model with 814 data points, predicting the outcome at $t+5$ using consortium-level predictors at $t+i$. As intercepts could vary by technology field and year, this intercept was estimated for each combination of technology field and year by the second component of the model. This latter model is an ordinal logistic regression model with 82 data points (5 technology fields × 12 years + 2 technology fields × 11 years), using field- and year-level predictors.

For each time lag *i*, four distinct models were estimated. All models include the control variables. In addition to these controls, model 1 includes the betweenness variable representing global brokerage. In model 2, this variable is removed, and the constraint variable is entered to assess the separate effect of local cohesion. Model 3 contains both predictors, and model 4 adds the interaction between both predictors. We use the 'ordinal'-package (Christensen, 2011) for estimating our models. Estimating ordinal regression models requires that the assumption of parallel regression is fulfilled: under this assumption, the coefficients that describe the relationship between the lowest and all higher categories of the response variable are similar compared to those describing the relationship between the next lowest category and all higher categories, and so forth. Only when this assumption is fulfilled, one can use one set of coefficients for all outcome categories. Although no formal test of this assumption for multilevel ordinal logistic regression is available at present, informal tests are available. We assessed the tenability of this assumption using one of the procedures outlined by Harrell (2001). The results of this test are reported in Appendix II, in which we draw the conclusion that except for two predictors, the parallel regression assumption is likely to be satisfied for each predictor separately. To aid model interpretation, effect plots were created for all salient effects of the estimated models. These plots were created using the 'effects'-package developed by Fox (2003). This package calculates marginal effects of a predictor of interest at the average of all other predictors. Both packages were implemented in the R statistical environment (R Development Core team, 2016). For interpretation and comparison purposes and to aid model convergence, all predictor variables were scaled using the default scale function available in R (default settings were used). Except when indicated otherwise, all pictures in this chapter were made using the 'ggplot2'-package (Wickham, 2009) available in R.

3.4 Results

Descriptives and correlations

Means, standard deviations and correlations for the consortium-level variables are provided in Table 7. Table 8 shows this information for the network-level variables (i.e. technology field and year dummies). It should be noted that for the analyses performed, 5 specifications of the same sample were used. This sample did not differ on any variable, other than the variables for global brokerage and local cohesion at the consortium level, and the 'year' variable at the network level.

With respect to the correlations at the network level, the scores of the technology field dummies indicate that the consortia studied in this chapter are distributed unevenly across technology fields. Especially the fields of Civil engineering, Mechanical engineering and Medical technology tend to be underrepresented. This is caused by the unequal distribution of consortia across technology fields in general, and the fields mentioned in the above have generally smaller consortium networks. The correlation between technology field dummies and the year control shows that whereas consortia in the field of Civil engineering tend to become less prevalent as years go by, consortia in the field of Life sciences tend to become more prevalent as years go by instead. These patterns are consistent across different lag specifications.

The dependent variable correlates with the size control and the control for geographical proximity: bigger consortia tend to have innovative outcomes that are in the higher outcome categories of the dependent variable, and their members are more geographically dispersed. A correlation with the predictor variables is only present for local cohesion. This correlation is consistently visible across the five sample specifications, indicating a lack of time-dependence in the positive linear association between generating innovative outcomes and a consortium having a cohesive ego network. No correlation is present between our outcome variable and global brokerage. This means that no linear association exists between occupying a brokerage position in the global network and generating innovative outcomes, regardless of the year in which this brokerage position is occupied.

Other than with consortium leader experience, consortium size correlates with all other consortium-level control variables. A consortium in the sample employed that has more members also has a longer duration, more financial resources, members that have more experience with one another, and are both more distant and more diverse from one another. Salient correlations are the ones between size and global brokerage and local cohesion. From these correlations we deduce that bigger consortia tend to broker more in the network and are locally embedded in less cohesive ego networks. Despite a substantial reduction in the sample size compared to the previous chapter, the correlation between member relational experience and consortium leader experience is still present, indicating that members building up experience with one another and consortium leaders gaining experience go hand in hand.

With respect to the two predictor variables, it is interesting to see that there are significant correlations between geographical proximity (across all lag specifications, except for i=5) and technological diversity (consistent across all lag specifications) on the one hand, and global brokerage on the other. The negative correlation between proximity and global brokerage tells us that when members become more geographically distant from one another, the consortium they are member of is more likely to span distant clusters in the consortium network. The positive correlation between technological diversity and global cohesion indicates that as members become more diverse, the consortium they are member of is more likely to span distant clusters in the network. This is in line with observations made by others, for example Sosa (2011) who claims that a node's knowledge diversity is positively associated with network brokerage. The positive association between geographical proximity and local cohesion tells us that being geographically close to one another facilitates the creation of a cohesive consortium ego network. Except for i=5, this correlation is consistent across years. Lastly, the correlation between global brokerage and local cohesion that is present for i=1 (r = -.08, p < .05), indicates that as consortia reach completion, they tend to either have a global brokerage position, or a locally cohesive ego network.

The descriptives of global brokerage and local cohesion warrant some extra inspection. Especially the standard deviation of global brokerage is rather large, indicating the presence of outliers that might influence significant results in the regression analysis (Zhang & Shaw, 2012). Figure 5 displays box and whisker plots for both variables for i=5 to i=1. Indeed, especially the global brokerage variable has a considerable number of outliers and most scores observed are concentrated in a small range of the total scale. Especially scores of 1 are rarely observed when using a betweenness centrality scale. These scores can be explained by consortia that are embedded in small networks, where a score of 1 can easily be obtained (if, for example, consortium IV would disappear from the network depicted in panel (c) of Figure 10, consortium I would have a betweenness centrality score of 1). The skewness in the distribution of global brokerage is not a surprise: a network measure is used, and nodes are rarely randomly distributed in a relational structure (Barabási & Bonabeau, 2003; Lusher et al., 2013). Although the distribution does raise concerns about the extent to which we can empirically discern consortia that differ in their brokerage position, these outliers are not removed from the analysis, as this would dismiss the exact reason for using network-based measures. In the visualizations of the relevant effects, however, these extremes will be included in the calculations but not shown for the sake of visual clarity.

In addition to the box and whisker plots for global brokerage and local cohesion, Figure 3 also provides scatterplots in which global brokerage is plotted by local cohesion with observations marked by both technology fields and years, as well as pictures in which consortia with different combinations of scores on global brokerage and local cohesion are highlighted. With respect to the scatter plots, for the fields Electrical engineering, Chemistry, Life science and Instruments, scores on both variables tend to cluster together on smaller ranges that are also closer to zero. For the other three fields, Mechanical engineering, Medical technology and Civil engineering, both variables cluster less and a larger range of scores can be observed. As noted earlier, the cause of

TABLE 7

Descriptives and correlations among consortium-level variables[14]

Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9
1. Innovative outcomes$_{t+i}$……………..	1.98	.80	1	3	-								
2. Size………………………………….	4.33	2.31	1	23	.15**	-							
3. Duration…………………………….	4.55	1.00	4	15	.02	.13**	-						
4. Financial resources………………….	543.35	356.09	13.87	3,738.36	.04	.23**	.27**	-					
5. Consortium leader experience$_t$………	1.11	1.71	0	11	.06	.05	-.00	.00	-				
6. Member relational experience$_t$………	1.04	2.10	0	15	.03	.10**	.02	.01	.64**	-			
7. Geographical proximity…………….	.28	.29	0	1	-.07*	-.30**	-.01	-.05	-.04	-.08*	-		
8. Technological diversity…………….	.63	.31	0	1	-.01	.37**	.07*	.03	-.04	.04	-.33**	-	
9. Global brokerage$_{i=5}$………………	.03	.07	0	1	-.00	.27**	.02	.05	.06	.01	-.06	.12**	-
10. Local cohesion$_{i=5}$………………..	.28	.21	.07	1	.08*	-.11**	-.06	-.08*	-.02	-.09**	.07	-.02	-.04
9. Global brokerage$_{i=4}$………………	.02	.06	0	1	.00	.27**	-.01	.07	.08*	-.00	-.08*	.13**	-
10. Local cohesion$_{i=4}$………………..	.27	.20	.07	1	.07*	-.11**	-.02	-.07*	-.00	-.08*	.08*	-.03	-.04
9. Global brokerage$_{i=3}$………………	.02	.05	0	.51	-.02	.28**	.01	.04	-.02	-.02	-.08*	.14**	-
10. Local cohesion$_{i=3}$………………..	.26	.19	.07	1	.08*	-.10**	-.04	-.07*	.00	-.07	.09**	-.03	-.04
9. Global brokerage$_{i=2}$………………	.02	.06	0	1	-.03	.23**	.00	.01	-.02	-.01	-.07*	.11**	-
10. Local cohesion$_{i=2}$………………..	.26	.19	.06	1	.08*	-.10**	-.03	-.07*	.02	-.04	.09**	-.06	-.02
9. Global brokerage$_{i=1}$………………	.02	.04	0	.53	-.01	.25**	.00	.04	-.05	-.03	-.08*	.12**	-
10. Local cohesion$_{i=1}$………………..	.26	.20	.06	1	.09*	-.12**	-.02	-.07*	.02	-.05	.11**	-.06	-.08*

[14] $n = 814$. **$p < .01$; *$p < .05$.

TABLE 8

Descriptives and correlations among network-level variables[15]

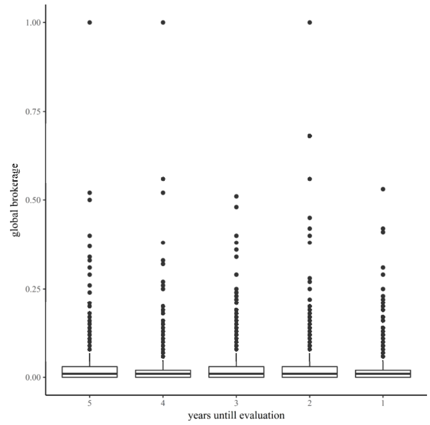
Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7
1. Chemistry………………………….....	.19	.39	0	1	-						
2. Civil engineering……………................	.07	.25	0	1	-.13**	-					
3. Electrical engineering…………............	.17	.37	0	1	-.22**	-.12**	-				
4. Instruments…………………………	.20	.40	0	1	-.24**	-.13**	-.22**	-			
5. Life sciences……………………….….	.26	.44	0	1	-.28**	-.16**	-.26**	-.29**	-		
6. Mechanical engineering………………	.03	.18	0	1	-.09**	-.05	-.08*	-.09**	-.11**	-	
7. Medical technology…………………..	.09	.29	0	1	-.15**	-.09*	-.14**	-.16**	-.19**	-.06	-
8. Year$_{i=5}$…………………………………	1995.07	3.26	1989	2000	.01	-.09**	.00	-.05	.08*	.01	-.01
8. Year$_{i=4}$…………………………………	1996.07	3.26	1990	2001	.01	-.09**	.00	-.05	.08*	.01	-.01
8. Year$_{i=3}$…………………………………	1997.07	3.26	1991	2002	.01	-.09**	.00	-.05	.08*	.01	-.01
8. Year$_{i=4}$…………………………………	1998.07	3.26	1992	2003	.01	-.09**	.00	-.05	.08*	.01	-.01
8. Year $_{i=1}$……………...………………..	1999.07	3.26	1993	2004	.01	-.09**	.00	-.05	.08*	.01	-.01

[15] $n = 82$. $^{**}p < .01$; $^{*}p < .05$.

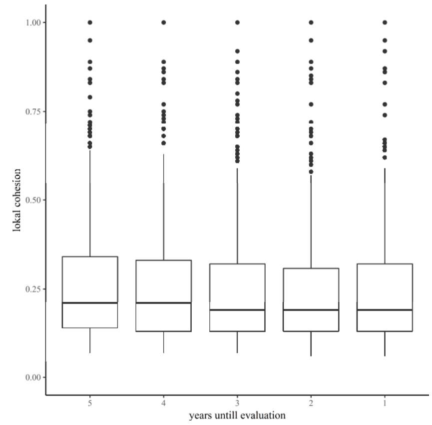
FIGURE 5[16]

Global brokerage and local cohesion: distributions, scatter plots and examples of R&D consortia with different combinations of both variables

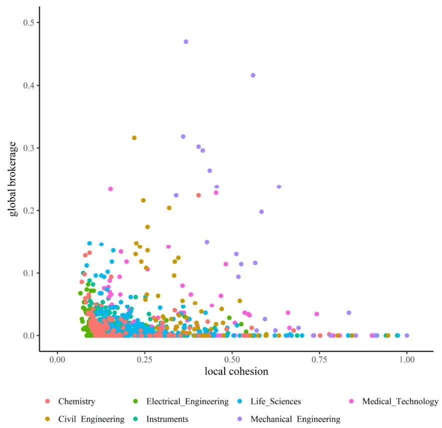
Distributions global brokerage



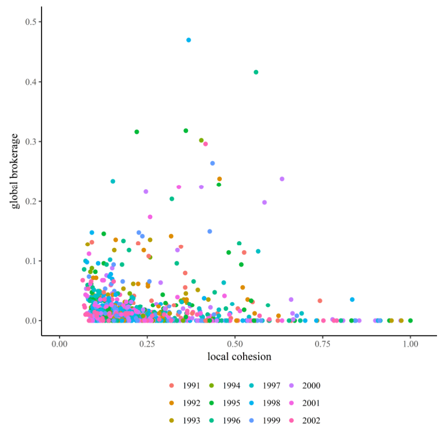
Distributions local cohesion



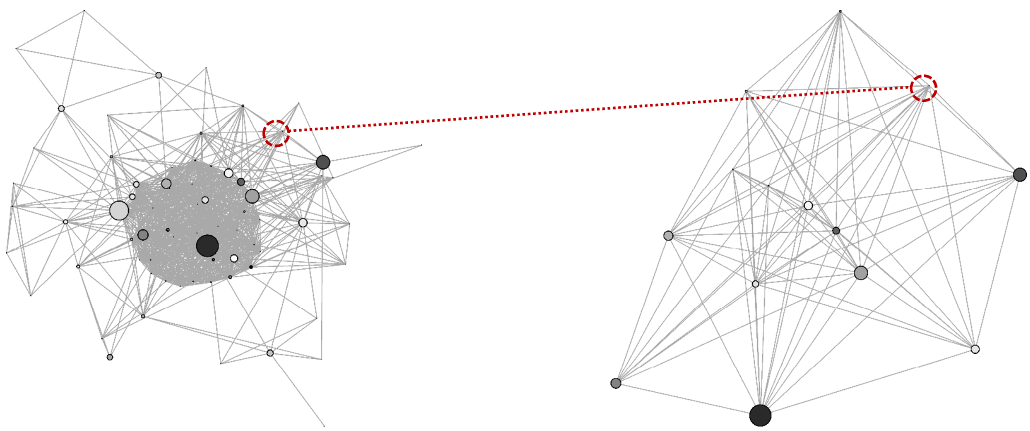
Global brokerage by local cohesion; Observations marked by technology field



Global brokerage by local cohesion; Observations marked by year.



Low global brokerage (left), low local cohesion (right) (Electrical engineering, 1999. Global brokerage = .00; local cohesion =.14)

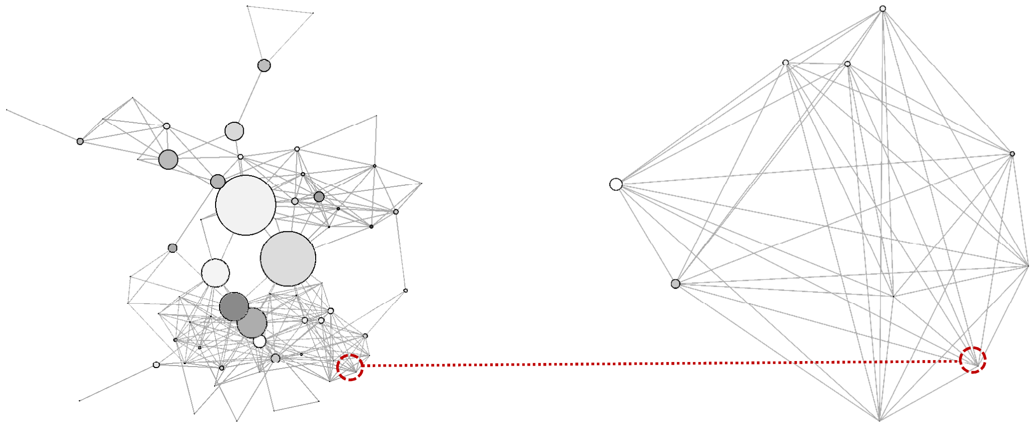


[16] Key to the network pictures: the left panel shows the position of the focal consortium in the complete network; the right panel shows its position in its ego network. Node size indicates the score on global brokerage, node colours (darker is higher) indicate levels of local cohesion.

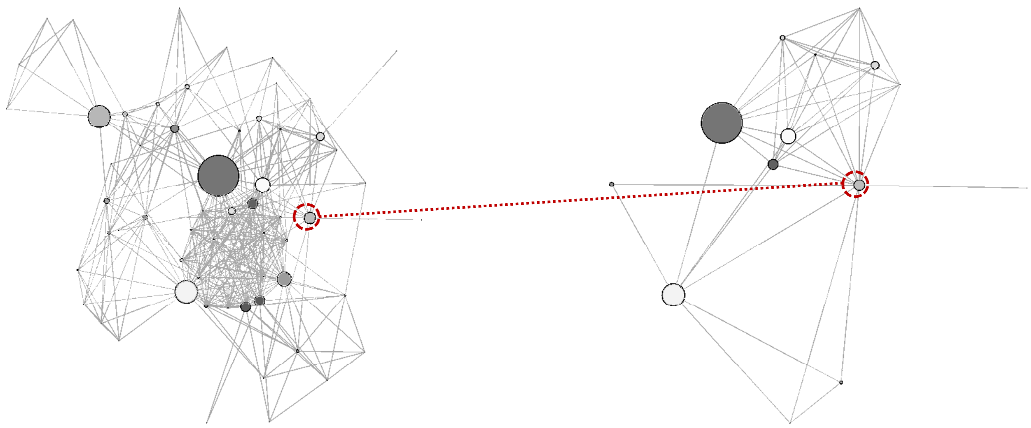
FIGURE 5 (CONTINUED)

Global brokerage and local cohesion: distributions, scatter plots and examples of R&D consortia with different combinations of both variables

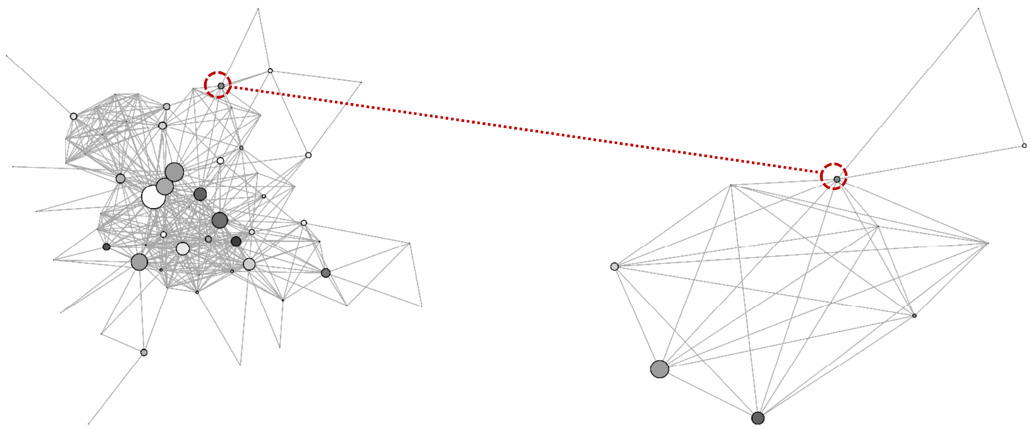
Low global brokerage (left), high local cohesion (right) (Life sciences, 1994. Global brokerage = .00; local cohesion = .29)



High global brokerage (left), low local cohesion (right) (Instruments, 1992. Global brokerage = .05; local cohesion = .15)



High global brokerage (left), high local cohesion (right) (Chemistry, 1990. Global brokerage = .03; local cohesion = .25)



this is that the first four networks are generally bigger compared to the last three networks. In this specific research setting, this means that these networks are generally denser, which makes it more difficult to obtain a brokerage position for individual consortia.

The density of the consortium networks observed in this chapter can be deduced from the pictures in Figure 3 that provide illustrations of consortia having different combinations between global brokerage and local cohesion (i.e. low-low, low-high, high-low and high-high). Based on a focal consortium, both the complete network in which this consortium is embedded, and its ego network is shown (this focal consortium is marked in both networks by a dotted circle, connected by a dotted line). Although illustrative, we aimed at comparability when selecting consortia for those pictures. Outliers, for example, were not considered. A consortium was considered to score low on the variables of interest when this score ranged from the minimum observation to the mean score (global brokerage: .00 - .03; local closure: .06- .29). Our selection was biased towards the lower scores in this range. A consortium was considered to score high on the variables of interest when this score ranges from the mean score to one standard deviation above this mean score (global brokerage: .03 - .09; local closure: .29- .52). Once again, our selection was biased towards the higher scores in this range. In addition –for comparability purposes– we made sure that complete network sizes as well as the size of the ego network of the focal consortium were the same across different combinations. Especially the features of ego network size (larger networks are less constraining) and density (more dense networks are more constraining) that are considered are visible in the ego network pictures: generally, the ego networks that have low scores on constraint are bigger and less dense.

Ordinal logistic regression results

Results of the multilevel ordinal logistic regression results using the average scores across the five sample specifications can be found in Table 9 until Table 13 (with *i* ranging from 5 to 1). The coefficients of the variables of interest in these separate analyses are summarized in Table 14. Complementary to these tables, marginal effect displays for selected models are provided in Figure 6 to aid effect interpretation. The logic behind displaying the selected effects will be explained as we proceed through discussing our hypotheses tests. With an eye on model convergence, all predictor variables were standardized. Consequently, each coefficient in the ordinal logistic regression tables represents the change in log odds when the corresponding predictor changes one unit, holding all other predictors at their average value.

Our results in general suggest that there are significant effects of both global brokerage as local cohesion on the likelihood of a consortium generating innovative outcomes. The relevant coefficients in the models (summarized in Table 14) suggest that this interaction is present one year after the start of a consortium. In addition, whereas the effect of local cohesion is unidirectional and robust over time, the effect of global brokerage -even though unidirectional as well- is not significant for each lag specification. All in all, our results offer several interesting insights not expected based on our theoretical model.

The benefits and drawbacks of global brokerage have been brought together in a hypothesis that proposed a negative moderation effect of time on the positive relationship between complete network brokerage and the likelihood of generating innovative outcomes. It can be seen in Table 14 that this significant negative effect is visible across time lags, although the coefficient is not significant 5, 3 and 1 year(s) before the evaluation of a consortium. The effect of global brokerage

TABLE 9

Results of ordinal logistic regression models predicting *p*(technological outcomes$_{t+i}$), *i=5*

Variable	Model 1	Model 2	Model 3	Model 4
[Innovative outcome = prototype]………..	-.96*** (.27)	-.89*** (.27)	-.91*** (.27)	-.93*** (.27)
[Innovative outcome = product]…………..	.81** (.27)	.88*** (.27)	.86** (.26)	.85** (.27)
1. Size………...…………………………...	.36*** (.09)	.34*** (.09)	.37*** (.09)	.39*** (.09)
2. Duration………………………………..	.00 (.07)	-.00 (.07)	.00 (.07)	-.00 (.07)
3. Financial resources……...………………	.07 (.08)	.08 (.08)	.08 (.08)	.08 (.08)
4. Consortium leader experience$_t$.…..............	.00 (.09)	-.01 (.09)	-.00 (.09)	.01 (.09)
5. Member relational experience$_t$.…..............	-.02 (.09)	-.00 (.09)	-.01 (.09)	-.02 (.09)
6. Geographical proximity…….....................	-.69** (.25)	-.64* (.25)	-.64* (.25)	-.64* (.26)
7. Geographical proximity^2…….....................	.62* (.27)	.56* (.27)	.56* (.27)	.56* (.27)
8. Technological diversity…………..……...	.19 (.26)	.18 (.26)	.18 (.26)	.19 (.26)
9. Technological diversity^2………………...	-.39 (.25)	-.40 (.25)	-.40 (.25)	-.40 (.25)
10. Global brokerage$_{i=5}$……..……....……	-.11† (.07)		-.09 (.07)	-.18† (.09)
11. Local cohesion$_{i=5}$……..…..…...……......		.18* (.08)	.16* (.08)	.18* (.08)
12. 10 × 11………………….........................				.14 (.10)
Deviance	1,676	1,674	1,672	1,670
Δdf	-	0	1	2
***p* (> χ^2)**	-	-	.04*	.04*
Year variance	0.28	0.28	0.28	0.29
Technology field variance	0.28	0.27	0.26	0.28

note: n = 814. ***p < .001; **p < .01; *p < .05; †< .1. Standard errors are displayed between parentheses

TABLE 10

Results of ordinal logistic regression models predicting *p*(technological outcomes$_{t+i}$), *i=4*

Variable	Model 1	Model 2	Model 3	Model 4
[Innovative outcome = prototype]………..	-.95*** (.27)	-.89*** (.27)	-.91*** (.27)	-.92*** (.27)
[Innovative outcome = product]…………..	.82** (.27)	.89*** (.27)	.87** (.27)	.87** (.27)
1. Size………..…………………………..	.35*** (.09)	.34*** (.09)	.36*** (.09)	.40*** (.09)
2. Duration………………………………..	-.00 (.07)	-.00 (.07)	-.01 (.07)	-.01 (.07)
3. Financial resources……..………………	.08 (.08)	.08 (.08)	.09 (.08)	.07 (.08)
4. Consortium leader experience$_t$.….............	.01 (.09)	-.01 (.09)	-.00 (.09)	.00 (.09)
5. Member relational experience$_t$.….............	-.03 (.09)	.00 (.09)	-.01 (.09)	-.01 (.09)
6. Geographical proximity……...................	-.68** (.25)	-.65* (.25)	-.65* (.25)	-.65* (.25)
7. Geographical proximity^2……...................	.60* (.27)	.57* (.27)	.56* (.27)	.57* (.27)
8. Technological diversity……….…….....	.18 (.26)	.19 (.26)	.19 (.26)	.20 (.26)
9. Technological diversity^2……………….....	-.39 (.25)	-.40 (.25)	-.39 (.25)	-.42† (.25)
10. Global brokerage$_{i=4}$……..……......……	-.11 (.08)		-.08 (.08)	-.22* (.10)
11. Local cohesion$_{i=4}$……..…..…...……......		.18* (.08)	.16* (.08)	.20* (.08)
12. 10 × 11…………………..........................				.23* (.10)
Deviance	1,677	1,674	1,672	1,667
Δdf	-	0	1	2
p **(> χ^2)**	-	-	.04*	.01**
Year variance	0.28	0.29	0.29	0.30
Technology field variance	0.28	0.27	0.27	0.28

note: n = 814. $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; $^{\dagger} < .1$. Standard errors are displayed between parentheses

TABLE 11

Results of ordinal logistic regression models predicting *p*(technological outcomes$_{t+i}$), *i=3*

Variable	Model 1	Model 2	Model 3	Model 4
[Innovative outcome = prototype]………...	-.98*** (.27)	-.89*** (.27)	-.93*** (.27)	-.92*** (.27)
[Innovative outcome = product]…………..	.80** (.27)	.89*** (.27)	.86** (.27)	.86** (.27)
1. Size………...…………………………...	.36*** (.09)	.34*** (.09)	.37*** (.09)	.38*** (.09)
2. Duration………………………………..	.00 (.07)	.00 (.07)	.00 (.07)	.00 (.07)
3. Financial resources……...………………	.07 (.08)	.08 (.08)	.08 (.08)	.08 (.08)
4. Consortium leader experience$_t$.…..............	-.00 (.09)	-.02 (.09)	-.01 (.09)	-.01 (.09)
5. Member relational experience$_t$.….............	-.02 (.09)	-.00 (.09)	-.01 (.09)	-.01 (.09)
6. Geographical proximity….…....................	-.66** (.25)	-.67** (.25)	-.65* (.25)	-.66** (.25)
7. Geographical proximity^2…….....................	.59* (.27)	.59* (.27)	.57* (.27)	.57* (.27)
8. Technological diversity…………..…….....	.17 (.26)	.20 (.26)	.18 (.26)	.19 (.26)
9. Technological diversity^2……………….....	-.38 (.25)	-.41 (.25)	-.39 (.25)	-.40 (.25)
10. Global brokerage$_{i=3}$……..……......……	-.17* (.08)		-.13† (.08)	-.15† (.09)
11. Local cohesion$_{i=3}$……..…..…...……......		.19* (.08)	.16* (.08)	.18* (.08)
12. 10 × 11………………….........................				.05 (.10)
Deviance	1,674	1,673	1,669	1,669
Δdf	-	0	1	2
***p* (> χ^2)**	-	-	.04*	.10†
Year variance	0.29	0.29	0.29	0.29
Technology field variance	0.29	0.27	0.26	0.27

note: n = 814. ***p < .001; **p < .01; *p < .05; †< .1. Standard errors are displayed between parentheses

TABLE 12

Results of ordinal logistic regression models predicting *p*(technological outcomes$_{t+i}$), *i=2*

Variable	Model 1	Model 2	Model 3	Model 4
[Innovative outcome = prototype]………....	-.98*** (.27)	-.89*** (.27)	-.93*** (.27)	-.94*** (.27)
[Innovative outcome = product]…………..	.80** (.27)	.89*** (.27)	.85** (.27)	.85** (.27)
1. Size……….......…………………………...	.36*** (.09)	.35*** (.09)	.38*** (.09)	.41*** (.09)
2. Duration………………………………..	-.00 (.07)	.00 (.07)	.00 (.07)	-.00 (.07)
3. Financial resources……...………………	.06 (.08)	.08 (.08)	.07 (.08)	.07 (.08)
4. Consortium leader experience$_t$..….............	-.01 (.09)	-.02 (.09)	-.02 (.09)	-.01 (.09)
5. Member relational experience$_t$.….............	-.02 (.09)	-.00 (.09)	-.01 (.09)	-.01 (.09)
6. Geographical proximity….…...................	-.69** (.25)	-.71** (.25)	-.71** (.25)	-.70** (.25)
7. Geographical proximity^2……...................	.61* (.27)	.63* (.27)	.63* (.27)	.61* (.27)
8. Technological diversity……….…….…...	.18 (.26)	.21 (.26)	.20 (.26)	.21 (.26)
9. Technological diversity^2……………….....	-.39 (.25)	-.42† (.25)	-.41 (.25)	-.42† (.25)
10. Global brokerage$_{i=2}$……..……......……	-.18* (.08)		-.15† (.08)	-.28** (.11)
11. Local cohesion$_{i=2}$……..…..…...……......		.18* (.07)	.15* (.08)	.19* (.08)
12. 10 × 11…………………........................				.18† (.10)
Deviance	1,673	1,673	1,669	1,665
Δdf	-	0	1	2
p **(> χ^2)**	-	-	.04*	.02*
Year variance	0.29	0.29	0.30	0.30
Technology field variance	0.28	0.27	0.25	0.27

note: n = 814. $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; †< .1. Standard errors are displayed between parentheses

TABLE 13

Results of ordinal logistic regression models predicting p(technological outcomes$_{t+i}$), $i=1$

Variable	Model 1	Model 2	Model 3	Model 4
[Innovative outcome = prototype]………...	-.97*** (.27)	-.89*** (.27)	-.93*** (.27)	-.93*** (.27)
[Innovative outcome = product]…………..	.80** (.27)	.89*** (.27)	.86** (.27)	.86** (.27)
1. Size………...…………………………...	.36*** (.09)	.35*** (.09)	.37*** (.09)	.39*** (.09)
2. Duration………………………………..	.00 (.07)	.00 (.07)	.00 (.07)	-.00 (.07)
3. Financial resources……...………………	.07 (.08)	.08 (.08)	.08 (.08)	.08 (.08)
4. Consortium leader experience$_t$….............	-.01 (.09)	-.02 (.09)	-.02 (.09)	-.02 (.09)
5. Member relational experience$_t$….............	-.02 (.09)	-.00 (.09)	-.01 (.09)	-.01 (.09)
6. Geographical proximity…….....................	-.66** (.25)	-.71** (.25)	-.69** (.25)	-.68** (.25)
7. Geographical proximity^2…….....................	.58* (.27)	.62* (.27)	.60* (.27)	.59* (.27)
8. Technological diversity……………..….....	.16 (.26)	.21 (.26)	.19 (.26)	.20 (.26)
9. Technological diversity^2……………….....	-.37 (.25)	-.42† (.25)	-.40 (.25)	-.41 (.25)
10. Global brokerage$_{i=1}$……...……......……	-.15* (.07)		-.11 (.07)	-.15† (.08)
11. Local cohesion$_{i=1}$……...…...…...……......		.20** (.07)	.17* (.07)	.20* (.08)
12. 10 × 11…………………..........................				.09 (.09)
Deviance	1,675	1,672	1,669	1,668
Δdf	-	0	1	2
p **(>** χ^2 **)**	-	-	.02*	.04*
Year variance	0.29	0.28	0.30	0.30
Technology field variance	0.28	0.27	0.26	0.26

note: n = 814. ***p < .001; **p < .01; *p < .05; †< .1. Standard errors are displayed between parentheses

TABLE 14

Summary of results for models with varying lags *i*

i	Global brokerage	Local cohesion	Interaction effect
5	-.18† (.09)	.18* (.08)	.14 (.10)
4	-.22* (.10)	.20* (.08)	.23* (.10)
3	-.15† (.09)	.18* (.08)	.05 (.10)
2	-.28** (.11)	.19* (.08)	.18† (.10)
1	-.15† (.08)	.20* (.08)	.09 (.09)

on the likelihood of being in one of the three outcome categories after five years can further be seen in panel (a) of Figure 6: as global brokerage increases, the likelihood that consortium members get stuck in the larger search space (indicated by the 'further development needed'-line) increases. This comes at the cost of both the likelihood of creating a prototype or realizing an innovation. The effect of time on this relationship is displayed in panels (c) and (d) of 4. Panel (c) shows the effect of global brokerage on the dependent variable for the two significant time lags: *i*=4 (4 years before consortium evaluation) and *i*=2 (idem, now 2 years). The steeper line for *i*=2 indicates that the negative effect of global brokerage is stronger at especially higher levels of global brokerage as the consortium comes closer to its moment of evaluation. Similarly, the chances on being innovative decreases more steeply for *i*=2, which can be seen in panel (d). Given the distribution of this variable, the confidence intervals broaden as the score on global brokerage increases. Yet, even when we consider the range in which most of the global brokerage scores fall (0-.10), the effect is salient, leading to about a 10% increase in the likelihood of getting in the class 'further development needed'. Hence hypothesis 1 is not supported. Instead, we find a negative effect of global brokerage on innovation that is especially salient 4 and 2 years before evaluation.

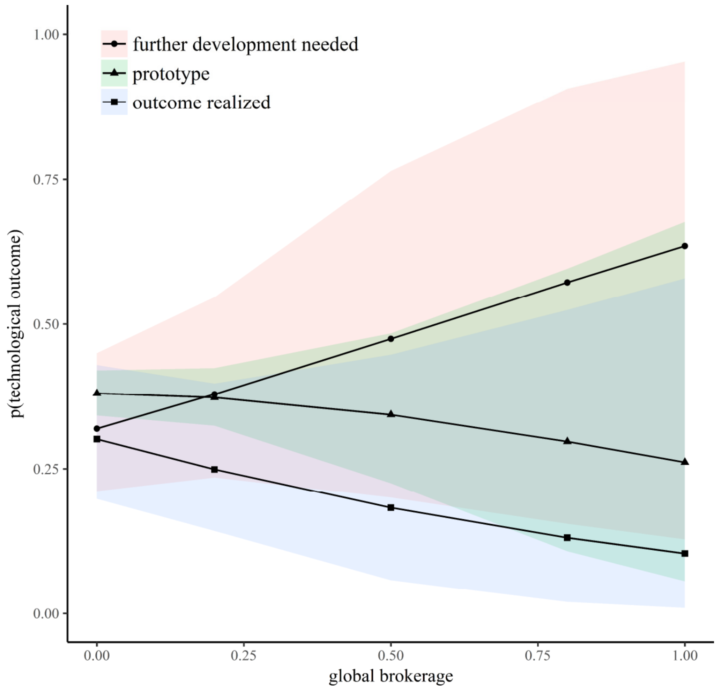
With respect to local closure we hypothesized that in early stages of the consortium, it could lead to consortium members become trapped in local search activities, with a detrimental effect on innovation. As time progresses, this negative effect would reduce and eventually become positive. The positive coefficients of this variable in the lagged models (Table 14) show the effect of local cohesion to be consistently positive and significant over time. This is also demonstrated in panel (b) of 4: the chances on realizing the consortium's initially envisioned outcomes increases as local cohesion increases, at the cost of the other two outcome categories. When this relationship was visualized over time (not displayed here), the patterns were strongly consistent with one another. Hence, we do not find support for hypothesis 2: although we find a generally positive effect of local cohesion on innovation, our expectations regarding its initially negative effect and the change of this effect over time were not confirmed based on our empirical analysis.

Our third hypothesis teases out whether global brokerage and local cohesion could have a mutually stimulating effect in generating innovation, especially after a consortium's start and before its final stage. It is in this stage of the consortium that combining the results from a broad knowledge search and mobilizing the local environment of the consortium with the aim of implementing this knowledge can stimulate an innovative climate in the consortium, and with that its innovation outcomes. This effect is present for *i*=4 (i.e. 4 years before the consortium's

FIGURE 6

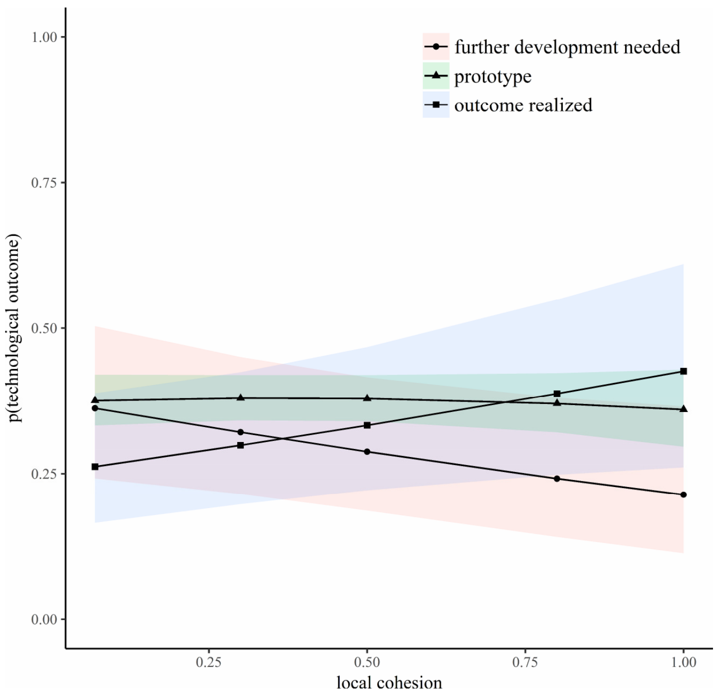
Marginal effects for significant coefficients (selection)[17]

Global brokerage



(a)

Local cohesion



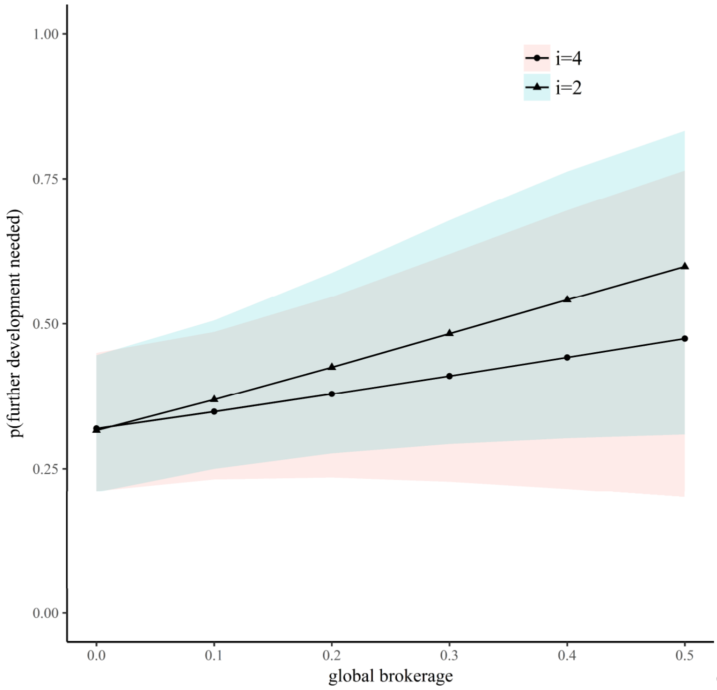
(b)

[17] Panels (a), (b), (c), (e) and (f) are based on Model 4 from Table 10; panel (d) is based on Model 4, Table 12.

FIGURE 6 (CONTINUED)

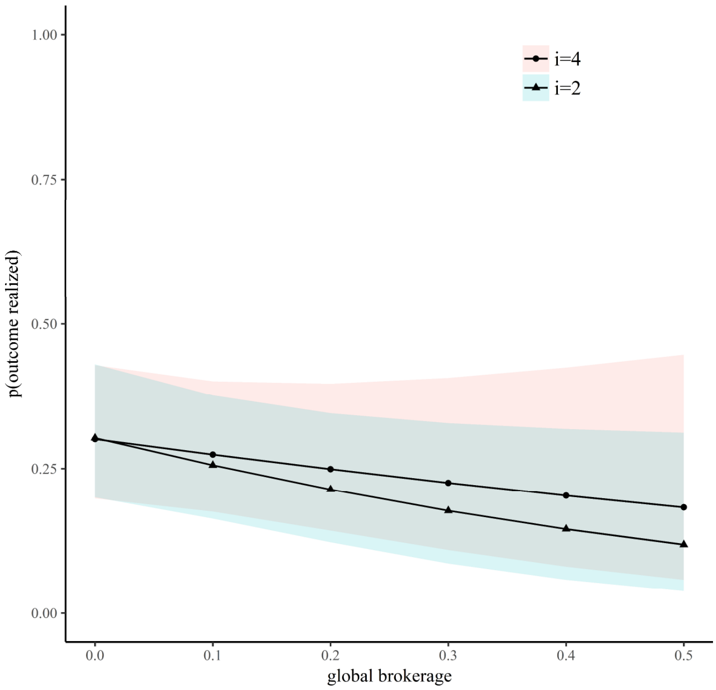
Marginal effects for significant coefficients (selection)[17]

Global brokerage (further development needed)



(c)

Global brokerage (outcome realized)

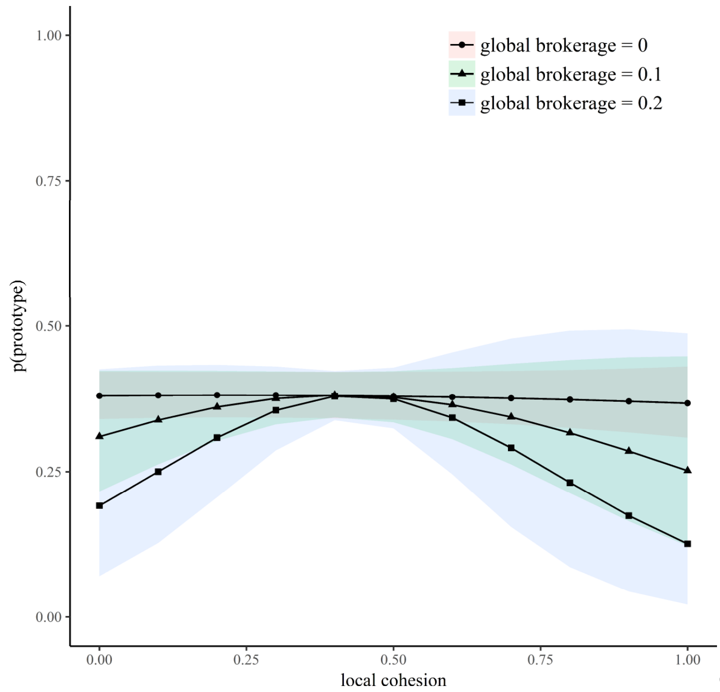


(d)

FIGURE 6 (CONTINUED)

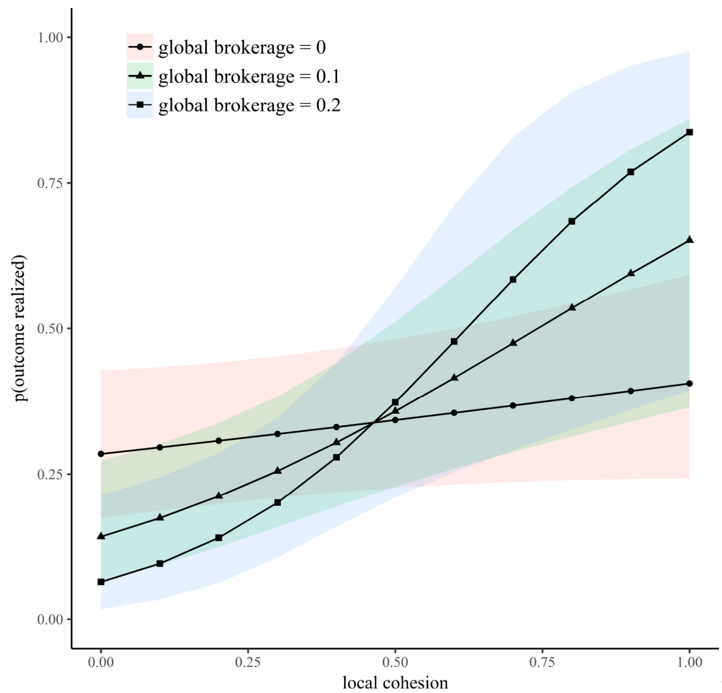
Marginal effects for significant coefficients (selection)[17]

Interaction effect (prototype)



(e)

Interaction effect (outcome realized)



(f)

outcomes are evaluated). The visualization of this effect tells an interesting story. Based on the outcome category 'prototype' (panel (e)) and 'outcome realized' (panel (f)), we deduct the following. With respect to the likelihood of generating a prototype, a clear 'sweet spot' is visible: the effect of local cohesion on the likelihood of generating a prototype increases as global brokerage increases, yet up to a certain point. After this point, this likelihood decreases. This inverted-u shape relation steepens as global brokerage further increases. With respect to the effect of cohesion on the likelihood of a consortium generating innovative outcomes, the positive effect of local cohesion is amplified as global brokerage increases: when global brokerage = 0, a linear effect is observed. This effect transforms to an s-curve that gets steeper as global brokerage increases. Hence, global brokerage and local cohesion amplify one another towards the mid stage of a consortium. Although one can debate whether the second year still belongs to the initial stage of a consortium or to a later stage, we conclude that hypothesis 3 is supported.

Robustness tests

When comparing the analysis in the current chapter with the one performed in the previous chapter, a concern can be that the effect of network integration was not considered in the models presented in this chapter. We argued that including the network integration dummies would be at odds with the perspective of time-dependency taken in this chapter, and that the resulting differences in sample sizes used in both chapters would make comparison of results difficult. Yet, the model that includes complete network brokerage and local closure at the start of the consortium (i=5) most resembles the model presented in the previous chapter. When running this model including the network integration dummies (as well as the interactions between these dummies and geographical proximity and technological diversity), we find that the effects of global network brokerage and local cohesion as reported in Table 9 remain unchanged. None of the variables involving the network integration dummies is significant. The reduction in the size of the sample used in this chapter and that of the sample used in the previous chapter is the most likely explanation for this.

A second concern with the current analysis could be that the outliers observed in the global brokerage variable and -to a lesser extent- the constraint variable might drive significant results in the regression analysis (Zhang & Shaw, 2012). Using the IQR-rule, we replaced any outliers within a technology field and year combination with their median value for that combination. With Q1 and Q3 being the 1st and third quartile and IQR being the interquartile range, this rule states that any observation that lies below Q1-1.5×IQR or above Q3+1.5×IQR can be considered an outlier. Repeating our analysis with the adjusted scores on global brokerage and local cohesion show robust effects with respect to the local cohesion variable. All significant terms involving the global brokerage variable, however, disappear. This underlines the value of including the inherently skewed betweenness centrality measure as operationalization of global brokerage: if including or not including outliers in the analysis is decisive for finding significant effects for global brokerage, this means that especially consortia with extreme values on this variable have a higher likelihood of generating innovative outcomes. In other words: only those consortia that have a network position that comes closest to Burt's (1992) original conception of brokerage are more innovative.

A third concern that we consider here is that the betweenness centrality measure is too restricted due to its exclusive focus on shortest paths. It might very well be that knowledge follows a more circuitous route, for example because of random communication or through intentional channelling via many intermediaries (Freeman, Borgatti, & White, 1991). Consequently, the betweenness measure might be unrealistic in its characterization of knowledge flows. We therefore also ran an analysis in which the betweenness measure was replaced by the flow betweenness measure. Contrary to betweenness centrality, this measure captures the overall knowledge flow between pairs of consortia along all the paths that connect both consortia (Freeman et al., 1991). Our analysis results are similar across all time lags for the effects of cohesion and the interaction effects but differ from the ones summarized in Table 14 with respect to betweenness centrality: only the negative effect of global brokerage for *i=4* remains significant, the other significant effect for *i=2* disappears. This does not change our initial findings much, however, else than that the negative effect (as opposed to the positive effect that was hypothesized) of global brokerage is not salient any longer as the consortium comes closer to its end.

A last, minor concern could be that the measure used for local cohesion was normalized to eliminate scores that exceeded one (Foss et al., 2015). However, using the non-normalized scores of the constraint measure did not change our results.

3.5 Discussion and conclusion

In this chapter, we took on the challenge of incorporating the effect of network position in networks of different orders on the likelihood of generating innovation and the role of time in the salience of this effect. We argued that initially, members of R&D consortia need to capitalize on the role of networks as pipes. In other words, initially access to distant information types about the distribution of knowledge elements or know-how in a certain technology field, as well as access to the latest developments and trends in this field needed to be ensured by being in a global brokerage position. Secondly, we argued that as the consortium progresses, the role of networks as prisms becomes more important. With the artefact that is developed in a consortium being matured, activation of members of neighbouring consortia becomes important, to embed the artefact in an existing technological trajectory (Dosi, 1982). It is in this stage where occupying a locally close position in the network is important as it enables knowing who to activate in this stage. Third, and lastly, we argued that somewhere amid the course of the R&D consortium, global brokerage and local closure positively interact with one another, as the benefits of global brokerage outweigh the drawbacks of local closure, and vice versa.

Using a dataset that included 814 Dutch R&D consortia dispersed over 7 distinct technology fields, our findings sketched a slightly different picture. Global brokerage, with interruptions, tends to negatively affect the innovative outcomes of R&D consortia regardless of developmental stage. Local closure, on the other hand, consistently has a positive effect in the innovative outcomes of R&D consortia over time. As we expected, both features indeed positively interact with one another, just after the consortium's starting year.

Theoretical and practical implications

With this chapter, we contribute to the existing literature on organizational networks in two related ways. First, we add to the debate on brokerage and closure in networks that it is especially the combination of global brokerage and local closure in early stages of an R&D consortium that is beneficial for the innovative potential of this consortium. Hence, brokerage and closure are complements rather than mutually exclusive, which is in line with Burt's (2005) suggestion. Our study shows the importance of unravelling network structural effects, as it suggests that the effects of the local network position of a consortium on its innovative performance differs compared to the effect of a consortium's global network position.

In the consortium networks that we study in this chapter, global brokerage is a hampering rather than a stimulating factor for innovation. A possible explanation for this could be that the early stages of idea generation and elaboration (Perry-Smith & Mannucci, 2017) already are behind the consortium members once the consortium starts. In other words, search does not play an important role anymore once a consortium starts, and the hypothesized positive effect of global brokerage cannot be observed simply because we do not observe these initial search stages. Instead, idea gestation time already has progressed when we start observing the consortia, and the flipping point from a positive effect to a negative effect of global brokerage has already occurred. This is also demonstrated by the interaction effect between brokerage and closure, which occurs relatively early in the existence of a consortium.

The literature suggests that this negative effect of brokerage on innovative outcomes can be explained because of the myopia that stems from occupying brokerage positions. For example, Flynn and Wiltermuth (2010) suggest that high brokerage is associated with the information that is exchange being superficial. Because the power that comes with such a brokerage position also is likely to make the broker weaker in perspective taking, such brokers might be more likely to assume that the agreement they share with others, for example the agreement resulting from knowledge arbitrage activities, is higher than what is warranted. This leads to an overestimation of the extent to which the broker's technology is being embedded in the network. Other authors propose alternative explanations for the negative effect of brokerage, for example by proposing that instead of network brokers, peripheral actors have a stake in the diffusion of their technology instead. Whereas peripheral actors consider this an opportunity to improve their network position, brokers may diffuse only in the presence of a new practice that could possibly disrupt the existing network order (Compagni, Mele, & Ravasi, 2014). This suggests that brokerage might be especially beneficial under conditions of technological turmoil instead of technological stability (Anderson & Tushman, 1990).

The limited role of search at the start of a consortium also might be an explanation for the consistent positive effect on innovation by the cohesion of a consortium's ego network. What is interesting about this is that apparently the creation of trust and circulation of fine-grained information do not need time to develop in such networks. At the same time, it is not realistic to assume that these mechanisms will come into play instantly the moment a consortium starts. An alternative explanation for the positive effect of local closure from the start of a consortium, especially in the context of technological innovation, could be found in the informal mechanism of trading know-how between those involved in R&D. As von Hippel (1988) suggests, as long as the knowledge being exchanged does not seem to be vital to the competitive position of the sender and the receiver of knowledge seems to be a potentially useful expert who might be of future value, technological know-how will be exchanged between consortia. Hence, the more joint member ties a consortium has, the higher the likelihood of knowledge exchange and its subsequent chance of generating innovation. Cohesive joint member ties could also point at the existence of a transactive memory system between consortia, which leads to an enhanced collective memory of task knowledge and coordination which in turn enhances innovation (Lewis & Herndon, 2011).

Our second contribution with this chapter is that we show that the direct effects of brokerage and closure in this specific setting are time-invariant. With this insight, we contribute to the contingency view on brokerage and closure: for R&D consortia to come fully to fruition, these consortia need dense local networks and in general should avoid obtaining a brokerage position in the complete network of consortia. An additional secondary finding here is that the network positions of R&D consortia studied in this chapter do not fluctuate much over time. An implicit assumption underlying our theory was that fluctuation in the network position would be the case for some consortia, as our arguments for innovative R&D consortia drew on a switch from global brokerage initially to local closure in later stages. Other studies have shown such network migration patterns, where nodes that started in the relative periphery of a future core technology moved more towards the core of the network throughout the years (Ahuja et al., 2014). As this is not the case for the consortia focused at in this chapter, testing the time aspect of our theoretical framework has proven to be challenging.

Our study offers insights for practice as well. First, the results show that positive network effects for R&D consortia occur at the first network order. This is a part of the network that can still be controlled by these members. This insight opens the door for active bottom-up network management. This can be achieved by, for example, a targeted selection of members active in other consortia, to establish cross-consortium links and, with that, enhance the cohesion of the focal consortium's ego network. Second, by focusing on the interaction between global brokerage and local cohesion and its associated time dimension, our results suggest that members of R&D consortia -in addition to building a dense local network- benefit from brokerage positions in the complete network in the consortium's early stages. This brokerage position, however, is difficult to manage by members of individual consortia. Managing this part of the network could be a task for innovation policy. As indicated earlier, interorganizational knowledge networks are important for innovation. Although this insight has been adopted by innovation policy, most policy measures are relatively untargeted and happen out of the control of those positioned in these networks (Meeus et al., 2008). Our results suggest that policy should more directly target these networks, through developing measures that aim at stimulating network brokerage for newly started R&D consortia, as well as stimulating enough structural dynamics in these networks for these consortia not to get trapped in this network position without being able to change this position.

Another implication of our results is that indeed, activation of members of neighbouring consortia might aid consortia to yield more innovative results. The question, however, is that local cohesion involves many assumptions: first, consortium members must know that they are embedded in a cohesive ego network. Second, they must act upon being positioned in such a cohesive network and third, they must have the coordinating abilities to do so to reap the innovative benefits of such a position. Hence, another implication for consortia leaders and members is that they should engage in mapping their local network environment to become aware and eventually follow a *tertius iungens* strategy to increase the chance of generating innovative outcomes (Lingo & O'Mahony, 2010).

Strengths, limitations and suggestions for future research

One of the strengths of our study is that it employs a large-scale dataset in exploring the role of time in the relation between global brokerage and local closure and the likelihood of generating innovation. This required a large-scale data collection effort yet makes that this study distinguishes itself from other work that relies on cross-sectional approaches. In addition, although the role of brokerage often has been studied in sparse networks (Ho & Pollack, 2014), the results of our robustness test show the value of using the -inherently skewed- measure of betweenness centrality for capturing brokerage in more dense networks. Excluding outliers in this variable in our analysis was decisive in finding significant effects, which means that especially consortia with extreme values on this variable have a higher likelihood of generating innovative outcomes. In other words: only those consortia that have a network position that comes closest to Burt's (1992) original conception of brokerage are more likely to generate innovative outcomes.

One of this study's limitations is that -despite the sample size employed and number of distinct technology fields- it focuses on a specific type of collaboration in a specific geographic context: funded consortia in the Dutch context that focus on public-private interaction. This raises the concern of generalizability to other settings. Hence, future research should focus on replicating this study's findings, for example for other types of collaborations and in other geographic settings.

Another limitation of this study is that the measures used for global brokerage and local cohesion are proxies for the mechanisms of access (networks as pipes) and activation (networks as prisms) that form the basis of our theoretical argument. Hence, even though both measures capture the structural position of a consortium, they do not capture the actual behaviour of consortium members. Hence, future research should focus this behaviour, for example by sampling consortia based on their network position and unravelling how this position relates to the behaviour of consortium members.

Although the dataset used in this chapter has several advantages, we believe that its potential is not fully tapped into yet. For example, it offers ample opportunities for further in-depth studies. In the current analysis, we employed a structuralist view on innovation. Further research could consider the functioning of joint consortium ties, and what exactly flows through it. Both tie functioning and flow have been suggested to be the most important platform for further theorizing relations (Daskalaki, 2010; Soda, Stea, et al., 2017). In addition, it would be interesting to further focus at the distinct technology fields, and to examine the extent to which the positive effects of local cohesion spill-over to other consortia in the ego-network (Clement, Shipilov, & Galunic, 2017). Lastly, it would be interesting to further explore tie multiplexity, by examining multiple networks between consortium members (Sasson, 2008). Also, especially to aid policy development, it would be interesting to devise an experiment in which nodes follow distinct network migration patterns and relate these patterns to their innovative outcomes.

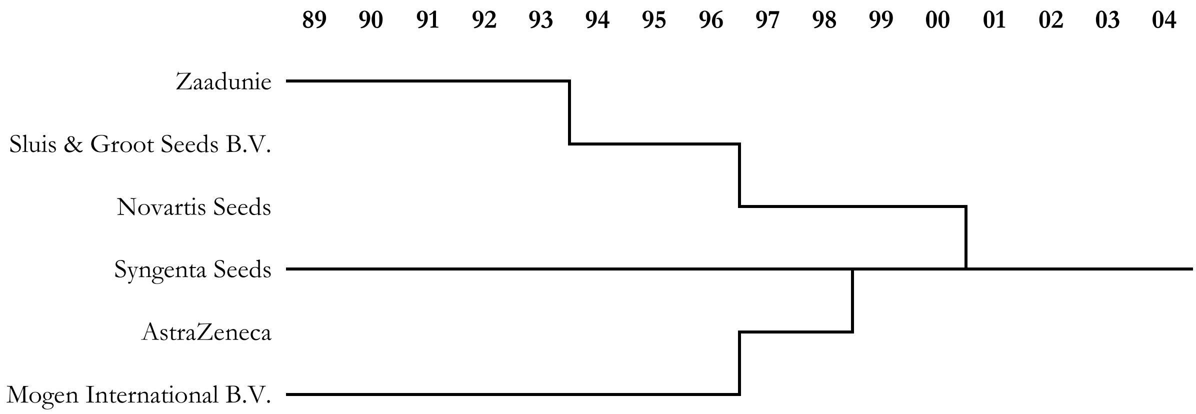
All in all, by exploring the role of time in the relation between global brokerage and local closure, our study offers valuable insights and hints for leveraging R&D consortium networks, both for the bottom-up management of these consortia by their members and the top-down management of consortium networks by policy. By teasing out the effects of both predictors, their interaction and the role of time, this study underlines the importance of unravelling network structural effects across network order and time.

Appendix I: Incorporating Mergers, Spin-offs and Aggregation Differences

When constructing the table that contained all organizations that participated in the users committee in one or more consortia in the time frame 1981-2004, we reduced an initial list of 15,539 organizational listings to a list containing 2,634 unique organizations. Two main issues are worth describing here. The first issue arose from organizational mergers, acquisitions, spin-offs and the like that took place in the observed time frame (1981-2004). An example of a sequence of mergers that eventually led to the merger of 6 distinct organizations in 1980 to one organization in 2000 is illustrated in Figure 8. Shown are changes in organizational entities because of mergers of several seed companies that were active in the Netherlands. Initially, three companies were active: Zaadunie, Syngenta Seeds and Mogen International B.V. In the early 1990s, Zaadunie was taken over by Sluis & Groot Seeds B.V., which in turn merged into Novartis Seeds in 1996. Novartis later merged with AstraZeneca into Syngenta Seeds. A similar pattern can be seen for Mogen International B.V., which first got acquired by AstraZeneca, and in turn merged with Novartis Seeds into Syngenta Seeds[18].

FIGURE 7

Merger history of several seed companies involved in one or more consortia



Such changes over time in organizational entities had 2 main consequences. First, consortium size was affected because of these organizational changes. Second, consortium member turnover took place. For example, the take-over of Zaadunie by Sluis & Groot Seeds depicted in Figure 7 resulted in the replacement of Zaadunie by Sluis & Groot Seeds in the user committee of the consortium. This could also lead to a joint member link with a consortium that was previously unconnected, because Sluis & Groot might already be involved in another consortium. Obviously also other types of organizational change could affect both consortium membership and joint member ties with other consortia.

[18] It should be noted that the years reported are not always accurate in terms of the exact years in which the organizational entities mentioned changed. AstraZeneca, for example, was founded in 1999. Because the funding organization reported projects five years after the start of the project, it could occur that AstraZeneca did exist in the year the report was written, and hence was mentioned as a user in a project that started in a year AstraZeneca did not exist yet. It was very well possible, however, that other project evaluations in the same year still mentioned its predecessor, Mogen International B.V. To synchronize these differences, we included the starting years of the projects in which the new name of an organizational entity appeared for the first time rather than the actual year of occurrence of this new entity.

The funding agency usually reported new names of existing organizations once the change in name took place. If the changes in organizational entities would not be accounted for, different identifiers would be assigned to the same organization, and over time more unique organizations would be represented than the amount of organizations that existed. In turn, with the data not being normalized fully, errors would occur with respect to counting the number of project members at a certain point in time, as well as with respect to specifying joint member ties between consortia.

We addressed this issue as follows. For each organization, not only a unique identifier was assigned to the name of that organization, but also a time frame during which the organization carried a certain name was specified. For organizations that did not undergo any change in the years in which the evaluation reports were issued, one record for that organization sufficed, with a time frame starting in 1980 and ending in the year 9999. Including the change histories of each organization, the table with organizations contained 3,044 records. For sake of illustration we show this coding system in Table 15. For organizations that did undergo changes over the years, this approach enabled us to construct organizational change records. The organization that started as Zaadunie, for example, got assigned the unique identifier (main id) of 2 in our example in. Although this unique identifier was not allowed to change for this specific entity, the names assigned to this entity could change. To facilitate this, each name was assigned a sub-identifier (sub id) as well as a time frame during which the name occurred. Whereas the unique identifier was linked to a unique entity, the sub-identifier was linked to a unique name, and hence could occur multiple times in the table as can be seen for Syngenta Seeds.

TABLE 15

Sample table containing organizational change records

main id	sub id	name	from	till
1	1.01	Syngenta Seeds	1980	9999
2	2.01	Zaadunie	1980	1994
2	2.02	Sluis & Groot Seeds B.V.	1994	1997
2	2.03	Novartis Seeds	1997	2001
2	1.01	Syngenta Seeds	2001	9999
3	3.01	Mogen International B.V.	1980	1997
3	3.02	AstraZeneca	1997	1999
3	1.01	Syngenta Seeds	1999	9999

The organization of Table 15 enabled a selection of the actual number of unique organizations present in each year. For example, listing the organizations that were present in 1984 could be done by specifying a query that selected only the unique records, based on the sub id-field, that included the year 1984 in the bandwidth that was specified by the 'from' and 'till' fields. This would yield three organizations: Syngenta Seeds, Zaadunie and Mogen International B.V. and is consistent with Figure 7. Should this search be applied to the year 1999, only two unique sub-id's (1.01 and 2.03) would be identified, and hence two organizational entities would be included in assigning project membership and determination of inter-project ties.

The second issue we encountered while constructing the organization table was that variations existed in terms of the extent to which distinct parts of an organization were reported. Not only did this occur with respect to parent organizations and their subsidiaries, it also applied in other cases such as businesses and their business units, research organizations and their knowledge centres and ministries, their directorate-generals and implementation agencies. Pinpointing a level of organization that was homogeneous across all these different levels proved to be a challenging task. The issue of homogenizing the level at which organizations are specified is addressed in the alliance literature for parent-subsidiary relations. Here, the common approach is to specify subsidiaries at the level of the parent organization (Ahuja, 2000a; Schilling & Phelps, 2007; Vanhaverbeke, Gilsing, & Duysters, 2012). This approach, labelled 'head office assignment' by Birkinshaw, Hood, and Jonsson (1998), is based on the premise that the parent organization to a large extent understands and controls all value creating processes that take place within the enterprise (Ciabuschi, Forsgren, & Martín, 2011) and is responsible for defining the overall strategic objectives and the alliances that follow from these objectives. Determination of where these strategies and alliances in turn will be implemented within the enterprise is of minor importance. This integrative view on strategy formation and implementation implies that the strategy of a subsidiary thus is strongly affected by its parent (Birkinshaw et al., 1998; Faems et al., 2005), implying that the subsidiary is no more than an executing agent of the parent and all outcomes of the alliance in the end accrue to the parent. For this reason, it should be the parent rather than the subsidiary that should be seen as the appropriate alliance partner.

A competing perspective, labelled 'subsidiary choice' by Birkinshaw et al. (1998) assigns a bigger role to the subsidiary and its management in determining its strategy. Here, subsidiary management is assumed to understand the capabilities and market of the subsidiary better than the parent organization. This is one of the 'raison d'êtres' of the parent-subsidiary structure. The subsidiary thus has more autonomy and might even be mandated for pursuing new strategic directions and initiating collaborations with other actors Birkinshaw et al. (1998). Rather than integrating all strategic decisions, these decisions are differentiated based on the subdivision of tasks within the organization that was deemed necessary. With the subsidiary having a more autonomous role, it seems more appropriate to use the subsidiary rather than the parent as the appropriate alliance partner.

In normalizing the table with organizations, we decided to combine both perspectives by letting the data reported by the funding agency speak for itself: when organizational business units were reported, this apparently meant that for this specific consortium that business unit was mandated and in turn was responsible for project participation and knowledge exchange. When, on the other hand, a parent organization was mentioned as a participant of a consortium, this apparently meant that the consortium was of strategic importance for the whole enterprise, and hence the parent should be interpreted as the relevant actor in that consortium[19]. The same was done for research institutions and ministries, which ensured that in the end all nodes were specified at the level at which knowledge exchange was most likely to happen. This also allowed us to keep as close as possible to the original data reported.

[19] Because of the dual-reporting system, it might happen that in the interim report the name of the subsidiary was reported, while in the utilization report the parent company was used. In these situations, we specified the organization at the level of the subsidiary for both reports.

Appendix II: Check of Parallel Regression Assumption

An important assumption underlying ordinal logistic regression is that the coefficients that describe the relationship between the lowest versus all higher categories of the response are similar to those describing the relationship between the next lowest category and all higher categories, and so forth. When this parallel regression assumption (or the assumption of proportional odds) holds, it is possible to use only one set of coefficients to describe the relationship between each pair of outcome groups instead of using different sets of coefficients. Although statistical tests are available for testing the assumption of parallel regression, they have been criticized for being extremely lenient with respect to rejecting the null hypothesis (i.e. the sets of coefficients are the same), indicating that the parallel regression assumption does not hold even in cases where it actually does hold (Harrell, 2001; Peterson & Harrell, 1990). In addition, formal tests are not readily available for multilevel models. In this Appendix, we therefore follow an alternative informal approach, using linear predictions from a logit model. To check the parallel regression assumption on its tenability, the assumption is relaxed by predicting the probability that, for each level of the dependent variable, this variable is greater than or equal to a given value using one independent variable at a time. When the assumption of parallel regression holds, the difference in logits between different levels of the dependent variable should be the same at all levels of the independent variable (Harrell, 2001).

Table 16 shows the linear predicted values that would be obtained if the innovative outcome variable was regressed on the independent variables one at a time, without the assumption of parallel regression. This assumption now can be evaluated by running a series of binary logistic regressions that vary in cut-off points for the innovative outcome variable and checking the equality of coefficients across these cut-off points. This is achieved by first transforming the original ordinal innovative outcomes variable into a new binary variable that equals zero if the original ordinal dependent variable is less than 2 (“further development needed”) and 1 if this variable is greater than or equal to 2 (“prototype” and “outcome realized”). The coefficients resulting from this regression are shown in column ‘y>=2’ in Table 16. Second, a new binary variable is created that equals zero if the original ordinal dependent variable is less than 3 (“further development needed” and “prototype”) and 1 if this variable is greater than or equal to 3 (“outcome realized”). The logits that result from this regression are shown in column ‘y>=3’ in Table 16. The distance in logits between different cut-off points for the innovative outcome variables should be roughly the same at all levels of the predictor variable, as this means that the distance between slopes is equal or in other words, the slopes are parallel. These distances are calculated in the column ‘Δ’. The column ‘Δmax – Δmin’ shows the difference between the largest and smallest distance between logits.

Other than the technology field dummies and duration, differences between distances are similar for all predictors, although the last column in Table 16 suggests several large differences between the maximum and minimum distance scores. However, often these are caused by one extreme score in a series of otherwise consistent differences (for example, see Global brokerage$_{i=5}$). Since our multi-level model considers differences between fields by estimating separate intercepts and duration is a non-significant control, potential issues with these predictors can be dismissed. Apart from Duration, we therefore conclude that the parallel regression assumption is likely to be satisfied for each predictor separately.

TABLE 16

Results of parallel regression assumption test

Variable	Range	n	y>=2	y>=3	Δ	Δmax - Δmin
Technology field	1	154	.261	-1.548	1.810	1.042
	2	55	1.771	-.405	2.176	
	3	136	1.060	-.606	1.666	
	4	159	1.124	-.606	1.730	
	5	208	.174	-1.316	1.489	
	6	27	1.050	-1.482	2.531	
	7	75	1.562	.027	1.536	
Year	[1991,1996)	259	.664	-.824	1.488	.242
	[1996,1998)	153	1.215	-.330	1.545	
	[1998,2001)	261	.984	-.745	1.730	
	[2001,2002]	141	.014	-1.584	1.598	
Size	[-1.442,-.143)	315	.392	-1.111	1.504	.459
	-.143	172	.949	-.836	1.785	
	.29	127	.927	-.399	1.326	
	[.723, 8.086]	200	1.020	-.619	1.639	
Duration	-0.585	540	.693	-.769	1.462	1.430
	0.51	164	.767	-.972	1.740	
	1.604	78	.693	-.693	1.386	
	2.699	20	2.197	-.619	2.816	
	3.793	5	1.386	-1.386	2.773	
	4.888	7	.288	-1.792	2.079	
Financial resources	[-1.487,-.631)	204	.418	-.829	1.246	.586
	[-.631,-.212)	203	.941	-.869	1.809	
	[-.212, .362)	204	.715	-.606	1.321	
	[.362, 8.972]	203	.892	-.941	1.833	
Consortium leader experience	-.647	422	.647	-.911	1.559	.111
	[-.0632, 1.1052)	277	.849	-.715	1.564	
	[1.1052, 5.7784]	115	.786	-.667	1.453	
Member relational experience	-.494	541	.688	-.912	1.600	.392
	-.018	89	.727	-.481	1.208	
	[.4576, 6.6425]	184	.879	-.677	1.555	
Geographical proximity	[-2.056,-.359)	213	.736	-.757	1.493	.370
	[-.359, .163)	197	.530	-.826	1.355	
	[.163, .692)	206	.985	-.643	1.628	
	[.692, 1.208]	198	.693	-1.032	1.726	
Technological diversity	[-.965,-.590)	238	.796	-.662	1.458	.446
	[-.59,-.285)	178	.940	-.753	1.693	
	[-.285, .284)	237	.770	-.952	1.722	
	[.284, 2.532]	161	.390	-.886	1.276	

Table 16 (CONTINUED)

Results of parallel regression assumption test

Variable	Range	n	y>=2	y>=3	Δ	Δmax - Δmin
Global brokerage$_{i=5}$	-.387	349	.884	-.871	1.755	.415
	-.247	174	.542	-.799	1.340	
	[-.106, .174)	137	.617	-.748	1.366	
	[.174,13.648]	154	.732	-.732	1.465	
Local cohesion$_{i=5}$	[-1.02,-.635)	233	.573	-1.082	1.655	.508
	[-.635,-.298)	182	.588	-.710	1.297	
	[-.298, .329)	197	.640	-.802	1.442	
	[.329, 3.461]	202	1.193	-.613	1.806	
Global brokerage$_{i=4}$	-.406	359	.857	-.857	1.713	.416
	-.240	166	.595	-.702	1.297	
	-.074	92	.879	-.488	1.366	
	[.0927,16.2107]	197	.574	-.974	1.547	
Local cohesion$_{i=4}$	[-.994,-.652)	208	.552	-1.048	1.600	.537
	[-.652,-.262)	221	.567	-.748	1.315	
	[-.262, .324)	186	.717	-.767	1.484	
	[.324, 3.544]	199	1.174	-.678	1.852	
Global brokerage$_{i=3}$	-.470	351	.920	-.851	1.772	.621
	-.273	168	.511	-.640	1.151	
	[-.077, .316)	140	.526	-.780	1.306	
	[.316, 9.545]	155	.772	-.925	1.697	
Local cohesion$_{i=3}$	[-.978,-.617)	223	.640	-.932	1.572	.537
	[-.617,-.307)	185	.474	-.886	1.360	
	[-.307, .364)	215	.771	-.624	1.395	
	[.364, 3.823]	191	1.092	-.805	1.897	
Global brokerage$_{i=2}$	-.387	342	.870	-.842	1.711	.609
	-.229	169	.347	-.756	1.103	
	[-.0708, .2450)	162	.986	-.665	1.652	
	[.245,15.4055]	141	.630	-.961	1.591	
Local cohesion$_{i=2}$	[-1.005,-.593)	235	.586	-.919	1.506	.528
	[-.593,-.284)	174	.591	-.880	1.472	
	[-.284, .333)	215	.645	-.728	1.373	
	[.333, 3.832]	190	1.199	-.701	1.900	
Global brokerage$_{i=1}$	-.486	329	.843	-.887	1.730	.576
	-.263	193	.453	-.701	1.154	
	-.040	103	.752	-.752	1.504	
	[.1836,11.3377]	189	.840	-.815	1.655	
Local cohesion$_{i=1}$	[-1.005,-.599)	230	.629	-1.019	1.648	.550
	[-.599,-.294)	179	.373	-.920	1.293	
	[-.294, .366)	209	.773	-.665	1.438	
	[.366, 3.769]	196	1.211	-.633	1.843	
Overall		**814**	**.734**	**-.808**	**1.542**	

4. Do Network Dynamics Differ Between Technology Fields? Describing Complete Network Dynamics Using Network States and State Changes[20]

Abstract

Existing literature suggests a differentiated development of networks in different technology fields. However, innovation policy often displays a homogeneous approach towards structuring these networks and ensuring network viability. The question if interorganizational technology field networks differ in their development is therefore open for further exploration. By considering both network structural characteristics and the node set that comprises a network, we propose an analytical framework that revolves around the concept 'network state'. We conceptualize a network state as a configuration of values in a five-dimensional state space –network centralization, network density, network size, the numbers of exiting nodes, and entrants– that captures all possible network states. This model of network states is used to explore the evolution of 7 distinct field networks of consortia over 23 years, using a latent profile analysis. This method allows a mapping of all possible dynamics of a network through tracing a sequence of state changes over time. Our findings reveal that network dynamics unfold over sequences of changes in five distinct states: formation, growth, stagnation, stability and disintegration. We find a core sequence of state changes of formation, via growth, to stability, but also find variations on and extensions of this pathway. The most important finding is that field network dynamics are anything but homogeneous. We find considerable differences in the duration of states across consortium networks in different technology fields. Based on the obtained insights, we formulate policy recommendations as a first step towards a more targeted and differentiated management of complete interorganizational technology networks.

4.1 Introduction

The adage that in order to adapt to fast changing environments, generating innovation through networked collaboration is key (Birkinshaw, Bessant, & Delbridge, 2007; Jarvenpaa & Välikangas, 2014; Laursen & Salter, 2006; Powell, Koput, & Smith-Doerr, 1996) has resonated well with policy makers. Driven by the philosophy that stimulating joint research and development between research institutions and industrial organizations is one of the key drivers of economic growth (Aldrich & Sasaki, 1995; Branstetter & Sakakibara, 2002; Meeus et al., 2008), governmental policies especially target the creation and consolidation of public-private links. Such policies aim for example at stimulating public-private mobility, public-private research consortia, and exchange and interaction between public and private organizations (Kivimaa & Kern, 2016; Meeus et al., 2008; Peterman et al., 2014; Salter & Martin, 2001).

In addition to the stimulation of collaboration between public and private organizations, a key task for policy is to maintain network viability, which boils down to sustain the inflow of new nodes in a network. Node entry impacts network viability in several ways, for example through adding diversity to existing network populations, enlarging partnering opportunities and signalling the value of new technological opportunities (Meeus et al., 2008). In addition to node entry, network size and nodes that exit a network have policy implications. Both aspects can be

[20] Previous versions of this chapter were presented at the 3rd Amsterdam Workshop on Social Networks and Organizations (Amsterdam, June 2013) and the 31st EGOS Colloquium (Athens, July 2015).

considered as gauges for network viability: whereas size reflects the attractiveness of a technology network, node exits is an indicator of –amongst others– its level of competition. Gauging both viability features aids policy makers in avoiding bottlenecks, such as lock-in effects or the emergence of competitive barriers to collaboration and innovation (Rondé, 2001).

Hence, government has an important role in the formation and subsequent dynamics of interorganizational networks geared towards technological development (Peterman et al., 2014). However, an important issue that warrants further exploration of the dynamics of such networks is that, whereas current innovation policy assumes that field network dynamics are homogeneous (Meeus et al., 2008), other literature on industrial dynamics suggests that these field network dynamics are heterogeneous instead. For example, it has since long been acknowledged that the most appropriate type of instrument aimed at stimulating innovation and technological change depends on sectoral patterns of production and use of innovations (Kivimaa & Kern, 2016; Pavitt, 1984). Although the organization of innovative activities within sectors is known to be rather homogeneous, profound differences with respect to this organization have been detected across sectors (Audretsch, 1997; Gort & Klepper, 1982; Lechevalier et al., 2014; Leiponen & Drejer, 2007; Luo, 2003; Malerba & Orsenigo, 1996; Pavitt, 1984). Some sectors, for example, are shaped by high degrees of knowledge accumulation, whereas others can be characterized by a sustained level of knowledge diversification (Alkemade, Heimeriks, Schoen, Villard, & Laurens, 2015). Considering that a link has been suggested between the structural and dynamic properties of the firm population of a sector and its underlying technology field (van Dijk, 2000), we expect developmental differences between networks that form and develop in different technology fields.

If network development is heterogeneous across technology fields, this implies that policy measures should be tailored to the specific developmental features of such technology field networks. However, such tailoring of policy to the field network and technological dynamics is not without constraints. Some authors have criticized the idea that networks can be rationally steered, and pose that the processes that drive network formation and subsequent dynamics can be far less coherent, controllable and rational than contended (Doz et al., 2000; Knights, Murray, & Willmott, 1993). This implies that policy has a limited role in early stages of network formation and development. Another group of scholars suggests that once networks have formed serendipitously, network members can become aware of one another and develop shared goals (Moretti & Zirpoli, 2016). The interdependencies that result from working towards these shared goals allow for more targeted policy interventions and coordination (Hite & Hesterly, 2001). This suggests that –depending on the pace and nature of network dynamics– there is a time for policy to let network development take its course, and a time to more actively steer this development. This timing, however, could be different for different technology fields.

Even when different pacing of field network and technology development is acknowledged, and 'planned change approaches' are no longer prevailing in innovation policy, it remains surprising how uniform policies for different technology fields are. Differentiation in policies for distinct fields and technologies, is surprisingly absent when one considers the measures available to governments for stimulating interaction between public and private organizations and sustaining network viability. As Meeus et al. (2008) observe, the bulk of measures available to governments, such as funding schemes or innovation platforms (Kivimaa & Virkamäki, 2014; Klein Woolthuis et al., 2005; Magro & Wilson, 2013; Meeus et al., 2008) draw upon generic network mechanisms without taking into account the developmental stage of a network. To what extent interorganizational technology networks differ in their development, however, remains a question that is open for further exploration. In this chapter, we investigate this question and present a method for describing the dynamics of such networks. This method in turn is applied to come to a comparison of seven distinct technology field networks.

To develop our model of state changes in field networks over time, we build on a research literature that explains causes and consequences, and typologies of organizational network development. First and foremost this literature refers to the nodes that comprise a network, the ties that connect those nodes and the structure that results from these connections (Ahuja et al., 2012, p. 435). Existing research on the topic of interorganizational network dynamics, seems to be biased towards drivers of tie formation between organizations. For example, scholars have explained tie formation as a function of attributes of the organizations involved (Ahuja, 2000b; Ahuja, Polidoro, & Mitchell, 2009; Baum et al., 2005; Mitsuhashi & Greve, 2009; Shipilov et al., 2011; Walker et al., 1997; Yue, 2012), relational attributes (Gimeno, 2004; Hallen, 2008; Li & Rowley, 2002; Rosenkopf, Metiu, & George, 2001; Shipilov & Li, 2012; Sytch & Tatarynowicz, 2013b), network structural features (Garcia-Pont & Nohria, 2002; Jiang, Jun, Cannella, & Xiao, 2017) or a combination of said predictors (Giuliani, 2013; Gulati & Gargiulo, 1999; Kenis & Knoke, 2002; Lomi & Pattison, 2006; Lusher et al., 2013; Snijders, 2001). In addition to explaining tie formation, scholars have considered the dynamics of ties after they have been forged, for example tie dissolution (Greve, Baum, Mitsuhashi, & Rowley, 2010; Greve, Mitsuhashi, & Baum, 2013; Hernandez et al., 2014; Rogan, 2014; Yue, 2012), tie persistence (Beckman, Haunschild, & Phillips, 2004; Dahlander & McFarland, 2013; Howard, Withers, Carnes, & Hillman, 2016; Kim, Oh, & Swaminathan, 2006), tie dynamics (Ibert & Müller, 2015; Quintana-García & Benavides-Velasco, 2004), and tie activation (Daskalaki, 2010; Mannak, 2015; Mannak, Raab, & Smit, 2012). Notwithstanding the importance and relevance of work that focuses on tie formation and dynamics, these studies do not offer a solid hold for describing and comparing the dynamics of interorganizational technology field networks, simply because they do not account for the set of nodes amongst which ties can be forged. The studies that look into the node dynamics and describe the development of such networks (e.g. Gay and Dousset (2005); Orsenigo et al. (2001); Powell et al. (2005)), are limited in their generalizability, since they focus on the life sciences field only.

In this study, we contribute to research on the development of interorganizational technology networks over time, by focusing on understudied aspects of the definition of network dynamics by Ahuja et al. (2012) that reflect the earlier mentioned focus of innovation policy in the realm of networks and innovation: *the structure of relations among organizations (i.e. network density and degree centralization), and the set of nodes –R&D consortia– that comprises a network (i.e. node entry, node exit and network size)*. These aspects are incorporated in a conceptual model that revolves around the heuristic of a *network state*. We model the development of field networks over time as a function of these five aspects or dimensions, which yields a series of states and state changes. Such a network state is bounded by a state space, which is the space of all possible network states. Using this heuristic allows for mapping network dynamics through tracing a path in the state space over time (Bickhard & Campbell, 2003; Kauffman & Oliva, 1994). This path is determined by initial conditions of the network itself, as well as various constraints on dynamics operating in the state space (Bickhard & Campbell, 2003; Makadok & Walker, 2007).

This model is explored using 7 distinct interorganizational technology networks in the Dutch context over a time span of 21 to 23 years. In these networks, nodes consist of R&D consortia, and the links between these nodes consist of joint membership ties. Using said parameters, we apply the technique of latent profile analysis to identify distinct network states. The outcomes of our analysis allow us to discern five distinct network states: formation, growth, stagnation, stability and disintegration. Although a common formation pathway lingers through the evolution of these 7 networks (i.e. from formation, via growth, to stability), we identify variations on and extensions of this pathway. In addition, we find considerable differences in the duration of states across networks.

With this chapter, we contribute to the existing literature on organizational networks and innovation in two related ways. First, organizational network scholars have been criticized to focus rather exclusively on network structure (Ghosh & Rosenkopf, 2015). By focusing not only on the development of network structure over time, but also by focusing on changes in the set of nodes that comprises a network, we add the population dimension to the study of networks dynamics and combine this dimension with the structural development of a network. Especially node entry and exit have been characterized already by Thorelli (1986) as key aspects that characterize network dynamics. The few studies on interorganizational network dynamics that included node turnover have offered interesting yet anecdotal insights with respect to the different roles played in a network by new entrants, incumbents and organizations leaving the network (Gay & Dousset, 2005; Orsenigo et al., 2001; Powell et al., 2005). New entrants, for example, have been suggested to either complement incumbent organizations (Kogut, Walker, & Kim, 1995; Orsenigo et al., 2001), or instead disrupt the existing status quo for these incumbents (Gay & Dousset, 2005; Kogut, Urso, & Walker, 2007) by introducing network heterogeneity. By establishing a clearer link between node turnover and technology dynamics, we make its role in network dynamics more explicit.

Second, despite many calls for research on interorganizational network dynamics (Brass et al., 2004; Freeman, 1991; Gulati, 1998; Johnston, Peters, & Gassenheimer, 2006; Kilduff & Tsai, 2003; Parkhe, Wasserman, & Ralston, 2006; Tasselli, Kilduff, & Menges, 2015; Wasserman & Faust, 1994), research on the topic has not thrived. Indeed, at first sight our research question (do technology networks differ in their development?) seems rather trivial. This simplicity is intentional, as answering this question turns out to be far from simple or trivial: many authors have pointed at the inherent difficulties involved in collecting datasets for the longitudinal analysis of complete networks. This is the main reason for the slow progress of research on the topic of network dynamics (Cattani & Ferriani, 2008; Lounsbury, 2000; Provan et al., 2007; Tsai, 2000; van den Ende, van de Kaa, den Uijl, & de Vries, 2012). Not only does this result in network dynamics studies considering only limited time frames (e.g. Gay and Dousset (2005); Orsenigo et al. (2001); Powell et al. (2005)), it also means that, to the best of our knowledge, none of these studies has investigated more than one technology field. This renders a comparison across networks in different technology fields and hence differentiation of innovation policy based on technology fields impossible. Using a dataset that tracks the network development of 7 distinct field networks over a longer period allows us to describe and compare technology field network dynamics in this study. Consequently, we offer insights in network dynamics across a broad array of different field networks, as well as over many years within each of these networks.

Our research also yields useful insights for those involved in innovation policy. The networks studied in this chapter emerge because of a governmental funding system. Given the importance of networks for both organizational and network-level outcomes[21], there is an important governmental stake in setting up policies in such a way that these networks are steered towards modes of organization that make them as effective as possible. In this light, getting insight in the predictability with which such networks develop over time and the duration of different developmental stages is fruitful and necessary in order to develop a more targeted and differentiated

[21] Whereas we have considered the effect of network structure on the outcome of individual nodes in Chapter 2, the effect of network structure on network-level outcomes will be considered in Chapter 5 of this dissertation.

approach towards steering such networks (Ahuja et al., 2012; Clegg, Josserand, Mehra, & Pitsis, 2016; Dagnino, Levanti, & Mocciaro Li Destri, 2016; Provan et al., 2007). Hence, our study marks a first step towards the more targeted management of these networks, by providing insights in their developmental patterns and parameters that drive these patterns.

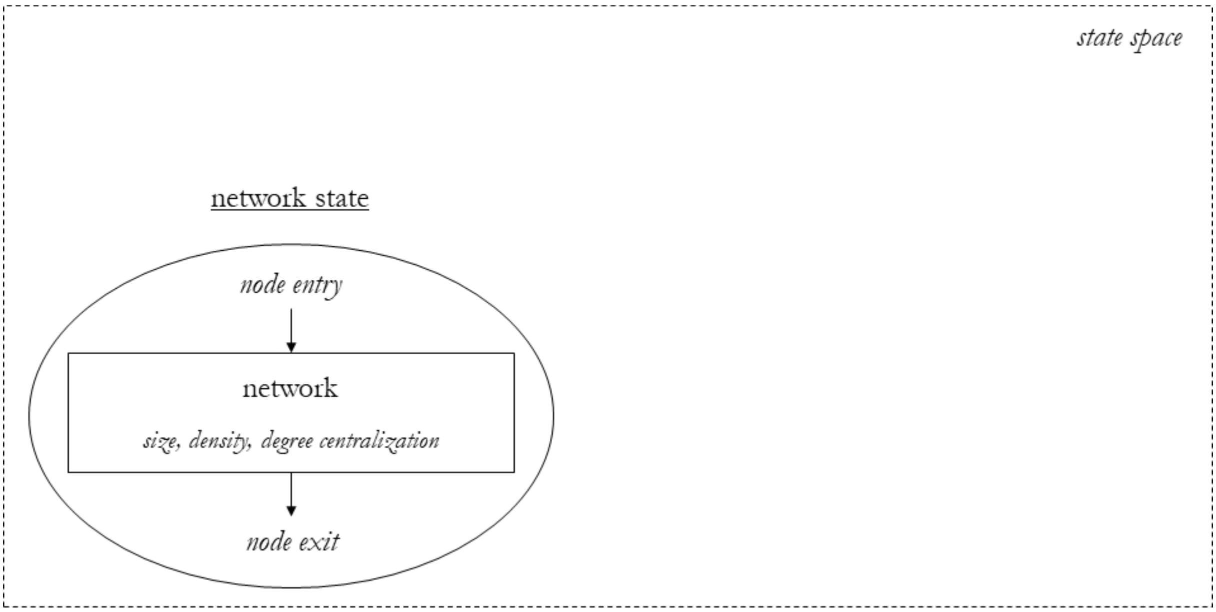
4.2 Theoretical framework

The existing literature on the topic of network dynamics does not offer a solid hold for describing and comparing the dynamics of interorganizational technology field networks. In this chapter we will therefore develop a framework that can be used for describing network dynamics and specify the parameters that will be considered. In turn, by applying this framework to different networks, a comparison between these networks can be made. We build forth on the work on network dynamics by Ahuja et al. (2012) and the industry dynamics literature in developing this framework: it will first be shortly described, and then the phenomenon it will describe, network dynamics, is linked to technology dynamics.

Ahuja et al. (2012) propose that the dynamics of any network can be conceptualized in terms of change in the nodes that comprise the network and change in the structure that results from the ties that connect those nodes (Ahuja et al., 2012, p. 435). Both aspects are included in our conceptual model in Figure 8. Central to this model is the heuristic of a network state. This state includes both the dimension of network structural features (i.e. network density and degree centralization) and the dimension of features related to the set of nodes that comprise the network (i.e. size, node entry and node exit). Network states are bounded by a state space, which is the space of all possible states of a network. Hence, all possible state sequences of a network will trace a path in this state space (Bickhard & Campbell, 2003; Kauffman & Oliva, 1994).

FIGURE 8

Conceptual model depicting network state features and the state space



Whereas different conceptual approaches towards explaining network formation and development exist (e.g. focusing on developmental processes (Doz et al., 2000; Ring & van de Ven, 1994) or using structuration theory (Berends et al., 2011)), we apply an empirical approach to discern distinct developmental phases. Movement of a network through the state space is determined by initial conditions of the network itself, as well as various constraints on dynamics operating in the state space (Bickhard & Campbell, 2003; Makadok & Walker, 2007). As our focus is on describing the dynamics of technology networks, we propose these constraints are posed mainly by the technology field in which nodes in a network operate.

Technology dynamics and network dynamics

Existing literature suggests that the dynamics of interorganizational innovation networks and technological development are closely intertwined. Various innovation scholars have elaborated on the importance of interaction for the process of innovation (Freeman, 1991; Lundvall, 1992; Martin, 2012; Meeus et al., 2001; Nelson & Winter, 1982; Pavitt, 1984; von Hippel, 1988). Indeed, many scholars have described the joint development of networks with a variety of technologies and bodies of knowledge, such as those focused on flight simulators (Rosenkopf & Tushman, 1998), biopharmaceuticals (Gay & Dousset, 2005; Gilsing, Cloodt, & Roijakkers, 2016; Orsenigo et al., 2001; Powell et al., 2005), batteries (Kulve & Smit, 2003), industrial process technologies (Luiten, van Lente, & Blok, 2006), industrial and consumer goods (Lin, Chen, Sher, & Mei, 2010) and standards with respect to consumer electronics (van den Ende et al., 2012). Hence, interorganizational R&D networks form around technologies, and the dynamics of such networks consequently are linked to the development of these technologies.

In earlier chapters we conceptualized technological development as the process of search in a technology landscape by network nodes. This chapter adds a dynamic perspective to this heuristic: the technological development that results from search in a technology landscape subsequently changes that landscape. New search directions might emerge and become more dominant. This makes existing search directions less salient or even obsolete. Before we can explore how this change in the technology landscape affects the selected network dynamics parameters, we first need to delve deeper into the nature of technological development and the link between technological development and network dynamics.

With respect to the nature of technological development, such development can be characterized in terms of technological paradigms and technological trajectories (Dosi, 1982). A technological paradigm embodies heuristics with respect to aspects and functions of a technology that should be the object of search, and aspects and functions of that technology that should be left unchanged or sacrificed. This includes the extent to which technological opportunities are present, the level of innovation cumulativeness, and the extent to which knowledge is codified (Safarzyńska, Frenken, & van den Bergh, 2012). With that, it reduces the relevant design space, and guides search in the remaining design dimensions (Frenken, 2006). The cumulative series of innovations within a technological paradigm create a technological trajectory. Along such a trajectory, dominant designs are incrementally improved to raise performance in certain functional attributes. Hence, technological development can be conceived as the progress along a technological trajectory that is defined by a technological paradigm (Bakker, van Lente, & Meeus, 2012; Dosi, 1982).

Inherent to this characterization of technological development is that this development has a natural tendency to converge to a dominant design. Technological breakthroughs, however, make that existing trajectories ultimately run into decreasing returns (Anderson & Tushman, 1990; Dosi, 1982; Drazin & Schoonhoven, 1996). Scholars have generally acknowledged that after such technological breakthroughs a period of technological ferment takes place. During this period, different designs compete with one another. What follows is a maturation stage, where selection among competing designs often leads to convergence on one dominant design that can be further elaborated on (Agarwal, Sarkar, & Echambadi, 2002; Anderson & Tushman, 1990; Grodal, Gotsopoulos, & Suarez, 2014; Schumpeter, 1934; Tushman & Anderson, 1986). Hence, for some time it is not clear which technological aspects and functions are viable for further development, and it is unclear which directions in the search space are viable to pursue. Once a new dominant design is established, future discontinuities start a new cycle from breakthrough, via ferment and maturation to dominant design (Ehrnberg, 1995).

With respect to the link between technological development and network dynamics, it must be recognized that often the described developmental cycle focuses on single technologies such as cars (Abernathy & Utterback, 1978), aircrafts (Frenken, 2006), or electronical components (Wade, 1995). Yet, the literature suggests a role of technological development in network dynamics as well (Capone, Malerba, & Orsenigo, 2013). At this level, however, the focus is on clusters of rather than single technologies (Castellacci, 2008; Teece, 2008). Hence, network dynamics are an aggregate reflection of the developmental cycles of all technologies that are developed in a network. How this is reflected in networks is an empirical question, yet this link will be tentatively explored for each of the selected network dynamics parameters in the remainder of this chapter.

An important assumption that we make is that on the aggregate network level as well, technological development tends towards the emergence of dominant designs. After all, the prevalence of breakthrough innovations is low. For example, in a study on the origins of breakthrough innovations, Kelley, Ali, and Zahra (2013) describe that out of the 29,195 patents the authors consider in the time frame 1987 and 1991, 298 patents are qualified as breakthrough patents. This is about 1% of the total sample. Hence, even on the aggregate network level, the likelihood for breakthrough innovations and subsequent eras of technological ferment to occur is low and most technologies that are developed will be in the subsequent maturation and dominant design stages. We expect this relative predictability in overall technological development (Dosi, 1982; Peine, 2006) to be reflected in networks that do not display considerable movement through the state space. In describing the tentative link between network dynamics and technology dynamics, we therefore will take the dominant design stage as a starting point and explain how parameters change should a technological breakthrough with its subsequent stage of ferment and maturation occur.

Network size. This dimension refers to the number of nodes that comprise a network (Ahuja et al., 2012). Network size in general reflects the attractiveness of a technology field (Afuah, 2013; Rosenkopf & Schilling, 2007; Suarez, 2005). This attractiveness is determined by, for example, the amount of resources available in a network (Brass et al., 2004; Meeus et al., 2008; Salavisa, Sousa, & Fontes, 2012), and available technological opportunities (Capaldo, 2007; Rodan & Galunic, 2004; Tang, Mu, & Maclachlan, 2008).

In the phase of established dominant designs, we expect network size in this situation to be stable over time (Malerba, 2002): the relevant design space of each technology is known, as well as the remaining search directions. Incumbent nodes will build forth on established dominant designs and the relative certainty in this situation can be expected to fill each possible position in the search space by incumbents. Uncertainty induced by a technological breakthrough, however, might lead to a change in size and a period of fluctuation because a period of technological ferment and subsequent maturation begins. The entry and exit dynamics associated with this fluctuation will be discussed next.

Node entry. Node entry (i.e. the number of new nodes that enter a network) is considered an important aspect in the generation of network dynamics (Hakansson, 1992; Mowery, 1988). In a technology field in which mainly dominant designs are further improved, low levels of node entry can be expected (Kogut et al., 1995; Kulve & Smit, 2003; Orsenigo et al., 2001; Owen-Smith, Riccaboni, Pammolli, & Powell, 2002; Powell et al., 2005). Under this condition, node entry is discouraged due to the presence of high entry barriers, for example steep learning curves and economies of scale due to standardization (Agarwal et al., 2002; Malerba, 2002). Yet, some level of node entry can be expected, either through coordination of incumbents that search for co-specialization when further developing their established dominant designs (Lévesque, Minniti, & Shepherd, 2013; Orsenigo et al., 2001), or because some level of incumbent inertia that is inevitable as time progresses creates opportunities for node entry (Agarwal et al., 2002; Dercole, Dieckmann, Obersteiner, & Rinaldi, 2008).

Node entry levels change in the face of a technological discontinuity. In the event this discontinuity leads to a new technology field, new entrants behave like first movers in the initial stages of technological development. When successful as carriers of the field, these entrants later attract others as time progresses (Owen-Smith et al., 2002). Later entrants, however, can become technology field carriers as well. A common pattern when a disruptive technology is introduced in an existing technology field is that incumbent nodes react slowly with the result that leadership passes to pioneering new nodes that have embraced the new technology (Dosi, Faillo, & Marengo, 2008; Gay & Dousset, 2005; Malerba, 2002; Orsenigo et al., 2001; Wade, 1996) and challenge the existing paradigm (Gilsing et al., 2016; Kash & Rycoft, 2000; Lin et al., 2010; Rosenkopf & Tushman, 1998). These later entrants do not necessarily have to be pioneers: some authors have suggested that incumbents from other technology fields can overtake an emerging one (e.g. chemistry-based pharmaceutical companies that enter the field of biotechnology (Roijakkers & Hagedoorn, 2006) with the aim of technological integration (M'Chirgui, 2009).

Hence, node entry levels increase after a technological discontinuity as it opens new search directions in the technology landscape. The subsequent period of technological ferment still offers opportunities as well, which means that node entry level remains high (Agarwal et al., 2002). As technological development progresses further to the state of maturation and new dominant designs, we expect node entry levels to dampen.

Node exit. In comparison with node entry, research pays less explicit attention to node exit from networks in relation to technology dynamics, although it is reported by several studies (Gay & Dousset, 2005; Orsenigo et al., 2001; Owen-Smith et al., 2002; Powell et al., 2005). In networks in which mainly dominant designs are developed, node exit is associated with increased competition resulting from technological crowding and specialisation (Lin et al., 2010; Powell et al., 2005; Stuart, 1998), failure (Casper, 2007; Ingram & Torfason, 2010) or mergers (Powell et al., 2005): despite the presence of dominant designs, no best search direction can be determined a priori and therefore the creation of new applicable artefacts is far from a sure outcome of R&D (Drejer & Jørgensen, 2005; Hung & Tu, 2014; Nelson & Winter, 1982). However, we expect the level of node exit in this situation to be relatively low.

We expect node exit to follow the same pattern as that of node entry when a technological discontinuity with its subsequent stage of ferment occurs. Incumbent nodes might drop out of the network if they do not adjust or cannot contribute on time to the new technology (Dosi et al., 2008; Malerba & Orsenigo, 1999; Powell et al., 2005). In the subsequent stage of technological ferment, nodes that leave a network are the result of selection processes in the underlying technology field: better alternatives are selected and poorer ones are rejected (Baum & McKelvey, 1999; Mohrman, Gailbrath, & Monge, 2006). Node exit levels dampen as technological development progresses further to the state of maturation and a new dominant design.

Network density. This aspect denotes the cohesion of the relational structure in a network. As such, it cements nodes in a network and involves mutual awareness between network members of what others are doing. This facilitates mutual understanding and insight in knowledge interdependencies (Erikson & Bearman, 2006; Fagerberg et al., 2012; Fagerberg & Verspagen, 2009; Hollenstein, 2003; Koza & Lewin, 1999; Oh & Jeon, 2007).

Network density relates to technology field development in the following way. Under conditions of incremental improvement, preservation of a relatively dense network can be expected, as the fruitfulness of research directions and with that insight in knowledge interdependencies is clear (Gay & Dousset, 2005). In situations of technological discontinuities and ferment, however, we expect density to drop. In such situations, existing paradigms are overthrown. As we have seen, this results in higher attrition of incumbents from the field network, and the attraction of new entrants to the network. Together with this shift in direction of technological development, old relations disappear and new relations form (Mohrman et al., 2006), yet the uncertainty regarding fruitful directions hampers mutual awareness in the network.

Network degree centralization. Degree centralization refers to the extent to which one or few nodes in the network are more central compared to other nodes in that network. This indicates the presence of a small amount key players in the network that introduce common thematic foci (Fagerberg et al., 2012) and undertake continuous efforts to integrate the knowledge available in the network (Ata & Van Mieghem, 2009; Burt, 2007; Fagerberg et al., 2012; Fagerberg & Verspagen, 2009). This enhances the collective perception of network members of viable technological alternatives and possible future developments, and focuses their commitment to a limited amount of core technologies (Afuah, 2013; Gay & Dousset, 2005; Soh, 2010) developed by central players (Gay & Dousset, 2005; Powell et al., 2005).

Under conditions of incremental technological change, technological development is in the hands of few incumbents. The literature suggests persistence in innovative activities by such nodes once roles are established (Cefis & Orsenigo, 2001; Triguero & Córcoles, 2013) and we therefore expect network centralization to remain stable over time in conditions of stability. In a situation of technological discontinuity and ferment, existing paradigms are overthrown. This results in a disruption of the network structure, as node turnover is likely to increase. The resulting uncertainty and the associated loss of key players will temporarily lead to lower levels of network centralization.

The dimensions of state change model seem to be loosely associated with technological developments and therefore we propose that for rather distinct technological fields we expect distinct and therefore heterogeneous field network dynamics. This is our main proposition for this chapter.

4.3 Data and methods

Research setting and data

The data that is used to study network dynamics in this chapter is drawn from a dataset that was developed in the context of a larger overarching research project (see, for example, the other chapters in this dissertation, Mannak (2015) and Mannak et al. (2012)). This dataset was built using evaluation reports that in total cover 1,928 Dutch R&D consortia, funded by a Dutch technology foundation[22]. The aim of this foundation is to realize knowledge transfer between the technical sciences and industry. In each consortium, an academic researcher designs a research and development project, and gathers one or more industrial organizations that see potential application value of the research results. Committed organizations are part of the 'users committee' that takes part in the research as from its early stages. Not only do these organizations discuss research progress and results in the light of potential application, they also contribute in kind and act as a testing-ground for the technlogy that is developed. A tie between two consortia is constituted by joint membership of one of the participating organizations or consortium leader in two consortia in the same year.

The first consortia started in the spring of 1981, and the most recent starting year that is included in the dataset is the year 2004. Because of joint membership in multiple consortia by both consortium leaders as industrial organizations, consortia are linked to one another (see Appendix I of this chapter for an elaboration). In Appendix I of Chapter 5, we describe the network boundary specification procedure that was followed. Following this approach, seven technology field networks were constructed, each on a yearly basis. Of the 1,928 consortia in the dataset, 153 consortia did not have any member reported. In addition, 141 consortia were present as an isolate in one or more networks, and 40 were present as a dyad. These consortia were all excluded from the dataset, resulting in a total of 1,594 consortia spread across 7 technology fields. Depending on the year in which a consortium network emerged for the first time, the number of observations for each network ranges from 21 to 23 years, resulting in a total of 156 technology field networks. The consortium networks that emerge as a result can be considered a reflection of the organization of knowledge flows in the larger innovation system. Hence, investigating this organization is especially important for a targeted specification of innovation policy measures.

The framework that we developed in this chapter is geared towards answering the research question if the dynamics of field networks differ between technological fields. The composed consortium networks suit this network states framework for two main reasons. First, contrary to for example alliance networks, the consortium networks studied in this chapter do not emerge merely serendipitously: given that the funding agency has an explicit focus on stimulating interaction, relationships within and across consortia are explicitly seeded through the funding scheme and driven by a desire to optimize innovative outcomes at the country rather than at the individual node level. On the other hand, the networks studied in this chapter are fundamentally self-organizing (i.e. joint consortium links are not mandated top-down). Hence, network dynamics are driven on the one hand bottom-up by the choices of individual consortium members to pursue a certain technological trajectory, and on the other hand by top-down management interventions such as integrating communities and creating intermediaries across research domains (Mohrman et

[22] As indicated in the general introduction of this dissertation, several topics regarding the construction of this dataset are elaborated on in the different appendices to the different empirical chapters in this dissertation. The topics covered are (1) data sources and database construction (Chapter 2), (2) node specification (Chapter 3), (3) tie and network specification (Chapter 4) and (4) network boundary specification (Chapter 5).

al., 2006). This makes the question regarding differences in network dynamics between technology fields especially salient, as insight in these differences opens the road for specifying network interventions that suit the developmental stage of a network.

Second, we noted earlier that collecting longitudinal network data is a time-intensive and even daunting task. Consequently, many studies on network dynamics –despite the tremendous effort put in collecting data– still fall short in generating results that allow for comparisons and generalizations across sectors. With a focus on seven different technology fields that each span time frames ranging between 21 and 23 years, our study is an important step forward on this dimension. Not only does our data allow us to study extensive time frames within technology fields, it also allows for comparing developmental patterns between a wide array of different field networks.

Measurements

Network size. This variable is expressed as the number of consortia in a network. We did not consider nodes that were isolated in the network, or part of a dyadic structure that was not connected to one of the network components.

Node entry. Taking *t* as the reference year, node entry is determined as the number of new consortia that entered the network at *t*. A consortium was considered "new" when its leader was not involved in any other consortium three years preceding *t*. Node entry was expressed as a count variable.

Node exit. Taking *t* as the reference year, node exit from a network was determined as the number of consortia that left the consortium network just before the network was observed at *t*. Following the same reasoning as with node entry, a consortium was considered to exit the network when its leader did not appear again in the three years after *t*. Node exit, too, was expressed as a count variable.

Network density. Cohesion through inter-consortium ties was captured in the measure of network density. This measure was calculated for all 156 networks by dividing the actual number of ties present in each network by the total number of theoretically possible ties in that network, taking into account that the joint member ties in the consortium network considered are undirected (Scott, 2000). Networks that consisted of multiple components were accounted for by calculating network density for each component individually, and then determining the weighted density average based on component size. We made use of the functionality available in the statnet suite (Goodreau et al., 2008) available in the R statistical environment (R Development Core team, 2016) in these calculations.

Network degree centralization. The extent to which joint member ties are organized around one or few nodes in the network –indicating joint foci on few technological trajectories– is expressed by the measure of degree centralization (Freeman, 1978). We calculate this measure with the normalized degree centrality scores of each consortium, to account for differences in network size. Networks that consisted of multiple components were accounted for by calculating degree centralization for each component individually, and then determining the weighted average based on component size. We made use of the functionality available in the statnet suite (Goodreau et al., 2008) available in the R statistical environment (R Development Core team, 2016) in these calculations.

Control variables. In addition to the parameters derived from the two key aspects of the network architecture concept, we included a *year* variable as a control in our analysis. As noted earlier, the movement of a network through the state space is –amongst others– determined by initial conditions of the network itself (Bickhard & Campbell, 2003; Makadok & Walker, 2007). Including a year variable in our analyses accounts for this, as it assumes path-dependence in the effect of time (Gulati & Gargiulo, 1999).

Data analysis

Different authors have pointed at the complexities and challenges involved in the development of methods needed for analysing longitudinal network data, especially because of the path-dependency of subsequent network observations (Emirbayer, 1997; Faust & Skvoretz, 2002; Stokman & Doreian, 1996; Tsai, 2000). The dominant approach that has emerged in the context of research on tie formation, is to represent network dynamics as a stochastic process (Carpenter, Li, & Jiang, 2012; Gargiulo & Sosa, 2016; Lusher et al., 2013; Rose Kim, Howard, Cox Pahnke, & Boeker, 2016; Snijders, 2001). Yet, the ERGMs and SAOMs involved in these approaches are less suitable for analysing complete interorganizational network dynamics for several reasons. First, one of the strengths of these models, namely their ability to distinguish between closely related structural processes (i.e. transitive closure, cyclic closure, closure due to having either a shared incoming or outgoing partner for triadic predictors of tie formation (Butts, 2008) requires the data to be directed. Only then, one unleashes the full potential of these models. Our data on interorganizational networks is undirected, which is often the case for such data (Sytch & Tatarynowicz, 2013b). Second, considerable technical challenges are faced when handling large networks (Kleinbaum, Stuart, & Tushman, 2013; Sytch & Tatarynowicz, 2013b) as well as networks that are characterized by node entry and exit (Huisman & Snijders, 2003; Krivitsky, Handcock, & Morris, 2011). Both are salient aspects of the networks that are studied in this chapter. In practice, these issues result in the need for a considerable amount of computational power and time. The current state of technology does not allow this

Given that the use of these sophisticated techniques currently is impossible for the network data focused at in this chapter, we resort to an approach that allows us to capture the movement of a network through the state space, albeit that some detail must be dropped. The strength of this analytical step consists of an overview of a sequence of state changes over time within technology fields. To achieve this, we employ the statistical technique of latent profile analysis. This is an exploratory technique that we use to probe whether the consortium networks systematically align in such a way that they form distinct states. Although in the past clustering methods such as hierarchical or k-means clustering were used to derive latent groupings from data (Kassambara, 2017; Short, Payne, & Ketchen, 2008), latent profile analysis provides a comparatively more reliable estimation of distinct states.

Latent profile analysis is a model-based approach that offers various model selection tools, and results in a probability-based classification through estimating a posterior probability of membership that can be evaluated using goodness of fit indices (Ebers & Oerlemans, 2013; Haughton, Legrand, & Woolford, 2009). In its essence, latent profile analysis can be thought of as addressing a missing data problem (Oberski, 2016). In the current chapter, we have observed several parameters and a control variable for 156 networks, and suspect that these cluster in distinct states. Our expectation is that, if our states are defined well (i.e. all relevant parameters are specified), subsequent network states generally will form smooth trajectories within the state space (Bickhard & Campbell, 2003). These states, however, are not observed when model estimation starts. As estimation progresses[23], parameters are devised that seek to identify the smallest number of unobserved states that is sufficient to account for the relationships among the observed indicators (Ebers & Oerlemans, 2013). An important –and unverifiable– assumption is that each state has a certain prior distribution –with an a priori unknown mean and variance– of its estimates. This assumption about what the hidden states look like enables us to obtain a posterior likelihood of a network belonging to a certain state (Oberski, 2016). Hence, although the estimates per state differ, the distribution of these estimates is the same across states. In this chapter we employ a Gaussian approach, meaning that state estimates are assumed to follow a normal distribution. Different packages are available for latent profile analysis (i.e. the commercially available package Latent Gold® (Vermunt & Magidson, 2016), and two packages available in R, MCLUST (Scrucca et al., 2016) and poLCA (Linzer & Lewis, 2011). A comparison of these packages (Haughton et al., 2009) concluded that MCLUST is most suitable for continuous data, which is characteristic of the parameters we focus at in this chapter. Hence, the MCLUST package is used for our analysis.

The a priori assumption that the estimates in each state follow a normal distribution should not be made light-heartedly (Oberski, 2016), especially in the case network data is modelled. As we already saw in Chapter 3, node-level network data (i.e. betweenness centrality) tends to follow a non-normal distribution. This also applies to complete network-level data. We addressed this issue in our analytical strategy in the following way: an important cause for our network data following a non-normal distribution, is that especially in the early stages of network development the networks observed are rather small. This leads to high scores on all indicators, which are much less likely to be observed once the networks are past the initial formation stage. Should outliers occur in these post-formation stages, however, this could point at shocks (i.e. a technological discontinuity) that profoundly affect network structure and population dynamics. Using a multivariate outlier analysis based on the approach described by Filzmoser, Maronna, and Werner (2008) and which is available in the 'mvoutlier'-package (Filzmoser & Gschwandtner, 2017) in R (R Development Core team, 2016), both types of outliers are identified and taken into account in our analysis.

4.4 Results

Descriptives and correlations

Table 17 shows the descriptives and correlations for the state parameters and the control variable. Although not included in the analysis, we also included different technology field dummies in this Table because these are used for grouping the results of the latent profile analysis. Means of these dummies are similar, indicating that network observations are equally spread across technology fields. Marked differences between technology fields can be seen when one considers the correlations between field dummies and state parameters. Most correlations between the dummy for Electrical engineering and these parameters are non-significant, indicating that networks in this field –except for their density scores– can be considered the 'average' case. Compared to this field, network size is bigger for the Chemistry, Instruments and Life sciences fields, and smaller for the

[23] Direct maximisation of the number of states is complicated, so iteration based on maximum likelihood estimation takes place in order to obtain maximisation (Hagenaars & McCutcheon, 2002). The expectation maximization (EM) algorithm is often used for this, due to its stability and reliable global convergence under most conditions (Scrucca, Fop, Murphy, & Raftery, 2016). Model fit then can be determined using a log-likelihood criterion which in latent profile analysis is the Bayesian information criterion (BIC), with the lower the BIC, the better the fit of the model.

TABLE 17

Descriptives and correlations[24]

Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1. Chemistry…………….	.14	.35	0	1	-											
2. Civil engineering……...	.14	.35	0	1	-.16*	-										
3. Electrical engineering…	.15	.36	0	1	-.17*	-.17*	-									
4. Instruments…………...	.13	.34	0	1	-.16*	-.16*	-.16*	-								
5. Life sciences…………..	.15	.36	0	1	-.17*	-.17*	-.17*	-.16*	-							
6. Mechanical engineering.	.14	.35	0	1	-.16*	-.16*	-.17*	-.16*	-.17*	-						
7. Medical technology…...	.15	.36	0	1	-.17*	-.17*	-.17*	-.16*	-.17*	-.17*	-					
8. Year…………………..	1993.35	6.47	1982	2004	.01	.01	-.02	.04	-.02	.01	-.02	-				
9. Network size………….	47.71	32.36	3	141	.31**	-.35**	.10	.23**	.36**	-.41**	-.25**	.50**	-			
10. Node entry…………..	7.26	5.68	0	31	.25**	-.30**	.14	.10	.33**	-.29**	-.24**	.22**	.69**	-		
11. Node exit……………	5.17	5.06	0	26	.23**	-.22**	.05	.12	.27**	-.24**	-.20*	.52**	.70**	.41**	-	
12. Density……………...	.25	.11	.07	.67	-.13	.27**	.42**	-.36**	-.32**	.13	-.02	-.13	-.42**	-.30**	-.26**	-
13. Degree centralization...	.33	.14	.08	1	.12	.03	.01	-.27**	-.24**	.26**	.09	-.23**	-.35**	-.32**	-.21**	.59**

[24] $n = 156$. $^{**}p < .01$; $^{*}p < .05$.

others. The correlations for node entry and exit harmonize with the correlation for network size when it comes down to technology fields, except for the field of Instruments: for this field, both the level of node entry and node exit are equal to that of the field of Electrical engineering. Hence, compared to other technology field networks that are larger than the field of Electrical engineering, the node entry and exit intensity in the Instruments field is low. Given the operationalization of both node entry and node exit (i.e. both require the consortium leader to be absent from the network for at least three years), this does not necessarily have to indicate that absolute levels of node entry and exit are lower for this field. A tendency for consortium leaders to disappear from the network yet being absent for less than three years before returning, or a stable set of consortium leaders that initiate consortia over the years could also be a plausible explanation. Correlation patterns between technology fields and parameters for structural dynamics sketch a more heterogeneous picture. For most fields that significantly correlate with the density parameter (i.e. Civil engineering, Instruments and Life sciences), the direction of the sign mirrors that of the correlation with size. This makes intuitive sense: larger networks are less dense because there are physical limits to the amount of joint member ties individual consortia can maintain. It is here where the field of Electrical engineering deviates from its average status. Its positive correlation with density indicates a higher level of mutual awareness across consortia, especially compared to the technology fields of Chemistry, Mechanical engineering and Medical technology, which are not significantly correlated with density. The parameter of the presence of a limited number of central players, degree centralization, displays more similar patterns across technology fields, as only the Instruments and Life sciences fields are relatively less centralized, and the field of Mechanical engineering is more centralized. Again, size is the explanation here, as smaller networks are more easily centralized compared to larger ones. More salient correlations with degree centralization are the ones that are not significant, as those indicate that –despite the substantial differences in size across networks– these networks tend to have the same level of network centralization.

With respect to the correlations between parameters that do not denote technology fields, one can deduct a clear growth pattern when assessing the correlations between the year variable and the variables for size, node entry, node exit and degree centralization. This is not the case for density, which appears to develop independently from the progress of time. Correlations among size, node entry and node exit show a consistent pattern: larger size means more entry as well as exit, and more entry as such also implies more exit. The behaviour of these parameters in relation to density and degree centralization, as well as the correlations between the latter two sketch a more intriguing picture: while one intuitively would expect these measures to move in opposite directions, the found correlations suggest this is not the case. Instead, both move in the same direction and are negatively associated with node entry and exit: more density is associated with more centralization of the network, and this structure emerges under conditions of low node turnover.

Results of Latent Profile Analysis

As explained in more detail earlier, we performed a latent profile analysis to delineate distinct network states. First, a posterior probability of membership was estimated, based on the specified parameters. This probability in turn was evaluated using goodness of fit indices. After several iterations, the analysis resulted in a probability-based classification of the cases observed (Ebers & Oerlemans, 2013; Haughton et al., 2009). Classification of observations is done by the algorithm in the MCLUST-package in such a way that the goodness of fit value of the total model -reflected in the BIC-score- is minimised.

TABLE 18

Averages and standard deviations of indicators per state

Latent profile predictors	States				
	State I	**State II**	**State III**	**State IV**	**State V**
	Formation (*n = 28, 17.9%*)	**Growth** (*n = 51, 32.7%*)	**Stagnation** (*n = 20, 12.8%*)	**Stability** (*n = 48, 30.8%*)	**Disintegration** (*n = 9, 5.8%*)
Year	1985 (1.74)	1994 (5.86)	1995 (4.51)	1997 (4.92)	1999 (2.58)
Size	20 (16.66)	35 (12.03)	17 (5.36)	77 (11.41)	119 (20.12)
Node entry	5 (6.53)	6 (3.68)	2 (2.15)	11 (3.97)	16 (6.19)
Node exit	1 (1.47)	4 (2.53)	2 (1.55)	9 (4.73)	13 (6.55)
Density	.26 (.16)	.27 (.10)	.30 (.10)	.22 (.07)	.10 (.01)
Degree centralization	.39 (.24)	.33 (.08)	.33 (.15)	.32 (.07)	.18 (.02)

Table 18 shows the average scores and standard deviations of the parameters in our framework for each found class. In addition to the Formation-state, which we constructed based on observations of outliers in the early years of the development of each network, four distinct states were identified by the conducted latent profile analysis. The covariances of each state have ellipsoidal distributions that are equal in both volume and shape but vary in orientation. The BIC of the final model was 1,840, which was the lowest of all 14 models considered. Hence, this model (the so-called EEV-model, see Scrucca et al. (2016) for an explanation of this model as well as the other 13 possible models) was selected[25]. Considerable data exploration preceded the estimation of this final model. As expected, multivariate outliers were detected both in the initial stages of network development (28 observations) and the post-formation stages (28 observations). After careful deliberation[26], we decided to leave out from the final model those networks causing outliers due to being in the initial stages of network development, and separately label the state of these networks upfront. The label used for this additional state was 'Formation'. Post-formation outliers were included in the dataset, and an auxiliary variable denoting outlier status (i.e. outlier or no outlier) was included as one of the latent profile predictors.

[25] Although the BIC is a popular choice in the context of gaussian-based latent profile analyses, it tends to select the number of components needed to reasonably approximate the density instead of the number of clusters as such (Scrucca et al., 2016). For this reason, other criteria have been proposed for model selection, like the integrated complete data likelihood (ICL) criterion. Using this criterion for our data yields the same conclusion regarding the model that fits the data best (EEV, 4 components, ICL = 1,843).

[26] Model estimation that includes all networks and outlier-status (0 = formation-based outlier, 1 = no outlier, 2 = other outliers) as an auxiliary variable resulted in 8 distinct states. The overlap of these states with the states presented in this section is considerable: 5 out of 6 networks are classified the same. With respect to the networks that are classified differently, especially the state of Stagnation showed different results. Of the 20 networks that are now presented as belonging to this stage, 10 were classified differently when including all networks in the model: 4 networks were grouped in a stage that is similar to the current Formation stage, and 6 networks were grouped in a stage that could be classified as a mild exacerbation of the current Decline state. Given (i) the match between our ex ante expectations of a distinct Formation stage and the identification of this state by the model including all networks, (ii) the argument that the Formation and Decline stage are rather similar, except for their timing and (iii) the marginal difference between the two Stagnation states identified by this model, we decided for an ex ante specification of a Formation stage and leave the corresponding networks out of our final model estimation.

Networks in the Formation state occur early in time and are relatively small on average. The large standard deviation (16.66), however, indicates that considerable variation in size exists across networks in this state. Except for the number of nodes leaving, this large variation in network size is also reflected in standard deviations of the other predictors. The most salient signs that networks in this state fit the formation state are the high entry/exit ratio (5:1 = 5.00) as well as the turnover/size ratio ((5+1)/20 = .30): compared to network size, relatively many consortia are attracted, yet only few have left. Contrary to the other states, which need to be interpreted in temporal relation to one another to deduct underlying technology dynamics, this is the only state that can be classified directly in terms of our theoretical description, as it reflects node entry in the event a new technology field network is established.

With respect to the most frequently observed state of Growth, we observed that networks classified in this state are somewhat bigger compared to the Formation state. This is associated with similar average density levels, and relatively less centralized networks, at least on average (the large standard deviations of this predictor for state I makes a direct comparison difficult). Generally, the averages of the latent profile predictors of networks in this state have smaller standard deviations, indicating less variability between parameters of networks in this state. Compared to the Formation state, networks in this state show a drop in the entry/exit ratio (6:4 = 1.50), even though the turnover/size ratio ((6+4)/35 = .29) remains the same. Hence, more nodes have left compared to the Formation state, but this does not outweigh the level of node entry in consortium networks that are in the state of growth. This combination of a generally increased level of stability and more nodes entering than leaving against the background of relatively high levels of node turnover has yielded the 'Growth' label for this state.

The state of Stagnation is the third state that we identified. This is one of the two states that we observed less frequently, and the state where many of the outliers that could not be attributed to the Formation state tend to cluster (71.43% (20 networks) of all 28 networks labelled as outliers). Clustering of outliers in this state is exclusive: none of the networks that were labelled as a non-outlier belong to this state. The state is characterized by the lowest entry/exit ratio (1:1 = 1.00) of all states identified. In addition, networks in this state are on average the smallest compared to networks in other states and are characterized by a relatively low turnover/size ratio ((2+2)/17 = .24). Hence, the development of networks in this state comes to a halt. What is salient about this state, however, is that density and degree centralization on average remain at the same level as those of both the Formation state and the Growth state. Although this can be attributed to the smaller sizes of the networks classified in the Stagnation state, it does suggest that network stagnation takes place in a way that preserves overall network structure.

The fourth state displays the characteristics of a Stability state. The choice for this label derives from the comparison with the Growth state. First, except for size, networks in the Growth and Stability state are relatively comparable in terms of node entry, node exit, and degree centralization. Differences are observed, though, in the entry/exit ratios between both networks and the turnover/size ratio: with ratios of (11:9) 1.22 and ((11+9/77) .26, networks in the Stability state display a relatively lower level of compensation for nodes that leave the network. Still, network growth occurs, but at relatively low levels. In addition, networks in the Stability state show a marked drop in the level of density, implying that the amount of joint member ties between consortia in networks in this state has declined.

TABLE 19

States and movement through the state space over time per technology field[27]

<table>
<tr><th rowspan="2">Year</th><th colspan="7">Technology field</th></tr>
<tr><th>CH</th><th>CE</th><th>EE</th><th>IN</th><th>LS</th><th>ME</th><th>MT</th></tr>
<tr><td>1982</td><td></td><td></td><td>Formation</td><td></td><td>Formation</td><td></td><td>Formation</td></tr>
<tr><td>1983</td><td>Formation</td><td>Formation</td><td>|</td><td></td><td>|</td><td>Formation</td><td>|</td></tr>
<tr><td>1984</td><td>|</td><td>|</td><td>|</td><td>Formation</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>1985</td><td>|</td><td>Growth</td><td>Growth</td><td>|</td><td>Growth</td><td>|</td><td>|</td></tr>
<tr><td>1986</td><td>Stability</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>1987</td><td>|</td><td>Stagnation</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>1988</td><td>|</td><td>|</td><td>|</td><td>Growth</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>1989</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>Growth</td><td>Growth</td></tr>
<tr><td>1990</td><td>|</td><td>|</td><td>|</td><td>|</td><td>Stability</td><td>|</td><td>|</td></tr>
<tr><td>1991</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>Stagnation</td><td>|</td></tr>
<tr><td>1992</td><td>|</td><td>|</td><td>|</td><td>Stability</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>1993</td><td>|</td><td>Growth</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>1994</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>1995</td><td>|</td><td>|</td><td>Stability</td><td>|</td><td>Disintegration</td><td>|</td><td>|</td></tr>
<tr><td>1996</td><td>|</td><td>Stagnation</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>1997</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>1998</td><td>|</td><td>Growth</td><td>|</td><td>|</td><td>|</td><td>Growth</td><td>|</td></tr>
<tr><td>1999</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>2000</td><td>|</td><td>Stagnation</td><td>|</td><td>|</td><td>|</td><td>Stagnation</td><td>|</td></tr>
<tr><td>2001</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>2002</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>Growth</td><td>|</td></tr>
<tr><td>2003</td><td>|</td><td>Growth</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>2004</td><td>|</td><td>|</td><td>|</td><td>|</td><td>Stability</td><td>|</td><td>|</td></tr>
</table>

We observed the state of Disintegration most seldom. Networks that were classified as disintegrated are marked by a significant structural deterioration: roughly speaking, both density and degree centralization have almost halved in this state compared to the other four states. Although this can be partially attributed to the increase in network size, this marked decrease in scores stands in no proportion to the differences between the other states when size is controlled for. Like the Stagnation state, this is one of the states in which almost all networks (8 out of 9) were labelled as non-formation related outliers in our preliminary analysis (28.57% of all 28 networks labelled as outliers). Indeed, the state of Disintegration shows similarities with the state

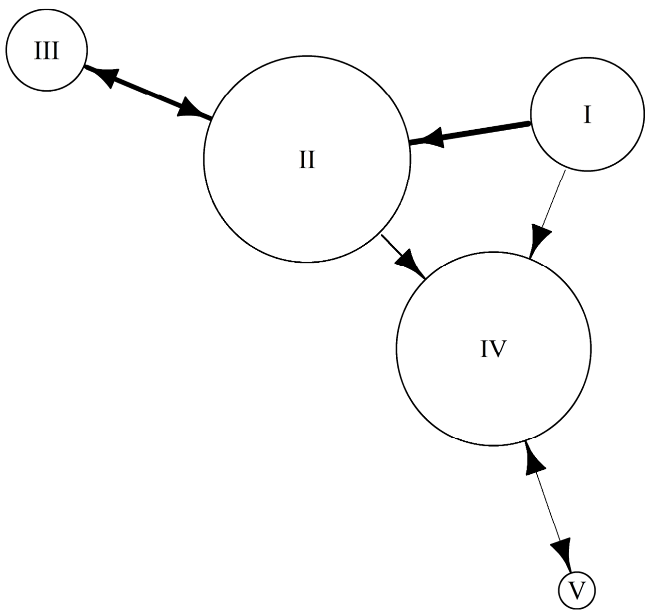
[27] Key to the abbreviations: CH = Chemistry, CE = Civil engineering, EE = Electrical engineering, IN = Instruments, LS = Life sciences, ME = Mechanical engineering and MT = Medical technology.

of Stagnation when considering the node turnover ratio, which is .24 for both states (see earlier for the calculation of this ratio for the state of Stagnation. The calculation for the state of Disintegration is (16+13)/119). Hence, compared to network size, about 24% of consortia either entered or just have left the network. The state of Disintegration also exhibits features of the Stability state, especially when we consider the entry/exit ratio (16/13 = 1.23). Although absolute levels differ between these states, both can be characterized as network growth coming to a halt. For networks in the stagnation state, this seems to be a less hard landing compared to networks in the disintegration state, however.

Table 19 provides an overview of the movement of the found states through the state space per technology field on the basis of the yearly calculation of the network state based on the five dimensions. We infer three main observations. First, we deduce that considerable differences exist in network dynamics between technology fields. Yet, a common pathway can be identified: despite variations, this pathway starts from the Formation state, via the state of Growth, to the state of Stability. This exact pathway can be observed for the fields of Electrical engineering and Instruments. Variations on this pathway are seen in the developmental patterns for the fields of Chemistry (where the Growth state is skipped, and networks move right away to the state of Stability), Life sciences (where the state of Stability is interrupted by a 9-year episode of Disintegration) and Medical technology (which starts with the Formation and Growth stage but does not transition to the state of Stability). The first two stages can also be seen in the network development of the fields of Civil engineering and Mechanical engineering. However, instead of transitioning to the state of Stability, both field networks start alternating between the states of Growth and Stagnation after they have first reached the Growth state.

FIGURE 9

Prevalence of states and common pathways through the state space[28]



Second, considerable variation exists between field networks when we consider the duration of states. The fields shown in the first five columns of Table 19, for example, are characterized by a Formation stage that takes at most four years. The other two fields (i.e.

[28] Key: I = Formation, II = Growth, III = Stagnation, IV = Stability, V = Disintegration.

Mechanical engineering and Medical technology), on the other hand, reside in this state for six and seven years, respectively. No clear patterns can be deciphered from these state durations. Whereas, for example, the fields of Electrical engineering and Life sciences have Formation states that last an equal number of years, the latter field network remains considerably shorter in the subsequent Growth state compared to the first. This insight is important, because as we will describe shortly the nature of each state differs considering our expectations regarding technology dynamics. For this specific comparison, we described earlier that except for network size, the Growth and Stability state are relatively comparable with respect to the parameters of node entry, node exit, and degree centralization, yet networks in the state of Stability have lower density levels compared to networks in the state of Growth.

Third, certain state sequences are observed more often compared to others, and some sequences are not observed at all. Figure 9 summarizes the prevalence of, and common pathways between states, with node size denoting state prevalence and arrows denoting the direction in which state changes can take place. This figure clearly shows the earlier described common pathway from Formation, via Growth to Stability. It also shows the mentioned shortcut from the Formation state directly to the Stability state. State changes from the Growth state to the state of Disintegration, however, are not possible: networks do not instantly quadruple in size and reconfigure profoundly. Other unobserved state changes are the state change from the Stability state back to the state of Growth or to the state of Stagnation. This implies lock-in: none of the networks that get into the stability state subsequently move to one of the other states, except for the Life sciences network, which disintegrates for some time before switching back to the stability state. We will discuss in the next section how the frequent observation of some state changes and the infrequent observations (or lack thereof) of others can be interpreted considering the underlying technology field dynamics.

Earlier, we linked the Formation state to the establishment of a new technology field network. Figure 9 also offers insights regarding the link between network dynamics and the other stages of technological development. Theoretically, we expect stability over time in the population parameters as well as high levels of network density and degree centralization which reflects that few consortia have obtained a dominant position in the network, guiding the efforts of other consortia around few technologies. The relative long uninterrupted time frames with which the Stability state sustains indicates that this could be the network state in which this occurs in the network, although especially network density is lower compared to the other states. The occurrence of a technological discontinuity is reflected in the state of Disintegration: its low prevalence and considerable increase in network size in combination with drops in the structural parameters and changes in the population parameters reflects all characteristics of such a breakthrough innovation. The states of Growth and Decline are more difficult to align with our theoretical expectations: even though the frequent alternating occurrence of these states, suggesting periods of technological ferment and maturity, these states are not preceded by the network state we associated with technological discontinuities, Disintegration.

4.5 Discussion and conclusion

Whereas the existing literature suggests a heterogeneous development of different technology field networks, innovation policy aimed at the formation and development of such networks is surprisingly homogeneous. As networks might develop in different ways and with different speeds, this homogeneity can be problematic. The question if network dynamics differ between technology fields, however, has hitherto remained unanswered. Through incorporating the two aspects of the definition of network dynamics by Ahuja et al. (2012) in a conceptual model that revolved around the heuristic of a network state, and linking this state to technology field dynamics, we mapped network dynamics in terms of the pathway followed by a network through the space state. The network dynamics of 7 technology field were described using this model. This allowed us to identify the five states of Formation, Growth, Stagnation, Stability and Disintegration.

Describing the dynamics of networks using state changes suggests the existence of a basic pathway from formation, via growth, to stability. Alternations of this pathway do occur, however, for example shortcuts from formation to stability, a network going back and forth from growth to decline, or networks switching from a state of stability to disintegration. This is the first indication that network dynamics indeed differ between technology fields. Our analysis also reveals considerable differences between networks with respect to the duration of different states. For example, whereas networks in the field of Chemistry and Medical technology can be characterized by few states that last for longer time periods, the fields of Electrical engineering and Instruments display more variation. The sequence of states for the fields of Civil engineering, Life sciences and Mechanical engineering deviates even more from this basic pathway, as none of these networks reach the state of Stability. This is the second indication that network dynamics indeed differ between technology fields.

In addition to these core findings, we demonstrate the importance of considering the aspects proposed by Ahuja et al. (2012) other than antecedents of tie formation (i.e. network size, node entry and node exit, network density and degree centralization) for comprehensively describing network dynamics. Taken together, both our research approach as findings provide a point of reference for existing and future research on the topic of the hitherto relatively anecdotal field of research on complete interorganizational network dynamics.

Theoretical and practical implications

The number of distinct states revealed by our analysis is limited, and the sequences of state changes followed through the state space do fit our tentative theoretical expectations regarding the link between technology dynamics and network dynamics. Both are an indication that most of the relevant parameters needed for the identification of states are specified (Bickhard & Campbell, 2003). Indeed, even a direct comparison is impossible, overlaps are detected when we compare our findings regarding the duration of states and state transitions in the field of Electrical engineering and Life sciences with the existing literature. For example, in one of the major sub sectors of the field of Electrical engineering, the information technology industry, Hanaki, Nakajima, and Ogura (2010) show that the IT network shows considerable growth from 1991 to 1995, with a trend towards a structure characterized by increasing density and local centralization (i.e. a small-world network). This trend coalesces with the evolutionary growth state in which our Electrical engineering network is from 1985 until 1995, before it switches to the state of stability. Indeed, this state is characterized by high density and centralization levels, and it would be interesting to extend the network analysis of Hanaki et al. (2010) to years beyond 1995 in order to see if that network also transitioned to this state of stabilization around that time.

Several authors have investigated the evolution of networks in the Life sciences field. Their findings match well with ours, even though a discrepancy in explanations exists. The global trend in this field described by others is that it shows a steady growth as from 1975, with increasing density levels (Orsenigo et al., 2001; Roijakkers & Hagedoorn, 2006). Whereas the field is dominated by its originators (small dedicated biotech firms) in the 1980s, the 1990s are marked by the entry of large, established pharmaceutical companies that tend to get more and more dominant as this decade progresses (Gay & Dousset, 2005; Gilsing et al., 2016; Orsenigo et al., 2001; Roijakkers & Hagedoorn, 2006). This is in line with the sequence of formation states that we observe for this field from 1982 to 1994. The pharmaceutical sector underwent a period of consolidation in the mid to late 1990s, marked by mergers and acquisitions (Powell et al., 2005). Our analysis reveals the state of Disintegration in this period. As we explained in the theoretical section of this chapter, later incumbents from other technology fields can overtake an emerging one. Hence, a possible explanation for the state of Disintegration in the field of Life Sciences is that a consolidation wave took place from incumbents from other technology fields that overtook this field.

Another issue that makes the link between the Disintegration state and technological discontinuity tentative at best is that said state does not transition towards the Growth and Stagnation states, which we associated with technological ferment and maturation. In addition, the state of Stability seems to imply network lock-in. A possible explanation is that even though most of the relevant parameters for describing network dynamics are specified, this set should be further expanded. For example node competencies play an important role in technology dynamics, as they determine the ability of individual nodes to adapt to discontinuities (Leiponen, 2006; Uzunca, 2017). Also, a consideration of the subfields of each technology field should be considered: Murmann and Frenken (2006) discuss that technology dynamics are not the same at different levels of field aggregation. This can be related to our findings with respect to the field of Electrical engineering: M'Chirgui (2009) finds a considerable growth in the number of inter-firm agreements as from 1999 until 2001, which is not reflected in the pattern we find for the field of Electrical engineering. It indicates that the seemingly homogeneous technology field network development masks subtle differences when one considers subfields.

In this chapter we applied an empirical approach towards discerning distinct developmental states and find that states can be predicted using relevant parameters, yet state changes are unpredictable. This raises the question to what extent theorizing regarding change can take place. Scholars have classified the question if technology indeed changes through a cyclical process marked by stages of discontinuity, ferment, maturation and dominant design as important, as it has major ramifications for the competencies of incumbent firms (Murmann & Frenken, 2006). van de Ven and Poole (1995) propose four distinct approaches towards theorizing about change in organization studies: life-cycle, teleological, dialectical and evolutionary (van de Ven & Poole, 1995). The life-cycle theory depicts development as a predictable pattern of change towards a known final state. An example of this is the development and commercialization of a new drug (van de Ven & Poole, 1995). The teleological approach describes change as a developmental progress towards a certain goal or end state. An example of such an approach are the different life cycle stages proposed in the organizational growth model by Greiner (1972). Key in this approach is that no necessary sequence of events is needed to reach the goal, and that this goal can be adjusted based on new insights obtained. Hence, teleological theories cannot specify the trajectories that will be followed (van de Ven & Poole, 1995). In the dialectical theory, change is explained as a process in which a disruption in the status quo because of opposing forces is resolved through creative synthesis. Processes that aim at resolving conflicts are an example of such dialectical processes (van de Ven & Poole, 1995). Lastly, the evolutionary approach describes change in terms of a recurrent, cumulative and probabilistic progression of variation, selection and retention, for example changes in organizational populations (Hannan & Carroll, 1992; van de Ven & Poole, 1995).

None of these change patterns are clearly revealed by our analysis. The common pathway that we found and that leads from Formation, via the state of Growth to the State of Stability suggests linearity (i.e. life cycle) in network dynamics, yet the differences between fields are too large to be conclusive about this. In addition, our theoretical arguments propose a cycle (evolutionary), yet this is revealed for none of the field networks as well. This suggests that theories of change can only be developed fruitfully for shorter time frames, and the topic should be approached empirically once these time frames, and with the associated uncertainty, get longer.

We claimed in the introduction that a major practical implication of our work is that it allows for a more targeted specification of policy measures directed at external network orchestration. According to Mohrman et al. (2006), policy can affect field networks in two distinct ways. First, it can impact variation, selection and retention processes in the technology field through regulating node entry and exit levels. Obviously, the direction in which network change should take place depends on which network states are most conducive for joint innovation. In general, however, we can say that our model provides clear levers for inducing state transitions. Should one desire to get a network out of its state of Decline, allowing more consortia to enter through making more funds available for that specific technology field would be a strategy. In a similar vein, networks can be taken out of a state of disintegration by reducing both node entry and node exit. The latter can be achieved by for example funding consortia that follow-up consortia that have not generated substantial results (and could be considered a failure), yet simply might need more gestation time to generate these results. Given a fixed budget, making more resources available for one technology field implies that less resources become available for other fields with its corresponding impact in network dynamics, however.

The second way in which policy can shape networks is through affecting linkages in the network via requirements for research proposals and through funding of various kinds of cross-over or within-field institutes (Mohrman et al., 2006). In this area we see opportunities in particular with respect to funding consortia that function as bottom-up network orchestrators, or network “weavers” (Ingram & Torfason, 2010) should one desire to get networks in the relative centralized state of Growth, for example. This could also aid the reliability of networks (Berthod, Grothe-Hammer, Müller-Seitz, Raab, & Sydow, 2016), even in times of turmoil, such as the state of Disintegration. Lastly, network structure can be affected through mandating specific joint consortium ties, although here the question is to what extent these mandated ties will be activated.

The most important insight of this study for policy is that indeed, policy should be differentiated based on the different state sequences and developmental paces of technology field networks. As stipulated in the introduction, rational design of networks is not always possible, and it is hence important to map the development of a network before deciding if policy measures should be devised, and if so which policy measures are most effective given the developmental history of the network.

Strengths, limitations and suggestions for future research

Despite the strong data basis that has driven our research, it is not without limitations. A recent critique on interorganizational network research that has been voiced is that not enough is done to overcome the implicit assumption of knowledge circulating freely within these networks (Ghosh & Rosenkopf, 2015). Frictions in interorganizational networks exist, for example due to the nature of knowledge and the composition of ties. An important limitation of the current study is that we do not consider properties of ties in our analysis. For example, even though ties in the networks studied are valued (i.e. the number of joint member ties between any two consortia), tie strength is binarized in our analysis in order to avoid additional complexities with respect to calculating density and degree centralization for valued graphs (Scott, 2000). One could argue, however, that switches between states become more difficult at higher average levels of tie strengths in the networks under consideration. Hence, a fruitful extension of our model would be to consider the role of tie strength. For example, can we delineate different states if we consider average tie strength in the latent profile analysis, and what is the relation between average tie strength in a network and the number of dominant designs focused at in a technology field network?

Another general issue in research on interorganizational networks related to ties is that not much attention is given to the changing states of these ties as such: not all ties are alive and equally available at a given point in time. Instead, they could for example be activated periodically, or remain in a dormant state for long periods prior to activation (Maclean & Harvey, 2015). It is hard to get data on these aspects from secondary data, but one strategy could be to scan minutes of meetings of the users committee, for example. Such a strategy has been employed successfully by Chappin (2008). In addition, a process-based approach to studying network dynamics could at least bring more general insight in the way consortium members perceive these joint member ties and in the reasons for, and frequency of activation of these ties. For example, antecedents of tie activation or tie deactivation could be studied, or the relation between the state of a tie and the type of knowledge that is being transmitted through it.

A third issue regarding ties that is specific to our study is that we focused on a specific type of tie. Other authors already have raised questions about the relation between the nature of the cooperative relationships and network dynamics (Park, 1996), as well as the effect of the funding programme on the types of linkages that are formed (Hayashi, 2003; Park & Leydesdorff, 2010). Future studies could focus on other types of relations to assess if similar network states and state sequence emerge in different collaborative settings or under different funding schemes.

A last issue we identify regarding tie specification in our study is that the funding scheme that is considered focuses on the Dutch context. Even though foreign organizations are allowed in the users committee, most members are Dutch. Because technology dynamics are not bound by country borders, especially considering the wave of internationalization that we have witnessed as from the 1980s, this means that the networks considered in this chapter are a cut out of a larger, global network that we do not fully observe. Future studies should incorporate this international focus.

Another limitation of our study is related to the specification of network boundaries (see Appendix I of Chapter 5). Usually, this is not as explicitly addressed in studies as we do in this chapter. An important reason for this is that system boundaries in most studies are already specified in the study design. In the introduction, we mentioned that most studies on network dynamics focus on the general field of Life Sciences (Powell et al., 2005), or a major sector within this field, such as the antibody sector (Gay & Dousset, 2005) or the pharmaceutical sector (Orsenigo et al., 2001). As this was not the case with our design, ex post classification was needed, which is inherently a subjective and not at all evident activity. This can be illustrated with the quote "All science is either physics or stamp collecting" that has been attributed to Ernest Rutherford (Bernal, 1939). As irony would have it, he was later awarded the Nobel Prize for Chemistry. Although we are no proponents of the rather binary "Rutherfordian" approach to classification, classification in general involves the risk that the empirical reality is reduced too little, too much or in a non-representative way. For example, not allowing for cross-technology main field links in this chapter could be disputed: competition between technology fields is much less salient compared to within technology fields, which could facilitate knowledge flows and hence make for stronger, more persistent joint consortium ties. Hence, we strongly encourage future studies on alternative boundary specifications, including a comparison with the results of the analysis presented in this chapter.

The last issue that has lingered throughout especially the discussion of the practical implications this research is that of the link between network dynamics and network effectiveness. In general, the link between networks and outcomes is an important motivation for studying network dynamics (Ahuja et al., 2012; Clegg et al., 2016; Dagnino et al., 2016). For example, Grabher (1993) has argued for regional industrial networks that the very conditions that made these networks stand out against the rest also led to the lock-in of these networks and their subsequent decline. It is interesting to assess for the networks studied in this chapter to what extent the duration with which a network remains in a certain state affects network outcomes. Other authors have suggested that different states might have different performance implications (Greve, 1999). Related to this, some authors have suggested that networks need to go through certain states in order to be fully developed (Carroll, Delacroix, & Goodstein, 1988; Gulati & Gargiulo, 1999). It would be an interesting research exercise to compare outcomes of networks that went through certain states (e.g. the growth state) with networks that did not go through these states. The relation between the duration of network states and network outcomes will be considered in the last chapter of this dissertation.

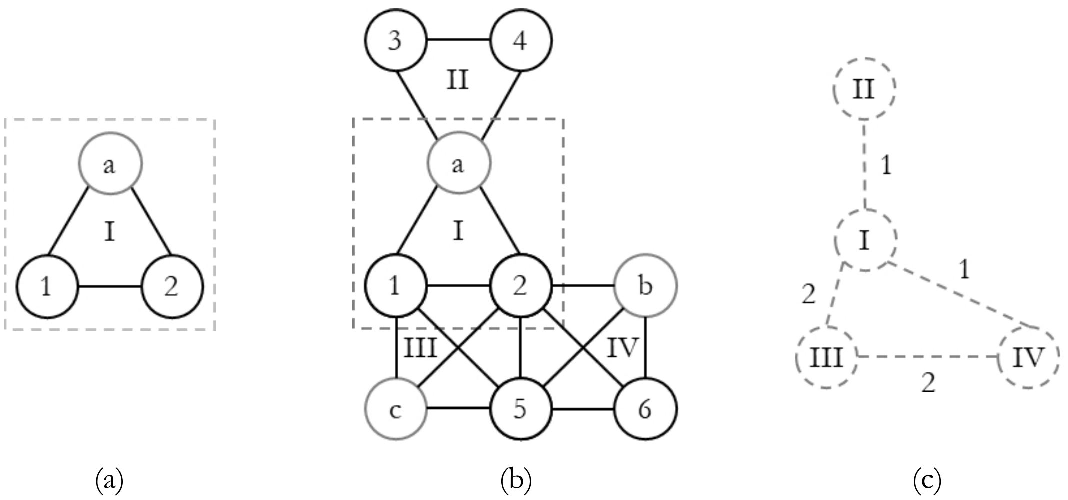
Lastly, at the start of this paper, we mentioned that our research question was simple, yet difficult to answer. Although we fruitfully applied the idea of network states and their pathway through state spaces, such descriptions should be subject to questions and further analysis (Bickhard & Campbell, 2003). Indeed, our research findings raise many more questions, as reflected in the above discussion. Even though the challenge in studying network dynamics will remain requiring sufficient data, future research that builds forth on our approach should especially focus more on the link between the movement of a network through the state space and the development of its underlying technology base.

Appendix I: Tie and Network Specification

Figure 10 displays the schematic that shows network construction approach in this dissertation. Panel (a) in Figure 10 shows the members of consortium I, which is the focal consortium in this example. This panel is constructed using the information provided on a consortium's evaluation (see Table 6 in Appendix I of chapter 2 for an example). The consortium leader is denoted with the letter *a*, whereas the organizational members are denoted by numbers. As indicated, no information regarding the internal relational structure of the consortium is available. Given the focus of the consortium on knowledge sharing, however, we assume that all consortium members are connected to one another.

FIGURE 10

Approach to network construction. Focal consortium I (panel (a)) is linked to two other consortia (II and III) through a joint project leader tie (*a*) and joint organization ties (*2)* (panel b). This is, in turn, simplified to the consortium network (c)



Panel (b) zooms out from consortium I and includes the links to other consortia through joint membership. From this panel, one can deduct that consortium leader *a* is also leading another consortium, labelled with the Roman numeral II. Besides consortium leader *a*, also organizations *3* and *4* are member of this consortium's user committee. In addition to this consortium leader-based joint member tie with another consortium, panel (b) shows that consortium I is also linked to a third consortium (III) through an organization-based joint membership tie via organization *2*. In addition to organization *2*, also consortium leader *b* and organizations *5* and *6* are member of this consortium's user committee.

Within certain constraints (Krackhardt, 1994), members of consortium II and III can be involved in other consortia as well. When added to the network in panel (b), this would create a second layer of consortia around the focal consortium. In the same vein, higher order layers can be added, and one can easily imagine how, for each technology field and year, the complete network emerges when members of all active consortia are included. The resulting complete network consists of a blend of interconnected consortium leaders and organizations. This network can neither be classified as a 2-mode network (ties between organizations are possible), nor as a 1-mode network (no ties between project leaders can exist). Consequently, calculation and interpretation of network measures based on this network would be tricky. In alliance research the methodological issue of having multiple nodes operating under the same collaborative umbrella is usually dealt with rather pragmatically, either by excluding these multi-partner collaborations from the analyses (Hu et al., 2017; Kavusan et al., 2016; Wassmer & Dussauge, 2012), or reducing them to dyadic relations (Ranganathan & Rosenkopf, 2013). In addition, instead of consortium leaders, the organizational affiliations of these leaders could be used instead. Neither of these approaches is desirable, however, as this would lead to severe information loss by ignoring the unique nature of multi-partner collaborations, as well as reducing hundreds of consortium leaders to about 12 research organizations with which these consortium leaders are associated.

The approach taken in this dissertation is shown in panel (c) of Figure 10: instead of project leaders and organizations, nodes are specified at the level of the R&D consortium. Ties between nodes represent joint member ties, either forged by project leaders, or the organizations involved in the consortium. Because multiple entities can create a link to another consortium (e.g. both organization *3* and *4* link to project leader *a* in panel (b) of Figure 10, values are attached to each tie, creating a valued graph. The networks that result from this procedure are used for determining the network measures described in the measurements section of this paragraph.

5. Variation, Selection and Retention of Knowledge and Network Innovative Performance: The Effect of Node Turnover, Network Integration and Field Stability[29]

Abstract

Although several scholars have addressed the issue of explaining the outcomes of interorganizational networks at the network level, the role of knowledge in the generation of these outcomes, especially in the case of publicly funded R&D networks is still understudied. The urgency of this topic derives from the observation that despite the many advantages of networks as flexible forms of organizing, studies have shown that overall system change can be detrimental for network outcomes. Building on the preliminary theory of network effectiveness as suggested by Provan and Milward (1995) and Provan and Sebastian (1998), we develop a model in which network innovative performance is explained by the level of node entry, stayers and node exit, and network integration. These act as proxies for mechanisms of knowledge variation, selection and retention. In addition, we consider the role of technology field stability. Using a sample of 93 R&D networks in the Dutch context, our analysis suggests an important role of said predictors in explaining network innovative performance. The effect of node entry (enabling knowledge variation) on innovative outcomes is found to be negative in the short run. This effect, however, switches to positive in the longer run. In addition, the effect of stayers (enabling positive knowledge selection) is positive on the short run. Lastly, our results suggest a crossover interaction between network integration (enabling knowledge retention) and field stability. We offer several levers for policy regarding the top-down management of publicly funded R&D networks.

5.1 Introduction

Whereas most research on interorganizational relationships has focused on the organizational antecedents and outcomes of network involvement (Brass et al., 2004; Kilduff & Brass, 2010; Zaheer et al., 2010), in the past two decades more and more attention has been given to the outcomes of networks as a whole (Provan et al., 2007; Provan & Milward, 1995; Turrini et al., 2009). This focus on explaining network-level outcomes is fruitful, especially for networks that address issues that cannot be solved by the actions of individual organizations alone. In this light, recent societal and academic calls for more attention to and research on so-called "grand challenges" (i.e. societal problems that only can be solved through the coordinated and sustained effort from multiple and diverse stakeholders (George et al., 2016)) makes research on the antecedents of whole network outcomes more timely than ever, as such challenges can only be solved through the well-orchestrated joint action of multiple organizations, rather than the actions of individual organizations (Dhanaraj & Parkhe, 2006; Provan & Milward, 1995).

Studies on interorganizational network outcomes have predominantly focused on public networks (Turrini et al., 2009). Driven by the conviction that clients will benefit from a reduced fragmentation and better coordination of services, service professionals, policy-makers and researchers alike have advocated the organization of public service delivery through a network form of organization (Turrini et al., 2009). The models proposed by Provan and Milward (1995) and Provan and Sebastian (1998) often have functioned as a benchmark in this area of research (Turrini

[29] Previous versions of this chapter were presented at the 30th EGOS Colloquium (Rotterdam, July 2014) and the DRUID Academy 2015 Conference (Rome, June 2015). The paper presented at the EGOS Colloquium was awarded the Andreas Al-Laham Best Paper Award by the Standing Working Group on Organizational Network Research.

et al., 2009). Both models explain network outcomes as a function of (1) network structural organization and (2) network contextual factors. For example, based on a study of four mental health care networks in the United States in the early 1990s, Provan and Milward (1995) develop propositions in which a positive relation between the level of centralized network integration and network outcomes is contingent on the level of system stability: said positive relationship will be less likely under conditions of instability compared to conditions of system stability.

Although the work on antecedents of network outcomes has generated a sizeable body of knowledge, we identify two aspects that are open for further research. First, compared to structural antecedents and network contextual characteristics as predictors of network outcomes, the role of knowledge in especially the generation of network *innovative* outcomes has been rather absent in the existing literature (Turrini et al., 2009). In the past, various scholars have stressed the importance of interaction and knowledge sharing for innovation (Freeman, 1991; Grant, 1996; Meeus et al., 2001; von Hippel, 1988). However, the subsequent wave of research that has been conducted on the topic has focused either at the role of networks for organizational innovativeness (Meeus et al., 2008; Perkmann et al., 2013; Pittaway et al., 2004), or on systems of innovation, in which the role of interorganizational relations is not explicitly considered (Edquist & Hommen, 1999; Lundvall, 1992).

Addressing the role of knowledge in the generation of network outcomes is especially relevant for publicly funded research and development (R&D) networks, as R&D is generally recognized by governments as a key driver for economic growth (Aldrich & Sasaki, 1995; Branstetter & Sakakibara, 2002; Meeus et al., 2008). Although the stimulation of collaboration between actors -and with that network formation- through public funding is considered a laudable goal (Defazio et al., 2009), the question regarding the role of knowledge and the organization of knowledge flows in such a way that these networks generate innovative outcomes is open for further investigation (Dhanaraj & Parkhe, 2006; Klerkx & Aarts, 2013; McDermott et al., 2009; Peterman et al., 2014; Provan & Lemaire, 2012; Sydow & Windeler, 1998; Turner et al., 1990).

The second aspect that is open for further research is the role of technology field stability. Networks are generally advocated as adaptable, flexible forms of organizing (Provan et al., 2007; Provan & Kenis, 2008). Slotte-Kock and Coviello (2010), for example, have suggested that purposeful changes and crises in networks might bring more benefits compared to stability. However, as indicated earlier, the study by Provan and Milward (1995) suggests that change in the environment of a network is detrimental for its functioning, and hence stability is an important aspect in the generation of network effectiveness (Provan et al., 2007; Provan & Milward, 1995). Therefore, stability might play a larger role in the generation of effective network outcomes than initially conceived (Schreyögg & Sydow, 2010), and a focus on field stability will guide us toward a better understanding of the requirements for building effective networks.

In this chapter, we build on the preliminary theory of network effectiveness that was suggested by Provan and Milward (1995) and Provan and Sebastian (1998) to develop a model that is applicable to public-private R&D networks. In addition, we focus on the role of knowledge in publicly funded R&D networks. More specifically, we are interested in the in- and outflow of knowledge from, as well as the retention of knowledge in these networks. We therefore use the variation, selection and retention mechanisms that initially were proposed by Campbell (1960). Derived from biological evolutionary theory, the use of mechanisms of variation, selection and retention has gained ground in many areas in the field of organization science (Baum & McKelvey, 1999). Our research question is twofold, and reads as follows: 1) to what extent is network innovative performance explained by node entry, stayers, node exit and network integration (which are indicative of mechanisms such as knowledge variation, selection and retention respectively), and 2) to what extent is the relation between said predictors and network innovative performance moderated by the level of technology field stability?

We analyse our research questions using 93 network observations from 7 distinct interorganizational technology networks in the Dutch context, each covering about 13 years. Nodes consist of R&D consortia, and the links between these nodes consist of joint membership ties. These networks differ from the networks studied by Provan and Milward (1995) and Provan and Sebastian (1998): whereas they focus on consciously created networks, in which interdependent members -even though autonomous- strive to achieve a common goal and jointly produce an output (Raab & Kenis, 2009), the networks focused at in this chapter have a more emergent nature, as they form as a consequence of joint member ties between consortia. Even though the networks differ, we believe drawing on the literature on network effectiveness mentioned above makes sense: first, a theoretical body has been developed in which the underlying mechanisms can be applied for the networks under investigation here as well. These mechanisms therefore can be tested. In addition, even though the collective outcomes of the R&D networks are slightly different, the generation of such outcomes is nonetheless important and recognizable for the networks considered in this chapter. Through performing the technique of beta regression and using different time lags between the independent variables and dependent variable in this analysis. This enables us to explore immediate and delayed effects (Monge, 1990) across the time window of five years, which is generally considered to be an appropriate time frame that can be explored when assessing the technological impact of R&D (Griliches, 1979; Hall et al., 1984; Pakes & Schankerman, 1984; Stuart, 2000; Vanhaverbeke et al., 2009). We show that these mechanisms can be fruitfully applied to explain complete network innovativeness, as they allow for incorporating the role of knowledge dynamics in the generation of network innovative outcomes.

In addition, the focus on node entry, stayers, node exit and network integration in this study offers a way towards solving the conundrum regarding flexibility and stability. We propose that, in addition to being able to retain knowledge, networks require a continuous rate of knowledge inflow through node entry and, up to a certain level, selection from this knowledge inflow through stayers and node exit. This helps in keeping networks adaptable and flexible, which is vital for network innovative performance. However, our theoretical model proposes that this is only the case when networks operate against the backdrop of a stable technology field, as field instability leads to the need for a reconfiguration of the network's ability to retain knowledge, which takes time and temporarily leads to lower levels of network innovative performance.

Our aim with this chapter is to provide levers for top-down network managers for optimizing the innovative performance of publicly funded R&D networks. The key insights that we deliver with this chapter is that mechanisms of knowledge variation, selection and retention do matter in explaining network innovative performance. We find that the effect of node entry on network innovative performance switches from negative in the short run, to positive in the very long run. In addition, our results tentatively suggest that node exit and stayers have a positive effect on network innovative performance in the short run. Lastly, we find that, compared to retention sparked by high levels of density-based network integration, low levels of network integration lead to higher levels of network innovative performance in the short run in unstable fields. As field stability increases, however, higher levels of density-based integration lead to higher levels of network innovative performance in the short run, compared to low levels of structural integration.

These insights are important, because they provide scholars and policy makers with a more refined insight in levers that could be used for optimally setting up networks for innovation. We therefore contribute to research on public-private innovation networks. Through stressing the importance of knowledge variation, selection and retention, we demonstrate that there is a need to sustain a certain level of node entry, stayers and node exit, while anticipating negative consequences of possible instabilities in a network's technological context. In addition, we contribute to the literature on networks and innovation more generally, as the importance of knowledge variation, selection and retention and system stability is likely to extend beyond publicly funded R&D networks as they might also hold for networks that emerge without governmental involvement. For example, Schilling and Phelps (2007) have suggested that alliance network structure affects the performance of firms embedded in such networks. Although it is well-known that the structural organization of such networks is sensitive to environmental instabilities (Madhavan, Koka, & Prescott, 1998), our results suggest that in addition to the role of network structure and field stability, knowledge variation and selection through node entry, stayers and exit play a key role in affecting the performance of such networks.

Regarding the relevance of our results for policy makers, public policies related to the funding of R&D through collaboration are currently rather unrelated to the network structure they generate, as discussed in the previous chapter (Meeus et al., 2008). Our results suggest that such networks are an object that are worth organizing themselves, and we offer several levers for policy regarding the top-down management of such networks by public funding agencies. In addition, the formation of the public-private R&D networks that are studied in this chapter results from a sampling exercise performed by a funding agency. By focusing on network innovative performance, we offer a criterion to benchmark the extent to which this sampling exercise - performed on the one hand by reviewers (which accepted some consortia and rejected many others), and on the other hand consortium leaders (who selected members) and the funding agency's programme management- has been fruitful. After all, if no innovative outcomes are generated, one could claim that this sampling exercise has not accumulated in a competent group of actors that can deliver innovative results.

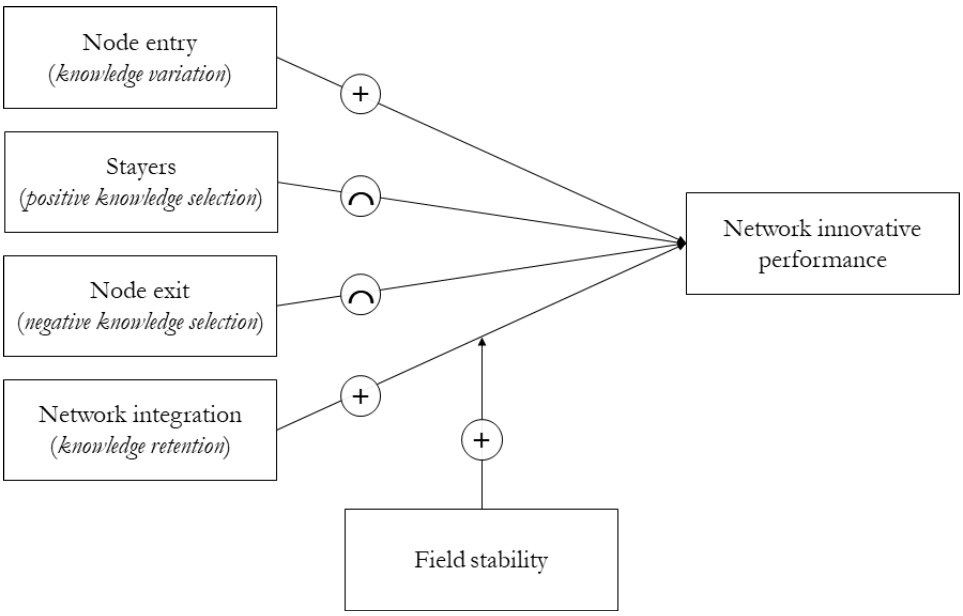
5.2 Theoretical framework

An important assumption underlying our research question is that it is sensible to consider interorganizational networks as systems that are worth studying in themselves, especially in the context of scientific and technological development. Taking knowledge and knowledge development as key ingredients for progress in these areas, Mohrman et al. (2006) argue that a sole focus on organizations might lead one to overlook where the knowledge that is needed for R&D actually is produced and leveraged. Indeed, in their seminal work on interorganizational collaboration in the biotechnology sector, Powell et al. (1996) argue that in industries with a complex, expanding and dispersed knowledge base, innovation takes place between rather than within organizations. Hence, it is only through focusing on the full network that one captures the system that is responsible for the generation of innovative outcomes.

Scholars have provided several arguments for this point. First, technological development is a collective endeavour (Lindenberg & Foss, 2011; Mohrman et al., 2006). Knowledge is constructed by individuals in a social context, and influences these individuals at the same time (Mohrman et al., 2006). For example, with respect to the phenomenon of network dynamics - focused at in the previous chapter- Orsenigo et al. (2001) have pointed out that scholars coming from different disciplines focus at this phenomenon, but from different perspectives. In general, this creates different academic groups that revolve around the same phenomenon even though members of these groups approach that phenomenon differently. Second, knowledge creation and leverage are enabled by knowledge sharing and knowledge recombination (Mohrman et al., 2006). This implies interaction between individuals that each have a unique set of experiences and knowledge (Anderson & Tushman, 1990; Koschmann et al., 2012). The publication of Wicaksono, Zhang, Pandraud, French, and Vincent (2006) is an illustrative example of such recombination: scientists from the discipline of microelectronics and mechanical engineering join forces, drawing on insect physiology in order to develop a strain sensor that can gauge the health of mechanical structures at both the micro- and macro-scale. Third, technological development is often carried out in service of and in close relation to application, as in the end technological development is geared towards meeting societal needs (Mohrman et al., 2006). The growing body of literature on the role of users in the innovation process (Bogers, Afuah, & Bastian, 2010) clearly reflects the importance of establishing a close relation between technological development and application. Lastly, technological development takes place at an increasingly large scale (Mohrman et al., 2006). The European Organization for Nuclear Research (also known as CERN) is an illustrative example of this, not only in terms of size (its Large Hadron Collider has a circumference of 27 kilometres), but also in terms of members (CERN had 22 members (states) in 2017). The complexity that comes with such scale underscores the necessity of linkages that allow knowledge to be shared (Cowan & Jonard, 2009; Gittell & Weiss, 2004). Hence, linkages between actors make knowledge available for multiple purposes and combine to yield novel frameworks and solutions as well as new meanings. Actors group around common bodies of knowledge and technology, and often multiple technologies are being developed within the resulting networks (Mohrman et al., 2006).

FIGURE 11

Conceptual model depicting the effect of node entry, stayers and node exit, and network integration on network innovative performance, including the moderating role of technology field stability



The question then becomes how to create and maintain network innovativeness. Figure 11 presents the conceptual model that guides our theorizing in this respect. Using node entry, stayers and node exit, and network integration as proxies for the variation, selection and selection of knowledge at the network level. Next, we develop hypotheses that predict the level of network innovative performance using the mechanisms of knowledge variation, selection and retention. In addition, we consider the moderating role of the stability of the technology field in which a network is embedded.

Network innovative performance. Different approaches for specifying network-level outcomes exist, for example outcomes as perceived by multiple stakeholders in the network, outcomes for the community, outcomes in terms of network sustainability (Provan & Milward, 1995, 2001; Turrini et al., 2009) or outcomes in terms of positive externalities for network members (Lavie, 2006b; Lincoln, Gerlach, & Ahmadjian, 1996; Schilling & Phelps, 2007). With network innovative performance, we refer to the capacity of a network to generate new products or processes that add value and are successfully adopted by the market (Crossan & Apaydin, 2010; Goes & Park, 1997; Turrini et al., 2009). Hence, we conceptualize and measure network-level innovation as the aggregate of nodal-level innovative outcomes.

As generally few scholars have focused on explaining network-level outcomes (Provan et al., 2007), few theoretical models are available for explaining network-level innovativeness. For our model, we therefore took one of the few models available as a starting point. Originally proposed by Provan and Milward (1995) and Provan and Sebastian (1998), this model explains the effectiveness of public health service networks by focusing on network structure and the systemic context of a network. This model has subsequently been explored and further expanded by various scholars in the field of public administration and public innovation (Turrini et al., 2009). Expansion of this model included adding more structural attributes as explanatory variables, as well as adding a new set of network functioning characteristics, which are all behavioural aspects that are at play in a network. It is especially the combination of these functioning characteristics with the systemic context of a network that hitherto have shown to be useful predictors for network-level innovation (Turrini et al., 2009). Taking these insights as our main source of inspiration, and acknowledging that knowledge and mechanisms of variation, selection and retention play an important role in the context of technological innovation and collaboration (Kogut & Zander, 1992; Mohrman et al., 2006; Turrini et al., 2009), we propose a model in which network innovativeness is reached through knowledge variation through node entry, knowledge selection through nodes that stay in a network and node exit, and knowledge retention through network integration.

Scholars that use explanations involving variation, selection and retention depict the three mechanisms as a process (e.g. Murmann (2013); Volberda, Van Den Bosch, and Mihalache (2014); Wooldridge, Schmid, and Floyd (2008)). When focusing at specific technological trajectories, this is a fruitful approach, as it allows for showing how technologies go through cycles of discontinuity and ferment (variation), the emergence of a dominant design (selection) and subsequently incremental change (retention) (Anderson & Tushman, 1990; Bakker et al., 2012). In our model, however, we consider knowledge variation, selection and retention as independent mechanisms that serve a purpose at the systemic level: the R&D networks studied in this chapter contain many consortia that work on a multitude of technologies, each in their own stage of development. Hence, for each cycle to move forward, knowledge variation, selection and retention generally are key mechanisms that need to be present. In addition to these mechanisms, we focus at the role of system stability (Argyres, Bigelow, & Nickerson, 2015; Provan & Milward, 1995) in order to spell out under which conditions of stability nodes in the network are most able to seize the opportunities provided by knowledge that is retained in the network.

Node entry. In the previous chapter, we explained that node entry especially occurs when incumbent nodes get more inert, and when technological breakthroughs occur (Agarwal et al., 2002; Dercole et al., 2008). In both events, new entrants are considered as pursuers of new opportunities, and with that node entry increases the likelihood of new knowledge being introduced in a network (Lewin, Massini, & Peeters, 2011; Meeus et al., 2008; Mohrman et al., 2006; Murmann, 2013; Romanelli, 1999; van de Ven, 1992; Wooldridge et al., 2008), for example through new approaches, techniques or practices (Mohrman et al., 2006), experimentation (Volberda et al., 2014), trials (Romanelli, 1999) or recombination and adaptation of existing knowledge (Davis, Eisenhardt, & Bingham, 2007; Rao & Singh, 1999).

We propose a positive relationship between the level of node entry and network innovative performance. As indicated, when the node set of a network does not change over time, nodes can become subject to what Grabher (1993) calls the trap of 'rigid specialization': despite a clear focus of each single node, overall technological development might not gravitate to an optimum. This is because existing knowledge of incumbent nodes is not confronted with the new insights and practices needed to adapt to their dynamic environment (March, 1991). Hence, the network as a system will become less innovative. The negative consequences of this lock-in effect for the innovative performance of a network will be avoided by knowledge variation caused by node entry. The result of this variation is that the different members in a network continuously will differ to a certain extent with respect to the knowledge held (O'Reilly, Harreld, & Tushman, 2009). This results in a viable, adaptable network (Grabher, 1993; Grabher & Stark, 1997; Pentland, Feldman, Becker, & Liu, 2012), which is considered to be key for network effectiveness (Romanelli, 1999).

Hence, node entry enables the exploration of new technological options within a network. It therefore indicates that the state of knowledge in this network advances (Mohrman et al., 2006), which is needed for network innovativeness. We therefore hypothesize the following:

Hypothesis 1: As the level of node entry in a network increases, the network's innovative performance increases as well.

Node exit. In the context of innovation, different knowledge elements flowing into the network are linked to different, sometimes alternative technological trajectories (Dosi, 1982; Malerba & Orsenigo, 1997). Given scarce resources (Baum & McKelvey, 1999), knowledge variation thus introduces rivalry between these alternatives (Anderson & Tushman, 1990; McGrath, Macmillan, & Tushman, 1992; Murmann, 2013; van de Ven, 1992), with the result that some alternatives will be selected, and some alternatives will not be selected. In this study, we capture both forms of selection with positive and negative selection respectively.

Hence, negative selection refers to the selection of alternatives that is reflected through nodes that leave a network (Baum & McKelvey, 1999; Mohrman et al., 2006). Node exit sparks a process of knowledge selection through the disappearance of knowledge from the network that does not fit with prevailing technological trajectories that are developed in the network (Baum & McKelvey, 1999; Bridoux, Coeurderoy, & Durand, 2016; Davis et al., 2007; McKendrick, 2001; Mohrman et al., 2006; Murmann, 2013; Volberda et al., 2014). We propose a curvilinear relationship between the level of node exit and the level of network innovative performance. Just like the mechanism of knowledge variation, knowledge selection through node exit is critical for the change that is needed for a network to adapt (Pentland et al., 2012). Low levels of nodes that exit a network indicate that no convergence towards prevailing technological trajectories takes place. Instead, both useful and non-useful knowledge variations will be randomly retained or discarded, without the network moving into a more innovative direction (Romanelli, 1999). As the level of nodes that exit a network increases, knowledge that does not fit with prevailing technological trajectories disappears from the network or is no longer used, focussing the efforts of the remaining network members, as well as the use of scarce resources (Murmann, 2013; Volberda & Lewin, 2003). In addition, consortia that leave a network mark non-viable paths for the consortia that remain and future entrants. This keeps these consortia from pursuing those paths again (Rao & Singh, 1999).

These aspects (i.e. focus of efforts and resources and marking non-viable paths) positively affect network innovative performance. This effect, however, takes place up to a certain point. Even though in general, selection is treated as purely informational in the literature (i.e. accurate information is obtained on which a decision is based (Reitzig & Sorenson, 2013)), the outcome of the knowledge selection process is uncertain (Murmann, 2013), as one of the key issues at "the heart of the R&D-innovation problem is that reasonable people will disagree about what technologies will be best when" (Nelson & Winter, 1982, pp. 186; Grodal, Gotsopoulos, & Suarez, 2014). Yet, knowledge selection will not be completely blind, but guided by the preferences and prior knowledge of those actors that remain in the network as a result of the selection process (Volberda & Lewin, 2003), as well as earlier successes (Miller, 1999). These actors can be member of the network (e.g. industrial organizations involved in science-industry networks (Mohrman et al., 2006)), or operate outside of the network (e.g. consumers, regulators, or social movements (Anderson & Tushman, 1990; Nelson & Winter, 1982). The point is that targeted knowledge selection decisions made by those involved can become myopic (Levinthal & Posen, 2007; Reitzig & Sorenson, 2013). Hence, knowledge selection is not necessarily an optimizing force (Barnett & Burgelman, 2007). This can be especially detrimental in the event knowledge selection takes place through adoption and imitation of a select number of incumbent nodes at the expense of many nodes that leave the network. Given that selection does not necessarily imply viability (Aldrich & Kenworthy, 1999; Grabher, 1993; Miller, 1999; Nelson & Winter, 1982; Romanelli, 1999), even when knowledge variation is high, excessive levels of knowledge selection through node exit might therefore lead nodes to become subject to the earlier explained trap of 'rigid specialization' (Grabher, 1993), decreasing the network's adaptability. This has detrimental effects on network innovativeness. For this reason, we hypothesize the following:

Hypothesis 2: Networks with moderate levels of node exit will be more innovative compared to networks with very low or very high levels of stayers and node exit.

Stayers. In addition to negative selection between alternatives that results from the inflow of different knowledge elements into a network, we propose that positive selection between technological alternatives occurs through nodes that stay in a network (Baum & McKelvey, 1999; Mohrman et al., 2006). Such consortia are indicative of the extent to which knowledge is selected by consortia that fits with prevailing technological trajectories through adoption of or imitation (Bridoux et al., 2016; Calori, Baden-Fuller, & Hunt, 2000; Lewin et al., 2011; McKendrick, 2001; Miner & Raghavan, 1999; Mohrman et al., 2006; Romanelli, 1999; Volberda et al., 2014). We propose a curvilinear relationship between the level of stayers in a network and the level of network innovative performance. Just like the mechanism of knowledge variation, knowledge selection is critical for the change that is needed for a network to adapt (Pentland et al., 2012). Low levels of nodes that stay a network indicate that no convergence towards prevailing technological trajectories takes place. Consequently, both useful and non-useful knowledge variations will be randomly retained or discarded, without the network moving into a more innovative direction (Romanelli, 1999). As the level of nodes that stay in a network increases, knowledge that fits with prevailing technological trajectories stays in the network, which focuses the efforts of the remaining network members, as well as the use of scarce resources (Murmann, 2013; Volberda & Lewin, 2003). This positively affects network innovative performance.

Similar to knowledge selection through node exit, this effect takes place up to a certain point. Our arguments for the mechanism that drives this effect runs in parallel with the arguments used for knowledge selection through node exit: the outcome of the knowledge selection process through nodes that stay in the network is uncertain, even though the literature treats selection as a purely informational phenomenon (Reitzig & Sorenson, 2013). This uncertainty is driven by the inherent uncertainty of the outcomes of R&D, as it involves different views between actors about which solution is most appropriate, and when (Nelson & Winter, 1982, pp. 186; Grodal, Gotsopoulos, & Suarez, 2014). Consequently, knowledge selection through nodes that stay in a network is steered by the preferences, prior knowledge and successes of those nodes that remain in the network (Miller, 1999; Volberda & Lewin, 2003). As such actors drive future knowledge selection decisions, myopia (i.e. through collaborating with certain consortia whilst not collaboration with other consortia) could become a decisive element (Levinthal & Posen, 2007; Reitzig & Sorenson, 2013), which means that knowledge selection is not necessarily an optimizing force (Barnett & Burgelman, 2007). When knowledge selection takes place through adoption and imitation of a select number of incumbent nodes at the expense of many nodes that leave the network, this can be especially detrimental. Hence, selection does not necessarily imply viability (Aldrich & Kenworthy, 1999; Grabher, 1993; Miller, 1999; Nelson & Winter, 1982; Romanelli, 1999), even when knowledge variation is high. As a result, excessive levels of knowledge selection might therefore lead nodes to become subject to the earlier explained trap of 'rigid specialization' (Grabher, 1993), which decreases the network's adaptability. For this reason, we hypothesize the following:

Hypothesis 3: Networks with moderate levels of stayers will be more innovative compared to networks with very low or very high levels of stayers.

Network integration. As explained in chapter 2, network integration refers to the organization of knowledge flows in a network. We propose that network integration aids the retention and integration of selected knowledge (Abrahamson & Fairchild, 1999; Baum & McKelvey, 1999; Calori et al., 2000; McGrath et al., 1992; McKendrick, 2001; Murmann, 2013; van de Ven, 1992; Volberda & Lewin, 2003; Volberda et al., 2014; Wooldridge et al., 2008). Network integration supports the transmission of selected knowledge, as well as the transmission of this knowledge over time from one generation of nodes to another (Davis et al., 2007; O'Reilly et al., 2009).

Similar to knowledge selection, a mechanism of knowledge retention is critical for the innovative performance of a network, as without a system for retaining selected useful variations, there is no way for the network to improve (Rao & Singh, 1999; Romanelli, 1999). Contrary to both knowledge variation and selection, however, knowledge retention counteracts the self-reinforcing loop between variations and selection (van de Ven, 1992; van de Ven & Poole, 1995): without knowledge retention, the process of knowledge variation and knowledge selection will go on endlessly, without any knowledge becoming ingrained in the network for a longer period.

As explained in chapter 2, we propose that network integration aids the retention of knowledge in a network in two related ways. The first way is through a cooperative process that cements nodes in the network and involves mutual awareness among network members of what others are doing. This, in turn, facilitates the retention of knowledge through mutual understanding and insight in knowledge interdependencies (Erikson & Bearman, 2006; Fagerberg et al., 2012;

Fagerberg & Verspagen, 2009; Hollenstein, 2003; Koza & Lewin, 1999; Oh & Jeon, 2007). The second way of achieving network integration involves the presence of a small amount of key players in the network that introduce common thematic foci (Fagerberg et al., 2012) and undertake continuous efforts to integrate the knowledge available in the network, leading to knowledge retention (Ata & Van Mieghem, 2009; Burt, 2007; Fagerberg et al., 2012; Fagerberg & Verspagen, 2009). This enhances the collective perception of network members of viable technological alternatives and possible future developments, and focuses their commitment to a limited amount of viable core technologies (Afuah, 2013; Gay & Dousset, 2005; Soh, 2010) developed by central players (Gay & Dousset, 2005; Powell et al., 2005). Hence, knowledge retention is enabled by network integration, allowing network members to build forth on this knowledge by further developing selected variations (Davis et al., 2007). We therefore propose that:

Hypothesis 4: As the level of network integration increases, the network's innovative performance increases as well.

Field stability. This concept refers to the absence of marked change in the technology field in which a network operates (Provan & Milward, 1995; Turrini et al., 2009). Such change can be manifest in what is called an 'environmental jolt' or 'exogeneous shock'. Examples of such jolts are scientific or technological breakthroughs (Cattani, Ferriani, & Lanza, 2017; Madhavan et al., 1998; Tushman & Nadler, 1986). It is important to recognize the conceptual difference between field stability and the concepts of node entry, stayers, and node exit. In this light, it is useful to make a distinction between network stability and field stability (Turrini et al., 2009). Node entry, stayers and node exit refer to knowledge dynamics within a network, in terms of knowledge variation, selection and retention. These dynamics lead to the network being stable but in a specific way (Farjoun, 2010; Kilduff, Tsai, & Hanke, 2006): even though network structure is preserved over time, node turnover occurs at a stable rate (Dhanaraj & Parkhe, 2006; Sasovova, Mehra, Borgatti, & Schippers, 2010). Complete convergence is never possible in such a network (McKendrick, 2001). Yet, when given enough time, network members can build up effective search routines that allow them to manage and exploit the status quo (Kim et al., 2006; Lavie, 2006a; Lewin et al., 2011; McKendrick, 2001; Nelson & Winter, 1982; Patel, Kohtamäki, Parida, & Wincent, 2015; Zollo, Reuer, & Singh, 2002), which can be maintained in networks that reside in stable systems. However, exogeneous shocks represent significant turning points in the evolution of a technology field (Cattani et al., 2017; Tushman & Nadler, 1986). Instead of knowledge in the network being subject to variation and selection, the network itself is now subjected to selection pressures (MacKay & Chia, 2012). This disruption leads to a shift in the rate of node entry, stayers and node exit, as well as the content of knowledge. In addition, search routines need to be adapted (Feldman, 2000). A scientific breakthrough, for example, might both attract a larger number of new nodes to the network in pursuit of new paths that are opened in the knowledge space, whereas others are pushed out of the network due to obsolescence of old paths (Geels, 2010; Lazzarini, 2015).

We propose a positive moderation effect of field stability in the relation between network integration and innovative performance. Network integration reflects the extent to which knowledge can be retained in a network. Especially the mechanism of knowledge retention has been suggested to need time to come into effect (Murmann, 2013). The consequence of an exogeneous shock is that new windows of opportunity are created (Geels et al., 2016; Guennif & Ramani, 2012; Shane & Venkataraman, 2003) and new dominant players might emerge in the network (Cantwell & Vertova, 2004; Meyer-Krahmer, 1992). In addition, networks might need high levels of flexibility to adapt to the new status quo, temporarily reducing the salience of network integration and its related mechanism of knowledge retention (Cattani et al., 2017; Wiegmann, de Vries, & Blind, 2017; Yin & Shanley, 2008). As such, the underlying network structure needs time to adapt and support network innovation again (Hermelo & Vassolo, 2010). In line with other scholars (Dhanaraj & Parkhe, 2006; Levén, Holmström, & Mathiassen, 2014; Provan & Milward, 1995; Turrini et al., 2009), we therefore hypothesize that:

Hypothesis 5: The positive relationship between knowledge integration and network effectiveness is positively moderated by the level of field stability

5.3 Data and methods

Research setting and data

We test our hypotheses using data that was collected as part of a larger research endeavour (for example, see the other chapters in this dissertation and (Mannak, 2015; Mannak et al., 2012). This dataset contains information on 1,928 Dutch R&D consortia, and was built using 23 evaluation reports issued by a technology foundation from 1985 until 2010[30]. These reports contain evaluations of consortia that existed somewhere in the time frame 1981-2004. The foundation aims at realizing knowledge transfer between industry and the technical sciences. In light of that aim, it funds R&D consortia designed by academic reseachers that have formed a committee of interested industrial organizations that see potential application possibilities of the consortium's results. Members of the committee meet at least twice a year during the consortium, and discuss the progress of the research and possible application areas of the results so far. Members can also contribute in kind to the consortium, for example by providing machines, materials and know-how. In additon, they might function as a testing-ground for the technology that is being developed.

The approach of this funding organization is a clear reflection of the von Hippel-agenda, in which a prominent role in the process of R&D and innovation is reserved for users (von Hippel, 1988). The benefit of doing so is twofold: for researchers, involving users is a test of the viability of their research programme, and for industrial participants it is a relatively accesible way to keep up to date with the most recent scientific developments. The funding programme is one of the few programmes in the Netherlands that organizes research in this way (Velzing, 2013), and leads to network formation: as explained in chapter 3, joint membership by consortium participants in multiple consortia simultaneously leads to the forging of joint member ties between consortia and with that, the emergence of consortium networks (see chapter 4 for the boundary specification approach regarding these networks. Out of the 156 networks studied in that chapter, 93 networks had outcome data available and hence were suitable for analysis in this chapter).

It is the innovative performance of those networks that is of primary interest in this chapter, as these networks are exemplary reflections of networks that should be considered at the system level: the funding system was established because of the recognition that research and development is one of the key drivers for economic growth (Aldrich & Sasaki, 1995; Branstetter & Sakakibara, 2002; Meeus et al., 2008). Hence, the networks that emerge as a result from this system reflect the organization of knowledge flows between industry and academia in the Netherlands. Seeing that public administration and innovation research suggests that the outcomes of such networks are influenced by their structure and functioning (Mohrman et al., 2006; Provan & Milward, 1995; Turrini et al., 2009), studying such networks is suitable and relevant for specifying more targeted

[30] As indicated in the general introduction of this dissertation, several topics regarding the construction of this dataset are elaborated on in the different appendices to the different empirical chapters in this dissertation. The topics covered are (1) data sources and database construction (Chapter 2), (2) node specification (Chapter 3), (3) tie and network specification (Chapter 4) and (4) network boundary specification (Chapter 5).

innovation policy. In addition, the networks studied in this chapter are deliberately created selection environments for new technologies. Involvement of industry acts as a selection mechanism that delineates feasible technologies from less feasible ones. Hence, knowledge variation, selection and retention need to take place in these networks. Lastly, due to the ex-ante measurement of outcomes by the funding agency, a time lag exists between measurement of the network structure and measurement of its outcomes, which meets the requirement of temporal separation between the independent variables and the dependent variable for making causal claims (Antonakis et al., 2010).

Measurements

Network innovative performance. Different measures of network outcomes have been proposed, but most of these measures focus on the effectiveness of information transmission through the network (Ahuja, 2000a; Kajikawa et al., 2010; Pitt, Merwe, Berthon, Salehi-Sangari, & Barnes, 2006). In our definition, we focus on the capacity of a network to generate new products or processes. Ideally, one would have a measure that captures the synergetic effect of networks. Such measures do exist, for example in the team literature where team synergy is expressed as team performance that exceeds the solo performance of even the best team member (Larson, 2007). Measuring network-level outcomes, however, is problematic (Provan & Milward, 1995) and a synergistic measure of network-level innovative performance is difficult to develop as it would imply separate performance measures for each node involved as well as for the network as a whole.

Our measurement approach in this chapter is as follows. As from the year 1989, the funding organization has developed a uniform evaluation method for each consortium it has funded. This evaluation is performed five years after the start of a consortium and carried out by an external committee of specialists. Focusing on the technological outcomes of the consortium, four distinct scores can be assigned: 0 (failure), A (further research is necessary), B (a prototype has been developed) and C (substantial results were generated). Similar to our approach in chapter 2, we consider the last score to reflect a consortium that has generated a succesful innovation. For each year, we determined the innovative performance of a network by dividing the count of consortia that received a 'C'-evaluation and that finished in that year by the total number of evaluated consortia in that year. The result is a ratio between 0 and 1, with a 0 indicating that the network did not generate any innovations at all in a certain year, and a 1 indicating that the network generated nothing else than innovations in that year.

Node entry. This proxy reflects the introduction of new knowledge to the network. We operationalized it by measuring the number of new entrants in a network in each year. Taking *t* as the reference year, node entry is determined as the number of new consortia that entered the network at *t*. A consortium was considered "new" when its leader was not involved in any other consortium three years preceding *t*. Hence, node entry is expressed as a count variable, ranging from 0 (the level of node entry is nil) to the maximum network size (representing the maximum level of node entry). This maximum score, however, is not likely to be observed.

Node exit. This proxy reflects the mechanism of negative knowledge selection. Node exit was determined by counting the number of consortia that left the consortium network just before the network was observed at *t*. Following the same reasoning as with node entry, a consortium was considered to exit the network when its leader did not appear again in the three years following *t*. We focus on consortium leaders as in this specific funding system, these leaders are the knowledge anchors. It is the consortium leader that has in-depth academic knowledge regarding the topic at hand, as well as knowledge regarding potential industrial collaboration partners. This knowledge flows out of the network the moment such a consortium leader leaves.

Stayers. This proxy reflects the mechanism of positive knowledge selection. The proxy was measured by determining the number of stayers in a network at *t*. This number was calculated by subtracting the sum of node entry and node exit from total network size at *t*. Like the measurement of node entry, the measurement of this proxy resulted in a count variable.

Network integration. This proxy reflects the mechanism of knowledge retention in a network. It captures both the integration and further development of selected knowledge. As we explained the underlying mechanisms using a structural lens, we use a similar operationalization as the one used for network integration in chapter 2. Hence, we use the two complementary measures of network density and degree centralization (Provan & Milward, 1995). Network density represents the "connectedness" of consortia through joint members (indicating mutual awareness) and degree centralization expresses the extent to which these joint member ties are organized around one or more central consortia (indicating common thematic foci). Both measures were calculated for each consortium network. Network density was calculated by dividing the actual number of ties present in a network by the total number of theoretically possible ties in that network (Scott, 2000). Ties in the consortium networks studied in this chapter were undirected. Network centralization was measured using the degree centralization measure (Freeman, 1978), which is based on the degree centrality scores of individual consortia in the network. These scores were all normalized before calculating degree centralization, to account for differences in network size. When a network consisted of multiple components, we first calculated degree centralization for each component individually. Then, a weighted average based on component size was calculated. For all calculations, we used the functionality available in the statnet suite (Goodreau et al., 2008) available in the R statistical environment (R Development Core team, 2016).

Contrary to the operationalization used in chapter 2, a simplified measure of network integration is used because in this study we have a relatively small sample. Instead of classifying the density and centralization scores using three groups (i.e. lower than the mean minus one standard deviation, in between the mean ± one standard deviation and larger than the mean plus one standard deviation), we construct measures based on a mean-split: all scores on the network variable smaller than the mean of that score in the technology field are considered to be low, whereas all scores larger than or equal to the mean of that variable in the technology field are considered to be high. As a result, four classes are constructed: low retention (both density and centralization scores are smaller than the mean), retention through density-based integration (density is equal to or larger than its mean and centralization is smaller than the mean), retention through centralization-based integration (comparable approach as for density-based integration) and high retention (opposite approach as the one followed for low integration). These four classes were captured using two dummies, with the class of low integration being the reference category.

Field stability. In the previous chapter, we determined distinct network dynamic states using a latent profile analysis. Five distinct states were identified (i.e. formation, growth, stagnation, stability and disintegration), and the sequence of states was linked to the development of the underlying technology field. The concept of field stability, which refers to the absence of marked technological change in the technology field in which a network is embedded, was operationalized using these network states. Using the sequence of dynamic states, system stability is operationalized by determining for each network the number of years that have passed since the last state change. This resulted in a count variable, with a possible range from 0 (the network has undergone a state change in the transition from the previous year to the current year) to the maximum number of years we observed a given network. Given the fact that each network was characterized by some state changes in each year, this maximum score is not reached for any of the networks we observed.

Control variables. In addition to the independent variables derived from our conceptual model, we include three control variables. First, although the first consortia started in 1981, a uniform evaluation method was implemented as from 1989. This means that for several networks, not all consortia in these networks received an evaluation. We calculated the innovative performance of these networks nevertheless, assuming that the outcomes of those consortia that did receive an evaluation are representative for all consortia in the network. By doing so, however, observations of the dependent variable are split in two groups: one group in which network innovative performance is calculated using complete information, and one group in which network innovative performance is calculated using incomplete information. To control for possible differences between both groups, we include a variable labeled "% Complete outcomes". This variable is a ratio between consortia that received an evaluation and all consortia that should have received an evaluation in a network, and can obtain values in the range (0,1]. Second, we controlled for technology fields. It is known in the literature that collaboration propensity varies between sectors, for example because of differences in reliance on scientific knowledge among technologies (Hagedoorn, 2002; Peri, 2005; Tamada et al., 2006). In addition, marked differences between technology fields exist, for example in terms of primary motivations (Martin, 2003), institutional contexts (Dimaggio & Powell, 1983), or innovation speed. Given a limited number of observations in our data, including all 7 technology fields as dummies in our analysis would cost too much in terms of statistical power. We therefore reduced the number of distinct technology fields by constructing a dummy Engineering technology fields that indicates if a network belongs to a technology field that is mainly science-dominated (i.e. Chemistry and Life sciences, score = 0), or to a technology field that is mainly engineering-dominated (i.e. Civil engineering, Electrical engineering, Instruments, Mechanical engineering and Medical technology, score = 1). Lastly, we included a year variable in our dataset. This accounts for possible path-dependencies in the effect of time (Gulati & Gargiulo, 1999).

Data analysis

Two considerations drove our choice for an appropriate analytical model and strategy. First, the dependent variable in this study is proportional. A traditional OLS approach is not appropriate for such data: by nature, proportional data is bound at 0 and 1, and running an OLS may yield fitted values of the dependent variable that exceed these lower and upper bounds (Ferrari & Cribari-Neto, 2004). One could transform the dependent variable such that the transformation assumes values on a real line that goes beyond 0 and 1, yet this leads to interpretation issues (Cribari-Neto & Zeileis, 2010). In addition, distributions of proportional data are often asymmetrical and regression models based on such data suffer from heteroskedasticity, especially when small sample sizes are considered[31] (Cribari-Neto & Zeileis, 2010). Hence, we resorted to the technique of beta regression. Beta regression models assume that the dependent variable is beta-distributed. This is a continuous probability distribution that is defined on the interval between 0 and 1. The distribution can assume a number of different shapes, depending on the parameterization of both the mean and a precision parameter (Cribari-Neto & Zeileis, 2010). As a result, beta regression

[31] Indeed, when we fit our data using an OLS and check if the resulting model meets the requirements (using the approach as outlined by Pena and Slate (2006)), data skewness and the model exhibiting heteroskedasticity are indicated as issues.

models are heteroskedastic by nature, and conveniently accommodate asymmetries in the data (Cribari-Neto & Zeileis, 2010). As the beta distribution does not include the scores 0 and 1 and our dependent variable contains these scores, we apply a transformation on the dependent variable that has been suggested by Smithson and Verkuilen (2006): taking y as the dependent variable and n as the sample size, this transformation is $(y \times (n - 1) + 0.5) / n$.

The second consideration regarded the choice of the lag structure between the independent variables and the dependent variable. Depending on the type of relationship studied, the time frame for innovative payoffs may vary dramatically (Saxton, 1997). As discussed in chapter 3, the literature suggests that exploring a time window of five years for assessing the technological impact of R&D is appropriate, as knowledge has been demonstrated to lose most of its economic value within five years (Griliches, 1979; Hall et al., 1984; Pakes & Schankerman, 1984; Stuart, 2000; Vanhaverbeke et al., 2009). In addition, exploring a time window of five years allows for exploring immediate and delayed effects (Monge, 1990). Hence, we implement this explorative approach in our analysis by including three distinct lag structures. The first lag structure explores a time lag of 1 year between the predictor variables and outcome variable. In other words: we assess the extent to which consortia that will finish at t are affected by the level of knowledge variation, selection and retention in the network at t-1. This lag structure therefore considers the short-term effect of our independent variables on the level of innovative outcomes of a network. The second lag structure links predictor variables measured at t-3 to network innovative performance measured at t. As such, it models the effect of our independent variables on network innovative performance in the long run. In the third lag structure, predictor variables measured at t-5 are related to network innovative performance measured at t. This structure models the effect of the independent variables on network innovative performance in the very long run.

For all models, 93 observations are available. Three models are estimated per time lag. In the first model, only the dummy variables are included. This model is the same for all time lags, as this model does not contain lagged independent variables. The second model adds the direct effects, whereas we add interaction effects in the third model. As our sample size is relatively small compared to the number of predictors, results will be relatively non-generalizable. Given the difficulty in collecting longitudinal network data as well as data regarding network performance, we nevertheless run these models to get some first insights. All variables except for the dummies are scaled in our analyses. The 'betareg'-package (Cribari-Neto & Zeileis, 2010) is used for estimating the models, which is available in R (R Development Core team, 2016). Similar to the other chapters in this dissertation, all visualizations are made with the 'ggplot2' package (Wickham, 2009) also available in R, unless indicated otherwise.

5.4 Results

Descriptives and correlations

Means, standard deviations, the minimum and maximum observation per variable as well as correlations are displayed in Table 20, Table 21, and Table 22. Given our analytical strategy, proxies for knowledge variation, selection and retention mechanisms, as well as technology field stability were related to network innovative performance at three distinct points in time: one year before consortia in the network finished and were evaluated, three years before these consortia finished and five years before these consortia finished. The data used for each time lag can be found in Table 20, Table 21 and Table 22 respectively. As reflected in the similar descriptives with respect

TABLE 20

Descriptives and correlations – 1 year before evaluation[32]

Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9	10
1. Network innovative performance………..	.31	.25	0	1	-									
2. % Complete outcomes…………………..	.88	.24	.09	1	.24*	-								
3. Engineering-based technology fields…….	.71	.46	0	1	.36**	.04	-							
4. Year……………………………………..	1997.81	3.91	1991	2004	.14	.69**	.01	-						
5. Node entry (knowledge variation)……….	8.40	5.54	0	31	-.21*	.05	-.51**	.03	-					
6. Node exit (knowledge selection)………....	6.84	5.35	0	26	-.01	.22*	-.48**	.32**	.45**	-				
7. Stayers (knowledge selection…………….	44.97	26.05	4	113	-.03	.11	.58**	.16	.65**	.52**	-			
8. Density-based integration (retention).........	.13	.34	0	1	-.01	-.10	.25*	-.04	-.15	-.12	-.17	-		
9. Centralization-based integration (retention)…..	.11	.31	0	1	.19	.04	.15	-.00	-.08	-.04	-.08	-.13	-	
10. High integration (retention)…………….	.30	.46	0	1	-.08	-.26*	-.10	-.23*	.12	-.02	.03	-.25*	-.23*	-
11. Field stability…………………………....	5.49	4.67	0	18	.04	.19	-.27**	.36**	.18	.29**	.33**	.02	-.06	.01

[32] $n = 93$. $^{**}p < .01$; $^{*}p < .05$. The reference category for the 'Engineering-based technology fields'-dummy is the category of 'Science-based technology fields'. The reference category for the 'Knowledge retention'-dummies is the 'Knowledge retention (low)'-category.

TABLE 21

Descriptives and correlations – 3 years before evaluation[33]

Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9	10
1. Network innovative performance………..	.31	.25	0	1	-									
2. % Complete outcomes…………………..	.88	.24	.09	1	.24*	-								
3. Engineering-based technology fields…….	.71	.46	0	1	.36**	.04	-							
4. Year……………………………………..	1995.81	3.91	1989	2002	.14	.69**	.01	-						
5. Node entry (knowledge variation)……….	7.95	5.55	0	31	-.13	-.06	-.55**	-.04	-					
6. Node exit (knowledge selection)………....	6.04	4.49	0	18	-.09	.10	-.47**	.23*	.39**	-				
7. Stayers (knowledge selection…………….	42.14	25.41	3	113	.02	.21*	-.54**	.31**	.61**	.54**	-			
8. Density-based integration (retention).........	.13	.34	0	1	.17	-.23*	.25*	-.10	-.05	-.03	-.05	-		
9. Centralization-based integration (retention)…..	.12	.32	0	1	.21*	.12	.16	.06	-.11	-.04	-.10	-.14	-	
10. High integration (retention)…………….	.29	.46	0	1	-.13	-.03	-.27**	-.27**	.20	.03	.09	-.25*	-.23*	-
11. Field stability…………………………...	4.66	3.95	0	16	.09	.22*	-.28**	.38**	.15	.30**	.35**	.13	-.10	.01

[33] $n = 93$. $^{**}p < .01$; $^{*}p < .05$. The reference category for the 'Engineering-based technology fields'-dummy is the category of 'Science-based technology fields'. The reference category for the 'Knowledge retention'-dummies is the 'Knowledge retention (low)'-category.

TABLE 22

Descriptives and correlations – 5 years before evaluation[34]

Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9	10
1. Network innovative performance………..	.31	.25	0	1	-									
2. % Complete outcomes…………………..	.88	.24	.09	1	.24*	-								
3. Engineering-based technology fields…….	.71	.46	0	1	.36**	.04	-							
4. Year…………………………………..	1993.81	3.91	1987	2000	.14	.69**	.01	-						
5. Node entry (knowledge variation)……….	7.68	5.56	0	31	.08	.19	-.54**	.18	-					
6. Node exit (knowledge selection)………....	5.71	4.44	0	18	-.16	.11	-.48**	.30**	.41**	-				
7. Stayers (knowledge selection…………….	38.13	23.90	4	113	-.01	.23*	-.48**	.38**	.64**	.53**	-			
8. Density-based integration (retention).........	.15	.36	0	1	.12	-.08	.27**	-.16	-.08	-.11	-.11	-		
9. Centralization-based integration (retention)…..	.15	.36	0	1	-.03	-.06	.20	-.02	-.16	-.04	-.13	-.18	-	
10. High integration (retention)…………….	.29	.46	0	1	.08	-.37**	-.05	.26*	.11	.21*	-.53**	-.27**	-.27**	-
11. Field stability…………………………...	3.89	3.31	0	14	.07	.17	-.24*	.34**	.22*	.31**	.27**	.16	-.20	.11

[34] $n = 93$. $^{**}p < .01$; $^{*}p < .05$. The reference category for the 'Engineering-based technology fields'-dummy is the category of 'Science-based technology fields'. The reference category for the 'Knowledge retention'-dummies is the 'Knowledge retention (low)'-category.

to network innovative outcomes, the % of complete outcome data available for each network and the technology field dummies across the correlation tables, and different descriptives with respect to the other predictors across the correlation tables, the same vector of network outcome data is regressed on different vectors of the explanatory variables. We now will compare the three resulting correlation tables.

With respect to the descriptives regarding network innovative outcomes in Table 20, one can see that its average level across networks is 31% (i.e. on average, 31% of consortia that finish in a network receive the highest evaluation possible in the funding scheme). Compared to the range of the variable, observations tend to be skewed to the left. In addition, the large standard deviation indicates considerable variation across networks with respect to the level of innovative performance. Earlier we explained that not all outcome variables of consortia that finished in a certain year were available for all networks, and that we assumed that network innovative performance based on the outcome data that was available was representative for all consortia. The positive correlation between network innovative performance and % of complete outcomes ($r = .24$, $p < .05$) indicates that as more outcome data is available for determining network innovativeness, the % of complete outcomes variable is higher. This effect is controlled for in all analyses. The positive correlation between the technology field dummy and network innovative performance ($r = .36$, $p < .01$) shows that engineering-based fields on average have a higher level of innovative performance compared to science-based technology fields. Lastly, the negative correlation with node entry ($r = -.21$, $p < .05$) shows that less innovative networks are associated with less knowledge variation in terms of new nodes entering the network.

The control variable that denotes the % of outcomes available for determining network innovativeness has an average score of 88%. This means that for most networks, outcome data for all consortia were available for calculating a network effectiveness score. The control variable is strongly correlated with the year control ($r = .69$, $p < .01$), which means that over time, the data available for determining network innovativeness got more complete. This time effect also explains the positive correlation of this control variable with node exit ($r = .22$, $p < .05$) and its negative correlation with high network integration ($r = -.26$, $p < .05$): as networks mature, node exit is more likely, and networks need time to get integrated.

Most networks (71%) are embedded in engineering-based technology fields. The various correlations in Table 20 indicate that marked differences exist between both types of fields in terms of node entry, stayers, node exit and network integration. Correlations of the year control with other variables are almost similar to the earlier discussed correlations with the control variable % of complete outcomes, except for field stability: as time progresses, technology fields get more stable ($r = .36$, $p < .01$). Large correlations exist between the proxies for knowledge variation and knowledge selection. Intuitively this makes sense: as more new knowledge enters the network, more selection takes place ($r = .45$, $p < .01$ and $r = .65$, $p < .01$ respectively). In addition, knowledge selection through nodes exiting and through nodes staying are highly correlated, as knowledge selection always implies retaining knowledge at the cost of other knowledge, which disappears from the network ($r = .52$, $p < .01$). None of these correlations are in excess of .8 though, which usually is considered to be a serious problem for the reliable estimation of coefficients with small standard errors (Gujarati & Porter, 2009; Pallant, 2005).

Interesting is the positive correlation between node exit and field stability ($r = .29$, $p < .01$): more nodes leaving a network are indicative of a more stable technological environment. Lastly, from the means of the knowledge retention proxies we deduce that almost half of all networks (i.e.

46%) belong to the 'low integration' category. The remainder is assigned to knowledge retention through centralization-based integration, and to a lesser extent retention through density-based integration and high network integration.

With respect to differences between correlations over the years, we observe a marked change over time in the correlation between network innovative performance and centralization-based network integration. This correlation is about .20 one and three years before network innovative performance is measured and drops to 0 five years before this measurement takes place. This indicates that the association between knowledge retention through centralization-based integration and network innovative performance fades in the long run. Some shifts take place in the correlations between the % of complete outcomes: correlations with this control variable shift from knowledge retention through exits to knowledge selection through stayers as the time lag increases. The earlier mentioned time effect also is at play here: in earlier observed networks, it is likely to observe more stayers compared to networks that are observed at a later point in time. Lastly, we observe a negative correlation with density-based integration in the third year (r =-.23, $p < .05$), as well as a positive correlation with field stability (r =.22, $p < .05$) in the same year.

With respect to correlations between the technology field dummy and other variables, no differences are observed except for high network integration which becomes negative three years before innovative performance is measured (r =-.28, $p < .01$). Correlations between year and other variables follow similar patterns across lags except for a shift from negative to positive with respect to the correlation with high network integration: in earlier years, networks are get more integrated as time progresses, whereas in later years this is the opposite. Lastly, differences with respect to field stability can be seen: five years before network innovative performance is measured, we see a positive correlation with node entry (r =.22, $p < .05$). Similar correlations exist between node exit and high network integration five years before network innovative performance is measured (r =.21, $p < .05$), and between stayers and high network integration five years before network innovative performance is measured (r =-.53, $p < .01$).

Results of beta regression analysis

The results of the beta regression analyses are shown in Table 23. Visualisations of relevant results are provided in Figure 12. As indicated in the methods section, in addition to an estimation of the intercept, the technique of beta regression yields a precision parameter for each model. Taking the inverse of this parameter results in an indicator of the dispersion of the dependent variable. As can be deduced from Table 23, all models have significant precision parameters. This indicates that the dependent variable indeed follows a non-normal distribution and justifies the use of a beta regression model.

As explained earlier, different time lags between the dependent and independent variables are considered: 1 year, 3 years and 5 years. Hence, Model 2 and Model 3 show the effect in the short run (1 year), Model 4 and Model 5 for the long run (3 years) and Model 6 and Model 7 for the very long run (5 years). By specifying the time lags in this way, we gain additional insight in the timing of salient effects on network innovativeness. Whereas models 2 to 7 relate to different time lags, Model 1 includes controls that are not time-variant. Hence, this model is the same for all time lags specified. With respect to these controls, we see the same behaviour of the % Complete outcomes control variable as the behaviour seen in the correlation matrix: networks for which the outcome data used in determining network innovative performance is more complete generally are

TABLE 23

Results of beta regression models predicting network innovative outcomes

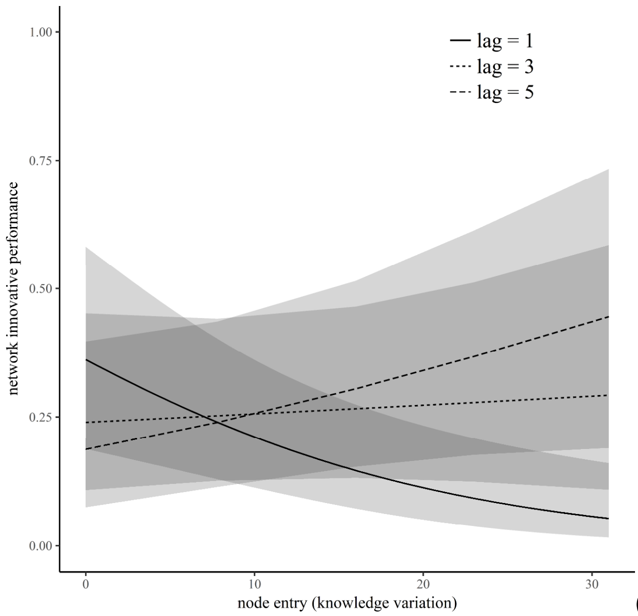
Variable		lag = 1 year		lag = 3 years		lag = 5 years	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept…………………………………	-1.11*** (.22)	-1.49*** (.29)	-1.44*** (.29)	-1.41*** (.30)	-1.61*** (.31)	-1.45*** (.31)	-1.46*** (.32)
1. % Complete outcomes…………...…….	.32* (.16)	.39* (.16)	.35* (.16)	.35* (.16)	.36* (.17)	.30† (.16)	.31† (.16)
2. Engineering technology fields……...…...	.50* (.25)	.97** (.34)	.76* (.34)	.77* (.34)	1.04** (.36)	1.10** (.35)	1.13** (.37)
3. Year…………………………...……..…	-.03 (.16)	-.12 (.16)	.07 (.17)	-.19 (.18)	-.27 (.19)	-.08 (.18)	-.13 (.19)
4. Node entry (knowledge variation)…….....		-.34* (.16)	-.38* (.16)	-.10 (.16)	-.04 (.16)	.50** (.16)	.51** (.16)
5. Node exit (knowledge selection)………..		.00 (.36)	.09 (.34)	-.13 (.43)	-.04 (.43)	-.83* (.42)	-.67 (.44)
6. Node exit (knowledge selection)²………		.08 (.33)	-.03 (.32)	.05 (.41)	-.06 (.41)	.71† (.39)	.55 (.43)
7. Stayers (knowledge selection)…………..		1.31** (.47)	1.04* (.52)	.99* (.47)	.51 (.52)	.63 (.43)	.43 (.48)
8. Stayers (knowledge selection)²………….		-.81† (.43)	-.61 (.46)	-.50 (.43)	-.07 (.47)	-.52 (.39)	-.34 (.43)
9. Density-based integration (retention)…..		-.24 (.37)	-.19 (.36)	.40 (.39)	.31 (.42)	.05 (.35)	-.06 (.39)
10. Centralization-based integration (retention)..		.37 (.39)	.48 (.37)	.73† (.37)	.65† (.38)	-.35 (.34)	-.31 (.43)
11. High integration (retention)…………...		.06 (.28)	.14 (.27)	-.16 (.30)	-.16 (.30)	-.26 (.29)	-.27 (.30)
12. Field stability………………………….			-.23 (.18)		.37* (.19)		.17 (.20)
13. 9 × 12………………..……………..…			2.07*** (.51)		-.23 (.46)		.05 (.36)
14. 10 × 12………………..…………….....			.22 (.36)		-.65 (.42)		-.05 (.60)
15. 11 × 12………………..………………			.26 (.26)		-.06 (.26)		-.14 (.26)
Precision parameter	1.93*** (.25)	2.36*** (.32)	2.93*** (.40)	2.33*** (.31)	2.50*** (.34)	2.42*** (.33)	2.46*** (.33)
Log likelihood	33.67	42.75	52.53	42.13	44.73	43.32	43.85
Residual df	88	80	76	80	76	80	76
χ^2	-	16.468*	34.133***	17.235*	23.233*	20.747**	21.395*

note: n = 93. ***p < .001; **p < .01; *p < .05; †p < .1. Standard errors are displayed between parentheses. The reference category for the engineering technology field dummy is the science-based technology field. The reference category for the knowledge retention dummies is low knowledge retention.

FIGURE 12

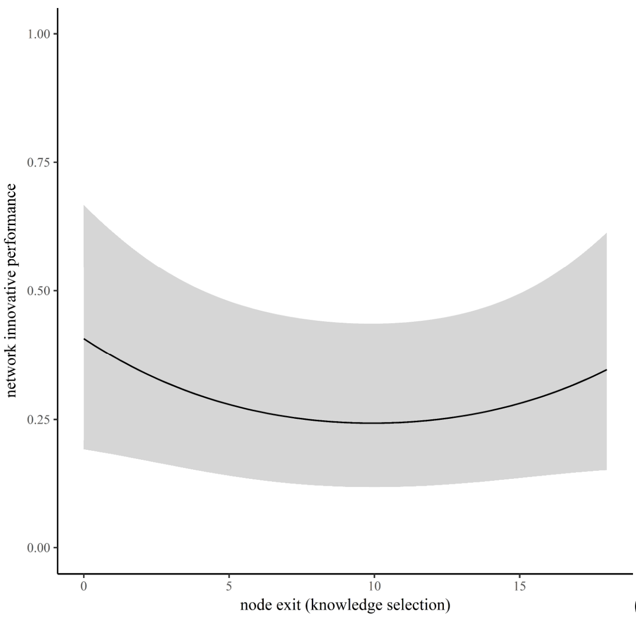
Marginal effects for selected coefficients

Node entry (knowledge variation), all lags, Models 3, 5 and 7



(a)

Node exit (knowledge selection), lag = 5 years, Model 6

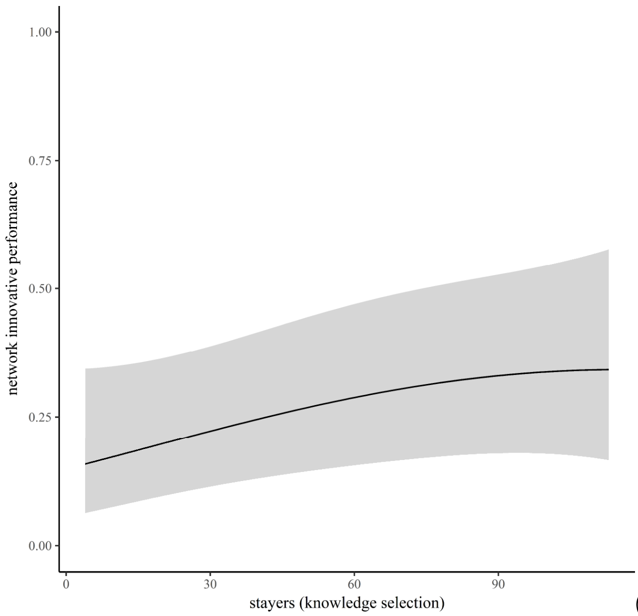


(b)

FIGURE 12 (CONTINUED)

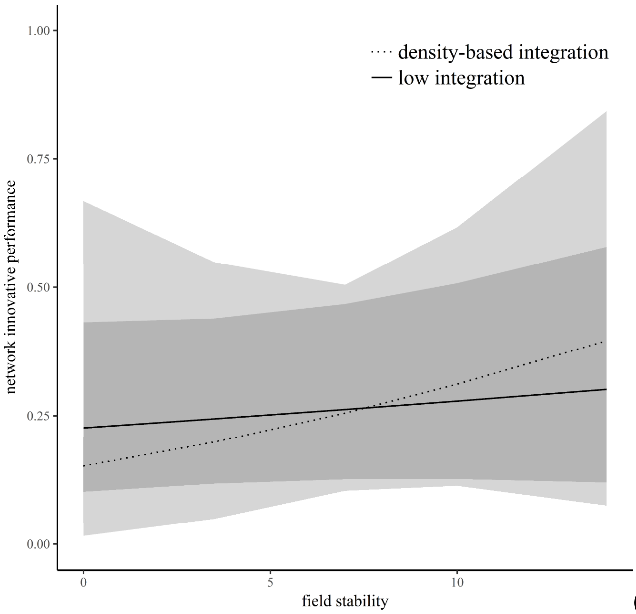
Marginal effects for selected coefficients

Stayers (knowledge selection), lag = 1 year, Model 3



(c)

Field stability × Density-based network integration, lag = 1 year, Model 3



(d)

assigned a higher score on the measure of network innovative performance. In addition, we see that engineering-based technology fields generate higher levels of innovative performance compared to science-based technology fields.

Several interesting findings emerge from our analyses. First, hypothesis 1 predicted a positive relation between the level of node entry in a network (reflecting knowledge variation) and the innovative performance of this network. When one compares the different models across the different time lag specifications, a switch in the effect over time can be seen. This is illustrated with marginal effect plot (a) in Figure 12. The effect of node entry on network innovative performance is significantly negative for the one-year lag, absent for the three-year lag and significantly positive for the five-year lag. Hence, whereas in the short run node entry leads to lower levels of network innovative performance, in the very long run node entry leads to higher levels of network innovative performance. Hence, hypothesis 1 is supported with respect to the long-term effect of node entry on network innovative performance, and not supported for the other two lag specifications. Instead, a negative effect of node entry is found for the short run.

Hypothesis 2 predicted that networks with moderate levels of node exit were more innovative compared to networks with very low or very high levels of said proxy. This curvilinear effect represents the mechanism of knowledge selection. The analysis results do not convincingly support this hypothesis: Model 2 and Model 6 suggest weakly significant curvilinear relations between knowledge selection through exits in the very long run. Marginal effect plot (b) in Figure 12 illustrates this effect. From this plot one can deduce that a u-shaped relation between knowledge selection through exits and network innovative performance is suggested in the long run. The effect disappears, however, when interactions are added in Model 3 and Model 7. Hence, hypothesis 2 is not supported.

Hypothesis 3 predicted that networks with moderate levels of stayers were more innovative compared to networks with very low or very high levels of stayers. Like node exit, this curvilinear effect represents the mechanism of knowledge selection. The analysis results do not convincingly support our hypothesis: Model 2 and Model 6 suggest weakly significant curvilinear relations between knowledge selection through stayers and network innovative performance in the short run. Marginal effect plot (c) in Figure 12 illustrate this effect. The plot suggests a marginal return from increasing levels of knowledge selection through stayers and network innovative performance in the short run. The effect disappears, however, when interactions are added in Model 3 and Model 7. The net effect that remains in the full models is a positive effect of knowledge selection through stayers on innovative outcomes in the short run (Model 3). Hence, hypothesis 3 is not supported. Instead, we find a positive effect of knowledge selection by consortia that stay in a network and the innovative performance of this network.

The predictors in Table 23 that relate to network integration (reflecting the mechanism of knowledge retention) test our fourth hypothesis. This hypothesis predicted that at higher levels of network integration, the innovative performance of this network increases as well. Although Model 4 and Model 5 indicate a weakly significant effect of centralization-based integration on the level of network innovative performance, our analysis results do not convincingly support this hypothesis. Hence, the level of innovative performance is not affected by the way in which knowledge is integrated and with that retained in a network, and hypothesis 4 is not supported.

Models 3, 5 and 7 consider the interaction effect as specified by hypothesis 5. With this hypothesis, we predicted that as knowledge retention mechanisms through network integration have more time to be expressed, the effect of network integration on the level of innovative outcomes increases. The significant positive interaction effect between density-based network integration and field stability in Model 3 indicates that this hypothesis is partially supported. The visualization of this effect (see marginal effect plot (d) in Figure 12)[35] shows a cross-over effect between knowledge retention through density-based integration and field stability: at low levels of system stability, knowledge retention through density-based integration leads to lower levels of network innovative performance compared to knowledge retention through low network integration. As the level of field stability increases, however, higher levels of innovative performance can be expected in networks characterized by knowledge retention through density-based network integration. Full support for hypothesis 5 would be found if all three interaction effects were significant. This would indicate that, compared to low network integration, networks with higher levels of integration consistently would be more innovative. Our analysis, however, only suggests an interaction effect involving density-based network integration and field stability, especially in the short run. Hence, hypothesis 5 is partially supported.

Robustness checks

One of the concerns with the existing analysis is that the observations of the independent variables are not independent from one another because of the longitudinal nature of the data. To address this issue, a multi-level model could be estimated, with one level being the technology fields and the other level being the observation years. However, to the best of our knowledge, multilevel beta regression models have not been developed at present. We therefore addressed this concern by estimating multi-level fractional logistic regression models. Such models can be estimated for the dataset under consideration, since the dependent variable can be thought of as a proportion of the number of successes from a total number of trials (Papke & Wooldridge, 1996). The results of these models are predominantly the same as the results presented in this chapter. Notable differences are that in the multilevel model, a direct negative effect of density-based integration in Model 3 is observed. In Model 5, none of the variables are significant any longer, whereas in Model 7 the effect of node entry becomes weakly significant (alpha = .10).

Another concern with the current analysis is the lack of statistical power. Ideally, we would at the very least need about twice as much observations as the number of observations used in the current analyses. This is an issue that is hard to address, yet we conducted the same analyses without the % complete outcomes control variable, as the correlation tables suggested this variable behaves similar to the year control. If we leave this control variable out, the results are similar: instead of the complete outcomes control, year now is significant in most models. The effect of stayers in Model 3 becomes weakly significant (alpha = .10), whereas the terms that represent the effect of knowledge retention through exits become significant. This suggests a u-shaped curvilinear effect.

5.5 Discussion and conclusion

Getting insight in the antecedents of network-level outcomes is fruitful, especially for networks that address issues that cannot be solved by the actions of individual organizations alone. In this chapter, we have extended and tested the preliminary theory of network effectiveness that was

[35] It is common to display interaction effects with the main effect on the x-axis, which in turn is differentiated in the plot by different values of the moderator. Considering that the main effect is measured with a dummy variable, and the moderator is continuous, this approach would lead to loss of information: including all scores of the moderator would make the plot impossible to interpret. Hence, we decided to switch the direct effect and the moderator effect in plot (d) in Figure 12.

proposed by Provan and Milward (1995) and Provan and Sebastian (1998). Driven by the research question to what extent network innovative performance is driven by node entry, stayers, node exit and network integration (causing mechanisms of knowledge variation, selection and retention respectively), and to what extent the relation between said predictors and network innovative performance is moderated by the level of technology field stability, we focused on the role of knowledge in publicly funded R&D networks. Through using different time lags between the independent variables and dependent variable in our analysis, we show that the role of knowledge variation, selection and retention can be fruitfully considered when explaining complete network innovativeness.

Through inviting industry participation in publicly funded R&D networks -that in turn are more demand driven and geared to industry issues- the expectation behind the public funding of joint R&D is that positive externalities are generated, both for members of the network and society. Our study suggests that such externalities are more likely to be generated under certain conditions of node entry, stayers, node exit and network integration and that these conditions change over time. The effect of node entry, for example, switches from negative in the short run, to positive in the very long run. In addition, the mechanism of knowledge selection was found to result in higher levels of network innovative performance in the short run. Lastly, we found that, compared to high levels of network integration, low levels of network integration lead to higher levels of network innovative performance in the short run in unstable technology fields. As field stability increases, however, higher levels of network integration lead to higher levels of network innovative performance in the short run, compared to low levels of network integration.

Our findings refine our understanding of the antecedents of the innovative performance of public innovation networks by providing novel insights. Through building on existing network outcome models by using the perspective of knowledge variation, selection and retention, we provide a deeper understanding of the effect of a continuous rate of knowledge renewal in networks and its role for network innovation. Our research findings might extend beyond the context of public innovation networks, and bear relevance for, for example, alliance networks as well. It has been suggested by other authors that alliance network structure affects the performance of firms embedded in such networks (Schilling & Phelps, 2007). Although it is known that the structural organization of such networks is sensitive to environmental instabilities (Madhavan et al., 1998), our results suggest that in addition to the role of network structure and system stability, knowledge variation and selection are key mechanisms in the generation of innovative outcomes by such networks as well.

Theoretical and practical implications

The results this study provide interesting insights. First, we found that the effect of node entry switches over time, from a negative effect on network innovative performance when a time lag of 1 year is considered, to a positive effect on innovative performance when a time lag of 5 years is considered. This result suggests that the mechanisms we described (i.e. high levels of node entry avoid a situation in which network members fall in the trap of rigid specialization) especially holds for network members that are in the early stages with their R&D consortium. These consortia are aided by the varied inflow of knowledge: in the first year, searching the knowledge space is key for defining the consortium’s goal, and this is facilitated by high levels of knowledge variation in the network in which the consortium is embedded.

This inflow, however, is detrimental for consortia that are close to finishing, as reflected in the negative effect of node entry on network innovative performance when a time lag of 1 year is considered. Here, the competitive effect of high levels of knowledge variation might lead to a devaluation of older variations that already have been further developed by incumbent consortia. A larger variation of technological possibilities being explored in a network and the promise these possibilities hold might lead to the perception that relative older knowledge is not relevant any longer and hence, consortia developing such knowledge are less attractive. In addition, high levels of node entry might dilute the attention of members of older consortia as they become involved in new consortia. This involves getting to know and understand new consortium members, which makes less time available for involvement in existing consortia. Hence, turbulence in the knowledge environment might make the results of older consortia obsolete and distract the members of these older consortia.

This negative effect of node entry on network innovative outcomes in the short run is counteracted by the positive effect in the short run of the selection of knowledge through stayers. Hence, whereas incumbent nodes suffer from high levels of node entry shortly before the consortium results should be delivered, these same incumbents benefit from high levels of this varied knowledge being selected. Although this presents a bit of a conundrum, one explanation might be that higher levels of network integration offer more opportunities for incumbent nodes to seek for the common ground with newer consortia so that they are better able to demonstrate where and how their results still bear relevance and might be further build upon.

The cross-over interaction between knowledge retention through density-based network integration and field stability shows that a specific mode of knowledge retention leads to higher levels of network innovative performance compared to low levels of knowledge retention as from a certain level of field stability. At lower levels of field stability, however, network integration leads to lower levels of network innovative performance compared to low levels of network integration. This demonstrates that networks need several years to reorganize after an environmental jolt before the benefits of the mechanism of knowledge retention through density-based integration can be reaped. In early years after an environmental jolt, it is better to have no mechanism of knowledge retention at all, possibly because in this situation future viable pathways are too opaque for consortia to effectively build mutual understanding and insight in knowledge interdependencies. In addition, the crossover interaction supports one of the propositions developed by Provan and Milward (1995), namely that system stability is a necessary yet insufficient condition for networks to be effective. Our results suggest that field stability in combination with knowledge retention through density-based network integration leads to innovative outcomes when this stability has persisted for several years.

Regarding the relevance of our results for policy makers, public policies related to the funding of R&D through collaboration at present are rather undifferentiated as to the networks that result from such funding (Meeus et al., 2008). Our results suggest that such networks are an object that are worth organizing themselves, and we offer several levers for policy regarding the top-down management of such networks by public funding agencies. First, recognizing the need for active network management and gaining insight in the organization of such networks and assessing the potential for an exogeneous shock are critical steps. Our findings indicate that funding R&D collaboration between science and industry is more complex than simply striving for collaborations. Funding agencies that fail to consider the complexities involved in the generation of innovative outcomes by networks may waste resources and perhaps might even frustrate the innovative outcomes of a network.

One way in which more targeted top-down network management could be shaped is through the establishment of a dedicated network management unit (Chiaroni, Chiesa, & Frattini, 2011; Dhanaraj & Parkhe, 2006; Provan & Kenis, 2008). Studies have shown that employing such a unit significantly improves network performance (Heidenreich, Landsperger, & Spieth, 2016). However, scholars also have suggested that networks may not be as malleable as theory might suggest (Hite & Hesterly, 2001; Siu & Bao, 2008). The implication of this is that a dedicated network manager should aim at steering the network through a combination of path-dependence and targeted intervention. This requires a thorough understanding of the development of the technology field, as well as the impact of, for example increasing the level of knowledge variation in a network which could be achieved through allowing more new members to enter the network.

Strengths, limitations and suggestions for future research

In the context of research on the innovativeness of complete interorganizational networks, one of the strengths of our study is that we employ a relatively large dataset for testing our hypotheses. From a statistical point of view, however, the n in this study is not big enough to generate statistically robust results. For example, even though we find a rather strong effect of knowledge retention through density-based integration, this effect is based on relatively few networks in our sample that could be characterized by such integration. Hence, results from this study are not readily generalizable to other publicly funded R&D networks or any other interorganizational network in which the focus is on innovation. Hence, although this is a considerable task, future research should aim at increasing the number of cases to improve statistical power, as well as trying to replicate the findings of this research in other network innovation contexts.

Another limitation of our study concerns some of the measures that we have used. First, although we strongly believe that focusing on networks rather than individual organizations is pivotal for studying the innovativeness of a network, the measurement of our dependent variable does not neatly delineate between network-level and node-level outcomes. Hence, we are not able to convincingly claim a synergistic effect of networked innovation. Second, our proxies for knowledge variation (i.e. node entry) and knowledge selection (in as far as it concerns nodes that leave a network) do not fully capture variation and selection within the funding system. It might very well be that new nodes come from or end up in other networks that we do not observe. In addition, node exit does not necessarily imply knowledge loss. Exit could also occur because of consortium leaders retiring or making a career switch. To the extent that knowledge is transferred to possible successors, this does not reflect knowledge retention. Third, our measure of field stability is derived from substantial switches in the level of especially knowledge variation and selection. Although correlations between said measures are not concerningly high, a more independent measurement of field stability, for example changes in the funding scheme (i.e. specific programs) over time would be more convincing, as well as a broader conception of field stability (i.e. a conception that goes beyond marked technological change). Again, even though refining the measurements used in this paper is a challenging task, future research should address these measurement issues.

Appendix I: Network Boundary Specification

Given our focus on the dynamics and innovativeness of different technology field networks, it is important to consider the approach we followed in specifying network boundaries. Network boundary specification, or deciding which consortium is part of a network and which consortium is not, is seen as an important first step in each network analysis (Laumann, Marsden, & Prensky, 1983). It revolves around the specification of the standard of common relevance (Newcomb, 1961) across consortia, for which it is reasonably assumable that joint member ties between consortia are regularly activated. Although few objective criteria for establishing these boundaries exist, two approaches towards the specification of network boundaries have been analytically distinguished in the past: the realist and the nominalist approach (Laumann et al., 1983).

In the realist approach, one treats networks as social facts only in that they are consciously experienced as such by the nodes that constitute the network. This approach therefore uses group membership as the basis for network boundary specification (for example, membership of the same school class or football team). The underlying proposition that underlies this approach is that the specification of the group that is used for including actors has subjective meaning to those actors[36]. The match between group specification and the subjective awareness of these groups by the network members becomes an empirical question rather than an underlying proposition that is made in the nominalist approach. In this approach, network boundaries are relative to the purpose of the researcher, which makes that the group or groups that are specified usually have no clear ontological status for its members. For example, studies in which a nominalist approach is adopted use geographical proximity or activity in the same industrial sector as the basis for network inclusion. Instead of studying the relational structure that emerges in a certain social context (as one does when using the realist approach), studies that adopt a nominalist approach focus on the question to what extent similarity in one or more node features induces relations between these nodes.

We follow a stratified approach in specifying network boundaries in this chapter. First, a realist approach is followed by including all consortia that have received funding. This is a direct result from using the evaluation reports of the funding organization that gives a comprehensive overview of all consortia funded as from 1981 to 2004. The group can be assumed to have subjective meaning to the actors involved: in addition to the meetings of the user committees, consortium members meet one another at yearly congresses, as well as other more topic-oriented conferences during the year that are organized by the funding agency. Events like conferences are an established form of inter-organizational interaction (Lomnitz, 1983) and several studies suggest that participation in conferences is an important informal mechanism of knowledge transfer between organizations (Berends et al., 2011; Henn & Bathelt, 2015; Kreiner & Schultz, 1993; Maskell, Bathelt, & Malmberg, 2006; Stam, 2010; Vlasov, Bahlmann, & Knoben, 2017).

The second step in specifying network boundaries follows a nominalist approach and refines the assumption that all actors involved belong to the same group simply because they received funding by the same funding organization. The general focus of this organization implies a great variety in terms of the research topics that are covered in the funded consortia. This, in turn, attracts researchers from different academic disciplines, as well as organizations from various industrial sectors. These differences in background do not evidently translate into a standard of common relevance among actors, and –when consortia are left undifferentiated– large variations

[36] Laumann et al. (1983) speak of a 'we'-feeling that should somehow be present among the group members.

in the likelihood of activation of joint membership ties exist. As this would be at odds with our theoretical model in which actors are assumed to develop technology within a certain technological paradigm and its corresponding trajectories, we mitigate this issue by specifying several subgroups based on technology fields.

The focus on potential application in the R&D consortia and consortium invites a classification of consortia based on the technology that is being developed. Technology classification schemes can be divided in two types. The first type classifies technology based on criteria that are external to the technology under consideration (Horner, 1992). One of the approaches here, for example, is to classify an artefact based on the branch of production where it is applied. Based on this main classification, further sub-classifications can be made on for example the natural law embodied in the artefact (Horner, 1992). Following this approach, a cement mixer would be classified under the main category of building and construction, and then sub-classified in the category of convective mixing. A related approach is to classify a technological artefact based on the purpose for which it was developed (Horner, 1992). Following this approach, a cement mixer, would be classified under the category of processing machinery. Various other approaches that use external criteria exist, and they all share the tendency to be biased towards the aim they are developed for, such as mapping industrial or innovative activity (Horner, 1992). For example, the patenting classification system is designed to meet the needs of searching for claims in patents, and hence this system is biased towards areas of greatest patenting activity (Horner, 1992). Moreover, the schemes need to be updated on a regular basis to facilitate results from an ongoing changing scientific and technological knowledge base, which causes the number of categories to expand over the years. This affects classification consistency (Schmoch, 2008).

The second type of technology classification focuses on the internal technological structure. These approaches are driven from the observation that schemes that use external criteria lack 'the bigger picture' and unifying concepts regarding technological development. They therefore do not allow for pinpointing the position of artefacts on a technological roadmap, nor the position of these roadmaps on a global technological atlas (Van Wyk, 2002, 2017). One of the approaches here is to develop a technological taxonomy, like taxonomies that exist in the field of biology. An issue with developing technological taxonomies, however, is that mapping technological development is less straight-forward compared to biological taxonomies and hence, valid classifications based on this principle have not yet emerged (Horner, 1992). Another approach that starts from the idea of the existence of an internal technological structure specifies two dimensions: technological function (i.e. transformation, transport and storage) and output (i.e. matter, energy and information) (Ropohl, 1999). Under this classification scheme, a cement mixer would be classified in the category of technologies that transform matter. A machine for mixing dough, however, would be classified in this category as well –an observation made by Teichmann (1974)– and hence one could question the ratio behind this approach, as both artefacts in the end clearly are a result of distinct technological trajectories.

Even though classification schemes that start from the existence of an underlying technological structure might be sounder theoretically, these schemes are currently underdeveloped and lead to rather generic technology classifications. Moreover, it is the question to what extent actors involved in the consortia that we focus on in this dissertation –academics and industrial organizations– are aware of these internal technological structures and can see, for example, the relevance of a machine for mixing cement for the further development of a machine for mixing dough. Classification schemes that use external criteria, subjective as they might be, at least have the benefit that they are developed by and for the community that participates in the development of technology. For specifying network boundaries, we therefore use a scheme that uses external rather than internal criteria. This involved classifying all 1,928 projects in the dataset, triangulating patent information and consortium descriptions by two researchers separately, who later harmonized their classifications through extensive discussion of classification differences.

About every one out of five consortia at least had one patent as its outcome. These patents were looked up using Espacenet and key information, amongst which the international patent classification (IPC) code, was registered in a data file. Patent classification codes are rather fine-grained and cannot be used directly for setting network boundaries. Hence, the classification codes found for each consortium were translated to a more general technology field classification. For this, a concordance table that translates patent codes to broader technology fields as proposed by Engelsman and van Raan (1994) and Schmoch (2008) was used[37]. These fields, including keywords that characterize them, can be found in Table 24 in Appendix II of this chapter. The insights that were obtained by classifying the first 20% of all consortia formed the basis for classifying the remaining consortia that could not be linked to a patent classification code. These consortia were categorized directly in one of the technology fields. It should be noted that each consortium was classified using the subfields listed in Table 24. Network boundary specification, however, took place using the main technology fields that include several subfields. This was done to allow for cross-disciplinary ties without stretching the assumption of actual knowledge flowing through these too much. Hence, whereas joint member ties between main technology fields (e.g. ties between a consortium active in the field of Civil engineering and a consortium active in the field of Chemistry) are not included in the final dataset, joint member ties between subfields within a technology field (e.g. ties between the subfields biotechnology and pharmaceuticals in the main Life sciences field) are included.

[37] In line with the evolving nature of using external classification criteria, this table was adjusted to match the specifics of the consortia in the dataset used. First, an important share of the projects classified in the main field of Instruments was classified in the subfield Medical Technology. Because the field of Instruments is mainly focused at measurement and control of industrial processes and the field of Medical Technology is more directed towards extending and improving life conditions (artificial livers, for example, are also part of the field of Medical Technology) their application areas differ and hence we decided to make a distinction between both fields. Second, the general field of Chemistry and Pharmaceuticals was split in the fields Chemistry and Life Sciences for similar reasons. Third, the generic field 'Consumption' mainly consisted of projects that were focused at Civil Engineering, and the name of this field was therefore changed accordingly.

Appendix II: Technology Field Classification

TABLE 24

Main fields, subfields and illustrative keywords[38]

Main field	Subfield	Subfield keywords
Chemistry	Basic materials chemistry	paints, petroleum, gas, detergents
	Chemical engineering	apparatus and processes for the industrial production of chemicals
	Environmental technology	filters, waste-disposal, water cleaning, gas-flow silencers, exhaust apparatus
	Macromolecular chemistry, polymers	chemical aspects of polymers
	Materials, metallurgy	metals, ceramics, glass, processes for the manufacture of steel
	Microstructure and Nanotechnology	micro-structural devices or systems, nanostructures
	Organic Fine Chemistry	cosmetics, non-pharmaceutical oriented organic chemistry
	Surface technology, coating	metal coating, electrolytic processes, crystal growth and apparatus for applying liquids to surfaces
Civil Engineering	Materials engineering	development of materials used in the construction of buildings, roads, bridges
	Geotechnics	exploration of mining opportunities and development of mining techniques
	Hydraulic engineering	development of devices and constructions to control water fluids, such as dams or groynes
	Structural engineering	construction of roads and buildings, as well as elements of buildings such as locks, plumbing installations, or strong-rooms for valuables
Electrical Engineering	Electrical machinery, apparatus, energy	generation, conversion and distribution of electric power, electric machines, electronic elements such as resistors, magnets, capacitors, lamps or cables
	Audio-visual technology	consumer electronics
	Basic communication processes	oscillation, modulation, resonant circuits, impulse technique, coding/decoding
	Computer technology	arrangements for controlling programmes, methods and arrangements for data conversions, e.g. image data processing, recognition of data, speech analysis

[38] based on Engelsman and van Raan (1994) and Schmoch (2008).

TABLE 24 (CONTINUED)

Main fields, subfields and illustrative keywords

Main field	Subfield	Subfield keywords
Instruments	Control	elements for controlling and regulating electrical and non-electrical systems, test arrangements, traffic control, signalling systems
	Measurement	measurement techniques and applications, e.g. measurement of mechanical properties such as oscillation, speed, length
	Optics	optical elements and apparatus, laser technology, optical switching
Life Sciences	Analysis of biological materials	analysis of blood for medical purposes, using biotechnological methods
	Biotechnology	non-pharmaceutical oriented biotechnology
	Food Chemistry	seed and crop optimization, food innovation
	Pharmaceuticals	medicinal preparations containing (non-)organic active ingredients
Mechanical Engineering	Engines, pumps, turbines	non-electrical engines for all types of application, especially those for the automobile industry
	Thermal processes and apparatus	steam generation, combustion, heating, refrigeration, cooling, heat exchange
	Transport	transport technology and applications, mainly automotive-oriented
Medical Technology	Treatment	products used in diagnosis and treatment of individuals, such as operating tables, massage devices, bandages
	Measurement	development of tools for measuring bodily functions or parameters, as well as measurement parts used in treatment (e.g. sensors used in surgery robots)
	Prostheses and implants	development of replacement organs, such as artificial livers, orthoses. Sometimes, use of animal organs is explored as well
	Imaging	development of imaging techniques such as echography, x-rays, magnetic resonance imaging scanners

6. Management or Muddling Through: Conclusions

6.1 Introduction

We started this dissertation with the observation that even though collaboration between science and industry is of key importance for both groups and for those actors who stimulate such collaboration, the network effects at multiple levels (i.e. the consortium- and network-level) that come with such collaboration are not fully understood. We focused on a specific form of organizing joint innovation: R&D consortia that pursue demand driven technical innovation, by exchange of scientific and technical knowledge between university and industry. Such consortia can be considered to specialize, as they focus on further developing a specific position in the technology landscape. The networks in which these consortia are embedded can be considered to mitigate possible risks of overspecialization by individual consortia, as links between consortia allow for generalization across consortia through knowledge sharing and coordination across consortia (van der Valk, Moors, & Meeus, 2009). In this context, this research sought to answer the following related research questions:

1) *To what extent does R&D consortium network structure affect innovative outcomes?*

2) *To what extent does the network position of R&D consortia affect innovative outcomes?*

3) *To what extent do network dynamics and technology field dynamics moderate the relationships explored in research question 1 and 2?*

To answer those research questions, we have pulled together explanatory mechanisms and arguments from a variety of research streams on complete networks, technological change, innovation, the knowledge-based view, interorganizational networks and network dynamics. When considering the relationship between network position and innovative outcomes, studies on alliance networks have constituted and dominated the research field to date. By introducing time and multiple levels of analysis in our analysis of R&D consortia, our findings suggest that the mechanisms underlying established relationships between key variables are quite complex and often time-dependent. When considering the relationship between network structure and innovative outcomes, the existing literature is scarce and dominated by case study designs. Performing a larger-n study in this dissertation allowed us to provide more general insight in complete network dynamics and antecedents of the innovativeness of such networks.

Hence, using multi-level perspectives that incorporate the role of time and a unique longitudinal dataset comprising 156 complete field networks, and 7 technology fields, with 1,928 consortia served as an important asset of this dissertation, and enabled us to formulate an answer to the research questions. Our findings contribute to the existing literature on R&D consortia because this literature to date has not considered ties between consortia because of consortium members that are involved in multiple consortia simultaneously. As a result, little is known about the extent to which consortium networks, in addition to consortium features, affect the innovative outcomes of consortia. In addition, little is known about the timing of such network effects. Understanding this relation, however, forms the basis for devising strategies for either capitalizing on or mitigating network effects by consortium managers. The answer to our research question adds to the existing literature that considers network innovativeness at the system level as well. This literature has predominantly focused on public sector networks and has left the question regarding efficient network structures for generating technological innovation at the network-level and the role of the dynamics of different technology fields unaddressed. For those involved in formulating innovation policy, understanding this relation forms the basis for designing policy measures that lead to the formation and development of innovative networks.

In this concluding chapter we consider the theoretical and practical merits of the studies that constitute the empirical part of this dissertation, as well as limitations and possible future research avenues. In the subsequent section of this chapter (section 6.2), we will provide a summary of our main findings for each of the empirical chapters. In section 6.3 it will be assessed to what extent the expected contributions to the academic literature have been realized, after which we will consider the practical implications of this dissertation in section 6.4. In section 6.5, we will discuss the limitations of the research reported in this dissertation and address possible directions for future research. In section 6.6 this dissertation will be concluded.

6.2 Summary of main findings

Without a thorough understanding of the constraining and enabling effects of collaboration networks for both consortium managers and innovation policy makers, management of network positions and structures remains speculative and intuitive. The empirical chapters in this dissertation addressed the relation between networks and innovation in the following ways. In Chapter 2, we addressed research question 1 at the level of the consortium: which antecedents determined the likelihood of an R&D consortium generating innovative outcomes. More specifically, we were interested in the role of the complete consortium network structure in the relationship between the consortium features geographical proximity and technological diversity and the likelihood of a consortium generating innovative outcomes. We tested our hypotheses using a dataset of 1,263 Dutch R&D consortia that each were active somewhere in the time frame 1989-2004. We found that consortia that are embedded in networks characterized by mutual awareness of consortium members of what members in other consortia are doing (i.e. consortium networks characterized by density-based network integration), are more likely to generate innovative outcomes compared to consortia in networks that are characterized by other types of network integration. In addition, we found an inverted U-shaped relation between technological diversity and the likelihood of a consortium generating innovation, yet this relation only occurs in those networks of which the structure can be characterized by density-based integration.

Whereas Chapter 2 considered research question 1 on the role of the complete consortium network structure in R&D consortia in generating innovative outcomes, Chapter 3 considered the role of the <u>position</u> of R&D consortia in consortium networks (research question 2) over time (research question 3). In the existing literature on the relationship between the position in an interorganizational network and the likelihood of a consortium generating innovative outcomes, no consensus has emerged with respect to the question which network position is most advantageous. This is especially salient in the debate that focuses on the question whether network brokerage or closure provides the most efficient structure for innovation. In Chapter 3, we analysed this issue by focusing on the effect of both global and local network position on the likelihood of generating technological innovation. In addition, we considered the role of time in the salience of both effects, as we expected a link between stages in the process of R&D and the fruitfulness of occupying a certain network position. We tested our theoretical predictions with a multi-level analysis of 814 Dutch R&D consortia, each of which started somewhere in the time frame 1989-2004 and lasted for at least five years. Contrary to our expectations, we found that -although not salient across all years- global brokerage had a negative effect on the likelihood of generating technological innovation. We also found that local cohesion consistently enhanced the likelihood of innovation over time. Lastly, a time-dependent effect was found for the interaction between global brokerage and local cohesion, especially in the maiden years of consortia: here, consortia that combined being in locally embedded networks with a brokerage position in the complete network were more innovative compared to consortia that had other combinations of local cohesion and global brokerage.

Chapter 2 and Chapter 3 considered the role of networks for the innovative outcomes of R&D consortia. In Chapter 4 and Chapter 5, we moved our focus to the level of the complete consortium network. In Chapter 4, we started from the observation that existing literature suggests a differentiated development of networks in different technology fields. However, Dutch innovation policy tends to approach these networks as homogeneous both with respect to structure and in ways to ensure their viability. To explore the validity of this assumption in this policy approach we addressed the question if interorganizational technology field networks differ in their development in this chapter. By considering both network structural characteristics and the node set that comprises a network, we proposed an analytical framework that revolved around the 'network state' concept. We conceptualized this network state as a configuration of values in a five-dimensional state space: network centralization, network density, network size, the number of exiting nodes, and entrants. This model of network states was used to explore the evolution of 7 distinct technology field consortium networks over 23 years, using a latent profile analysis. This method allowed a mapping of all possible dynamics of a network through tracing a sequence of state changes over time. Our findings revealed that network dynamics unfold over sequences of changes in five distinct states: formation, growth, stagnation, stability and disintegration. Although we found a core sequence of state changes of formation, via growth, to stability, we also found considerable variations on, and extensions of this pathway. In addition to suggesting a terminology to talk about network dynamics at the complete network level, the most important findings of this chapter were that (1) field network dynamics are anything but homogeneous, and (2) the duration of states across consortium networks in different technology fields differs considerably across such fields.

In Chapter 5, our focus was on the role of knowledge in the generation of network-level innovative outcomes. Although several scholars have addressed the issue of explaining outcomes of interorganizational networks at the network level, the role of knowledge in the generation of these outcomes, especially in the case of publicly funded R&D networks is understudied. In addition, this topic is important to consider since, despite the many advantages of networks as flexible forms of organizing, several studies have shown that overall change in a network's environment can be detrimental for network outcomes. Hence, we used our insights regarding technology field network dynamics from Chapter 4 for determining technology field stability and considered the role of such stability in the generation of network-level outcomes (research questions 1 and 3). Building on the preliminary theory of network effectiveness as suggested by Provan and Milward (1995) and Provan and Sebastian (1998), we developed a model in which network innovative performance is explained by the level of node entry, stayers and node exit, and network integration. These acted as proxies for mechanisms of knowledge variation, selection and retention. Using a sample of 93 R&D consortium networks in the Dutch context, our analysis suggested an important role of said predictors in explaining network innovative performance. The effect of node entry (enabling knowledge variation) on innovative outcomes was found to be negative in the short run. This effect however, switches to positive in the longer run. In addition, the effect of stayers (enabling positive knowledge selection) was found to be positive on the short

TABLE 25

Overview of main findings with respect to the relation between networks and innovation

Level of analysis	Chapter	Hypothesis	Predictor(s)	Hypothesized effect	Finding(s)
Consortium	2	2.2	Geographical proximity	Inverted u-shape	Not supported
		2.4	Technological diversity	Inverted u-shape	Not supported
	3	3.1	Global brokerage (1), time (3)	(3) negatively moderates positive effect of (1)	Not supported, negative effect salient 4 and 2 years before evaluation
		3.2	Local cohesion (2), time (3)	(3) positively moderates positive effect of (2)	Not supported, an overall positive effect is found over time
		3.3	(1), (2), (3)	Positive effect of interaction between (1) and (2) when (3) marks the period in-between the start and end stage of a consortium	Supported
	2	2.1	Network integration	Inverted u-shape	Supported with respect to density-based network integration
		2.3		Positively moderates 2.2	Not supported
		2.5		Negatively moderates 2.4	Not supported, an inverted u-shaped relation is found when network integration is density-based (i.e. positive moderation)
Network	5	5.4	Network integration (retention)	Positive effect	Not supported
		5.1	Node entry (variation)	Positive effect	Supported when a time lag of 5 years is used
		5.2	Node exit (negative selection)	Inverted u-shape	Not supported
		5.3	Stayers (positive selection)	Inverted u-shape	Not supported, a positive relation is found when a time lag of 1 year is used
Technology field	4	4.1	Technology field	Moderates pace and nature of dynamics	A basic pathway is found, yet considerable differences between fields are observed in terms of state durations. Also, alterations on the basic pathway across fields are found
	5	5.5	Technology field stability	Positively moderates 5.4	Supported with respect to density-based network integration

run. Lastly, our results suggested a crossover interaction between network integration (enabling knowledge retention) and technology field stability.

The findings of each chapter are summarized in Table 25. Rows in this table are sorted by the 'Predictor(s)'-column, with predictors at the lowest level of analysis (i.e. the level of the consortium) being listed first, and predictors at the highest level of analysis (i.e. the technology field) being listed last. In addition, findings regarding network integration (for which the effect on innovation was considered at both the consortium and the network-level) are grouped. As a general observation it can be said that, even though our findings were not always according to what was expected theoretically, networks do matter for innovation at multiple levels of organization, and so does a consideration of network and technology field dynamics. First, the network position of R&D consortia affects innovative outcomes of such consortia in the following way: the global brokerage position of R&D consortia in the complete network negatively affects consortium outcomes. When the moderating role of time is considered in this relationship, we found that this negative effect is especially salient in the consortium's execution stage (i.e. after the year in which a consortium started, but before the year in which it ends). In addition, the local cohesion of a consortium's ego network positively affects its innovative outcomes, regardless of the stage a consortium is in. Both global brokerage and local cohesion reinforce one another during the midst of a consortium, leading to a higher likelihood of a consortium generating innovative outcomes.

Second, the consortium network structure affects the innovative outcomes of R&D consortia in the following way: consortia that are embedded in consortium networks that can be characterized by density-based network integration are more likely to generate innovative outcomes compared to consortia that are embedded in networks that are characterized by other forms of network integration. In addition, we find that in consortium networks that can be characterized by density-based integration, the relation between technological diversity of members and the likelihood of a consortium generating innovative outcomes follows an inverted U-shaped pattern. With respect to the relative effects of consortium features, a consortium's position in the consortium network and the consortium network structure, positional effects (i.e. local cohesion and global brokerage) are considerably weaker compared to consortium-level effects (Chapter 3). Both effects are less important compared to network-level effects (i.e. network integration, Chapter 2). Hence, in the generation of innovative outcomes by R&D consortia, network structural features seem to be more important than consortium features and a consortium's position in the network.

As already described above, we considered the moderating role of network dynamics on the consortium-level by considering the moderating role of time. On the network level, the role of network dynamics was considered by focusing on node entry, node exit and stayers. It was found that entry of new nodes has a long-term (i.e. time lag of 5 years) effect on network innovative outcomes. Stayers positively affect network innovative outcomes within a time lag of 1 year. In addition, the moderating role of technology field dynamics was considered on the network level. Although no direct effect of network structure on the generation of network-level outcomes was found, we did find an interaction effect between density-based network integration and technology field stability. Hence, as technology fields become more stable, density-based network integration enables the retention of knowledge in networks, which enables these networks to reach higher levels of innovation.

6.3 Theoretical contributions

In section 1.4 of this dissertation, we identified three overarching theoretical contributions. The first contribution is that in this dissertation, R&D consortia and consortium networks are considered as a distinct form of organization. The second contribution is that, in our quest to explain the innovativeness of such R&D consortia and consortium networks, we considered the relation between consortium and consortium network features and innovation using a multi-level perspective. The third contribution is that while considering said relation between features of R&D consortia and consortium networks, and innovation, we included the role of time, for example by exploring various time lags between antecedents and outcomes, but also by considering factors such as the building up of collaboration experience across consortium members and consortium leaders, and field stability.

Few scholars focusing on R&D consortia consider such collaborations as an emergent form of organizing in its own right. In addition, a scarce literature exists on complete networks and their dynamics. Hence, we pulled together a variety of other research streams (i.e. whole networks, technological change and innovation, network dynamics, knowledge-based view and interorganizational relations) to shed light on the main research questions that are addressed in this dissertation. Throughout this apparent mix of academic work, however, one seminal publication has recurred several times as a beacon of light throughout the chapters in this dissertation: Provan and Milward's (1995) preliminary theory of network effectiveness. In this work, the authors develop a conceptual model that explains network effectiveness by various structural and contextual factors (i.e. network integration, external control, system stability and resource munificence). Many of the ideas that are elaborated in this dissertation pursue an extension of this preliminary theory. We therefore carve out the main theoretical contributions of this dissertation using the work of Provan and Milward (1995) as the main benchmark.

With respect to the first contribution (i.e. considering R&D consortia as a distinct form of organizing at both the consortium level and the level of the consortium network), we have applied the ideas of Provan and Milward (1995) and scholars that have built forth on these ideas (Turrini et al., 2009) to a new, rather underexplored setting. Network effectiveness has usually been studied in whole network research. Work in this realm considers networks as consciously created groups of three or more autonomous organizations in which the actors involved strive towards reaching a joint goal and jointly produce an output (Raab & Kenis, 2009). By applying the insights from this research area to R&D consortia and consortium networks, we have considered new boundary conditions of the existing preliminary theory of network effectiveness: although the formation and development of R&D consortia and consortium networks are consciously initiated and stimulated, the nature of the task at hand differs (i.e. technological development in R&D consortia versus service delivery in whole networks) and generally actors are much less aware of one another and joint goals, especially at the complete network level.

Indeed, our findings suggest that different mechanisms are at play in the relation between consortium and network features and innovative outcomes. For example, Provan and Milward (1995) propose that for networks to be effective, a necessary condition is that these networks should be integrated through a single core agency. In chapter 2 of this dissertation, such integration would resemble 'centralization-based network integration'. We find that this form of network integration does not have an explicit effect in the networks studied in this dissertation. Density-based integration, however, does. Hence, it seems that in the consortium networks studied in this dissertation a different source of integration is at play than the one suggested by Provan and

Milward (1995). In addition, our findings in Chapter 3 suggest that especially consortia that are embedded in locally cohesive networks (i.e. dense networks) consistently are more innovative over time. Lastly, the results of Chapter 5 suggest that, as the stability of a technology field increases, network density has a positive effect on network innovativeness when a time lag of 1 year is considered. Hence, in the absence of shared goals, it is not active coordination through a central agency that leads to innovative R&D consortia and consortium networks. Instead, a more emergent coordination through joint member ties is what makes these consortia and networks innovative. This juxtaposition that results from considering different boundary conditions makes that R&D consortia and consortium networks should not be treated like whole networks[39], but instead should be considered as a distinct form of organizing. This contribution echoes other work in the realm of R&D consortia that stresses the importance of consciously organizing and managing consortia to effectively govern the jointly created pool of resources (Allarakhia & Walsh, 2012; Roelofsen et al., 2011; Sydow et al., 2012).

With respect to the second theoretical contribution of this dissertation (i.e. the use of a multi-level perspective), Provan & Milward (1995) explicitly moved away from a focus on relations between nodes and addressed the issue of the effectiveness of networks as a whole. From that perspective, it is sensible to focus at one level (i.e. the network-level) only, even though the preliminary theory of Provan & Milward (1995) has a multi-level element as it proposed the concept of system stability: networks that operate in an environment that is unstable due to state-wide changes in the funding and delivery of services are proposed to be less effective compared to networks that operate in a stable environment, as environmental instability leads to uncertainty with, in turn, "unpredictable consequences" (Provan & Milward, 1995). The nestedness of network phenomena, however, calls for an explicit incorporation of multiple levels of analysis in network research (Contractor et al., 2006; Lusher et al., 2013; Zappa & Lomi, 2015) and Zappa and Lomi (2015). By considering multiple levels of analysis in each chapter in this dissertation, we have extended the preliminary theory of network effectiveness of Provan and Milward (1995) in two related ways.

First, little consideration is given in the model of Provan and Milward (1995) to features of network nodes, such as geographical proximity and technological diversity. Also, scholars that have built on this model in the realm of public policy studies have barely touched upon this issue (Turrini et al., 2009). The other way round, the large and established literature on networks and innovation is dominated by a focus on nodes, and rarely considers the effect of node features and network features in tandem[40] (Soda, Tortoriello, & Iorio, 2017). By considering both the node and network level in explaining consortium innovativeness in Chapter 2 using a large-n study, we have explored the boundary conditions under which certain effects occur. For example, a key finding in Chapter 2 is that the inverted-u shaped relationship between technological diversity and consortium innovation only occurs under conditions of density-based network integration. Hence, only when a joint knowledge base is created in the network that facilitates efficient search and flexibility and that allows for specialization of individual nodes and mutual technological adjustment, technological diversity facilitates consortium innovativeness, but only up to a certain point. After that point, the positive effect of the varied body of knowledge and subsequent potential for

[39] Recall that in research on alliance networks, multi-partner collaborations are usually excluded from the analysis or stripped down to dyadic collaborations. Hence, few studies on alliance networks have considered multi-partner constellations such as R&D consortia, and even fewer studies have considered the relation between complete networks and innovation. Hence, we focus in this discussion on comparing our results with the insights derived from the research field on whole networks.

[40] For one of the exceptions, see Schilling and Phelps (2007).

knowledge recombination is offset by collaboration difficulties and efficiency losses. In addition to exploring boundary conditions of certain effects, our theoretical extension also suggests that features at the network level (i.e. network density) that might lead to network innovativeness do not always lead to individual network nodes being innovative (i.e. multiple consortium membership).

Second, network studies that consider multiple levels rarely consider the environment of a network. We are the first that have made the mechanism that relates stability of the environment (i.e. field stability) in which a network is embedded to the effectiveness of such a network more explicit. Whereas Provan and Milward (1995) related the absence of system stability to uncertainty that could have unpredictable consequences, we have specified this mechanism in the context of R&D consortium networks that are embedded in technology fields that can have various degrees of stability: in stable technology fields, search routines can be build up which allow network members to manage and exploit the status quo. Yet, significant turning points in the underlying technology field necessitates an adaptation of such search routines, which takes time. Indeed, the positive moderation effect of technology field stability on the relation between density-based network integration and innovative outcomes in Chapter 5, based on a large-n study (at least relative to the available academic work on complete networks to date), supports the hypothesis that was derived from this mechanism and more generally supports one of the propositions of Provan and Milward (1995).

The third contribution of this dissertation is that the role of time is considered in the relation between features of R&D consortia and consortium networks, and innovation, as well as consortium network dynamics. The model of Provan and Milward (1995) does not explicitly consider time, although here as well, the concept of system stability implicitly incorporates a temporal dimension. Recent studies, however, have suggested that the value of a network for its nodes and as a whole does not remain constant over time (Ahuja et al., 2012; Gilsing et al., 2016). In this dissertation we incorporated the role of time in two ways: first, different time lags are explored in the relation between consortium and network features and innovation. Second, network development is considered over time. Both are extensions of the preliminary theory of network effectiveness: acknowledging time lags helps in understanding the boundary condition *when* a certain effect occurs (Whetten, 1989) and conceptualizing network dynamics aids in operationalizing and testing the effect of system stability and aids in developing a vocabulary that supports academic conversations about the phenomenon of complete network dynamics.

With respect to the first incorporation of time in this dissertation, different time lags were considered between consortium features and innovation in Chapter 3, and between consortium network features and innovation in Chapter 5. Findings in Chapter 3 suggest that consortia have a continuous need of being embedded in a locally cohesive network to be innovative. Being globally central in the network hurts innovative performance, especially during the consortium's execution stage (i.e. after the year in which a consortium started, but before the year in which it ends). Findings in Chapter 5 suggest that node entry has a positive effect on network innovation on the long run (i.e. after five years). Stayers, on the other hand have a positive effect on network innovation on the short run (i.e. after one year). This suggests that some of the proposed mechanisms are not always at play in both consortia and consortium networks, and invite a further theoretical conceptualization for the field of network research with respect to time lags between predictor and outcome variables.

With respect to the consideration of network dynamics, Chapter 4 in this dissertation represents one of the first attempts to analyse network dynamics at the network level and it makes suggestions for a terminology that aids in talking about that phenomenon. In this chapter, the focus is on the role of node turnover, which is rarely done even though it is essential for a better understanding of network dynamics. This importance is demonstrated in Chapter 5, in which it is suggested that for complete networks to sustain their innovativeness, both knowledge variation through node entry and knowledge selection through stayers needs to be ensured. By focusing on technology field dynamics, we contribute to the literature on interorganizational network dynamics by providing a more explanatory narrative of such dynamics (as opposed by the often rather descriptive accounts of such dynamics that are provided in the existing literature (Gay & Dousset, 2005; Orsenigo et al., 2001; Powell et al., 2005), and demonstrate the importance of considering system stability that has been proposed in the literature on whole networks (Provan & Milward, 1995; Provan & Sebastian, 1998).

6.4 Practical implications

In addition to the theoretical merits of the studies reported in this dissertation, our findings also bear significance for practice. In the introduction of this dissertation, we posed that both consortium managers as policy makers simultaneously manage and muddle through with respect to R&D collaborations. With respect to consortium design, consortium managers can manage several inputs, such as selecting the most suitable partners, setting up a clear collaboration structure and organizing a filing system that allows for sharing knowledge embedded in documents such as minutes, research reports and white papers in order to deliver a certain innovative output. Network-level effects stemming from network volatility, complete network structure and the partners of one's partners, although also acting as an input for the consortium, are more difficult to control and hence make generating a certain output more challenging. It is at especially this level at which one is convicted to muddle through.

When we consider Table 25, several implications for consortium managers as well as innovation policy can be derived. First, for managers of R&D consortia, it is important to recognize the importance of not only features of potential individual members, but also features of the consortium that emerge as the aggregate of individual member features. For example, our findings suggest an important role for technological diversity for the generation of consortium innovative outcomes in dense networks. Hence, consortium managers should at least be aware of the role of both aspects: although it would go too far to claim that one can only start a consortium the moment technological diversity is at the optimal in-between level (one can think of many situations in which this simply is impossible), at least being aware of possible detrimental effects of low or high levels of technological diversity helps to mitigate such effects.

In addition, our findings demonstrate that the innovative outcomes of R&D consortia are partly determined by network-level as well as network positional features (i.e. local cohesion and global brokerage). Yet, the agency of consortium managers does not extend to the network-level, which leaves little room for changing this network once a consortium is embedded in it. In addition, our results in Chapter 3 suggest that the position of R&D consortia remains rather stable over time in terms of centrality. Even though one could set-up a "network migration" strategy that aims at aligning the network position of a consortium with the different stages in the process of R&D, such a strategy involves orchestrating joint memberships with other consortia, which is something that might not always be in the realm of control of the consortium manager. Hence, we suggest that it is especially important for consortium managers to consider potential network positions and structures upfront (i.e. before starting a consortium): it is in the partner selection strategy where we see most room for determining the final position of a consortium in an R&D network. Considering network structure also helps in selecting viable future avenues for research: parts of the network that are characterized by high density levels imply that many different consortia revolve around a certain topic, and hence chances for success for those initiating new consortia might be lower in those parts. Determining in which R&D consortium network a consortium becomes embedded is much more difficult to control by individual consortium managers, as this is often determined by the technology field in which such a consortium leader is active. Similar to anticipating possible detrimental effects of technological diversity, however, consortium managers can strive to anticipate possible detrimental effects of network position and network structure: forewarned is forearmed.

With respect to organizing complete network structures, we see a prominent role for innovation policy. Our findings suggest that both R&D consortia as consortium networks are most likely to be innovative under conditions of density-based network integration. This source of network integration resembles a mode of network governance that has been proposed by Provan and Kenis (2008): density-based integration resembles shared participant-governed networks, in which network members typically have ongoing and jointly coordinated interaction on a relatively equal basis in the process of innovation (Provan & Kenis, 2008). Such governance can be stimulated through organizing regular meetings of consortium managers or organizing symposia during which consortium managers and members interact with one another and exchange findings across consortia. Regardless of the choice of governance mode, network mapping by the funding agency should be a key first step and different paces of network formation and development across technology fields should be considered.

6.5 Limitations and directions for future research

Despite the contributions of the research reported in this dissertation, several key limitations and future research avenues can be identified. First, the data used throughout this dissertation stems from a specific funding scheme that is active in the Netherlands. This raises the question to what extent the findings reported in this dissertation are applicable to other settings. Although we expect our findings to hold in other networks that involve industry-university interaction focused at jointly conducting basic R&D, an interesting question could be to explore the boundaries of nature of the task at hand. We already mentioned, for example, the possibility to investigate the issues addressed with respect to consortium-level outcomes in other empirical contexts, such as alliance constellations. Obviously, also data on other funding schemes could be collected. A comparable funding scheme in the Netherlands was that of the innovation oriented research programme (Velzing, 2013), which was later absorbed by the top sector approach that started as from 2012. Similar programs in other countries obviously also could be investigated.

A second limitation that stems from the data used is that -even though the size of the dataset offers ample opportunity to study the topics focused at in this dissertation- it provides a rather generic view on the relation between networks and innovation. For example, being able to incorporate networks embedded in different technology fields offers ample opportunity to control for technology field differences. It is, however, also interesting to focus on each technology field in more detail to get a better hold on what is going on in such fields and how that relates to collaboration with respect to R&D and innovation. Hence, future research could focus on any one of the seven technology fields considered in this chapter to get a more in-depth insight regarding the topics covered in this dissertation within technology fields.

The third limitation is that Manski's (1993) reflection problem applies to studies that focus on the relation between networks and innovation: it could be possible that the performance of an R&D consortium is the result of exogeneous effects (other consortia in a technology field also perform well), endogenous effects (consortia performance tends to vary across technology fields), or correlated effects (consortia performance tends to vary because consortia face similar institutional effects (Manski, 1993). Although we do use lagged models, our models do not completely circumvent the problem of simultaneity or unobserved environmental causes (Hasan & Bagde, 2015). Getting more insight in the specific lag structure between R&D and innovation or specifying an instrumental variable that conveys influence from the environment to the consortium could address the reflection problem, although such data is difficult to obtain.

The fourth limitation of the studies reported in this dissertation is that we approach the relation between networks and innovation from a structuralist perspective. Although we do show that network structure has a profound effect in the generation of innovative outcomes by both R&D consortia as consortium networks, using a structuralist perspective involves making assumptions that have been challenged by some scholars. For example, Ghosh and Rosenkopf (2015) challenge the assumption that knowledge always flows through networks. These authors claim that frictions in interorganizational networks exist, for example due to the nature of knowledge and the composition of ties, which might hamper the unconditional flow of knowledge (Ghosh & Rosenkopf, 2015). Although this issue could partly be mitigated by incorporating tie strength when calculating the network measures used in this dissertation, this would still be a proxy for actual knowledge flows. Hence, future research should consider in more depth the role of joint member ties between consortia, motivations of members to share knowledge in consortia, the content of these ties as well as the characteristics of knowledge that flows through these ties (e.g. tacit vs. explicit, specific vs. general) (Aven, 2015; Daskalaki, 2010; Reagans & McEvily, 2003; Wang & Soule, 2012).

A fifth limitation of the work reported in this dissertation is that the role of time in the relation between networks and innovation is approached rather empirical, except for Chapter 4. Future research should delve deeper into the processes that drive collaboration in R&D consortia over time. One could, for example, follow the formation and development of several R&D consortia from the start until the end, and link the collaboration dynamics observed to the different stages that have been identified in the process of research and development and innovation (Ibert & Müller, 2015). This could, for example, elucidate the role of joint member ties at different points in time.

The last limitation of the studies reported in this dissertation is that -even though each chapter builds on the premise that consortium managers and innovation policy makers should focus on network management- we know little about the extent to which those actors are aware of these networks, let alone the extent to which they manage network positions and structures. Most studies have considered knowledge flows in the context of R&D as involuntary. Yet, more recently authors have suggested that actors might need to take positive action instead, to share knowledge with others and spur innovation processes at both the consortium and the network level as a result (Ahrweiler, Pyka, & Gilbert, 2011). In this light, several authors have explicitly focused at actors deploying networking strategies (Bensaou, Galunic, & Jonczyk-Sédès, 2014). Others have even focused at more specific roles, for example the role of brokers as "network architects" (Pollock et al., 2004). Further investigating such targeted action in networks helps increasing our understanding of the strategies available to shape networks (Hallen, 2008). Hence, future research should consider agency in the formation and development of networks.

6.6 Concluding remarks

With this dissertation, we suggest that there is value in considering the role of higher-order network effects in the relation between networks and innovation. Doing so provides levers to move away from muddling through with respect to these effects, and towards a more targeted management. The insights generated in this dissertation form a fruitful starting point for further research on this topic. As illustrated by the questions raised in the previous section -which are just some examples of the many interesting issues one could focus at- numerous and promising opportunities await those who want to embark further on the path of obtaining more insight in the relation between networks and innovation through conducting multi-level studies.

References

Aalbers, H. L., Dolfsma, W., & Leenders, R. T. A. J. (2016). Vertical and Horizontal Cross-Ties: Benefits of Cross-Hierarchy and Cross-Unit Ties for Innovative Projects. *Journal of Product Innovation Management, 33*(2), 141-153. doi:10.1111/jpim.12287

Abernathy, W. J., & Utterback, J. M. (1978). Patterns of Industrial Innovation. *Technology Review, 80*(7), 40-47.

Abrahamson, E., & Fairchild, G. (1999). Management Fashion: Lifecycles, Triggers, and Collective Learning Processes. *Administrative Science Quarterly, 44*(4). doi:10.2307/2667053

Adler, P. S. (2001). Market, Hierarchy, and Trust: The Knowledge Economy and the Future of Capitalism. *Organization Science, 12*(2), 215-234. doi:10.1287/orsc.12.2.215.10117

Adler, P. S., & Kwon, S. W. (2002). Social Capital: Prospects for a New Concept. *Academy of Management Review, 27*(1), 17-40. doi:10.5465/amr.2002.5922314

Afuah, A. (2013). Are network effects really all about size? The role of structure and conduct. *Strategic Management Journal, 34*(3), 257-273. doi:10.1002/smj.2013

Agarwal, R., Sarkar, M. B., & Echambadi, R. (2002). The Conditioning Effect of Time on Firm Survival: An Industry Life Cycle Approach. *Academy of Management Journal, 45*(5), 971-994. doi:10.2307/3069325

Agrawal, A. (2006). Engaging the inventor: exploring licensing strategies for university inventions and the role of latent knowledge. *Strategic Management Journal, 27*(1), 63-79. doi:10.1002/smj.508

Aguinis, H., Gottfredson, R. K., & Culpepper, S. A. (2013). Best-Practice Recommendations for Estimating Cross-Level Interaction Effects Using Multilevel Modeling. *Journal of Management, 39*(6), 1490-1528. doi:10.1177/0149206313478188

Aharonson, B. S., & Schilling, M. A. (2016). Mapping the technological landscape: Measuring technology distance, technological footprints, and technology evolution. *Research Policy, 45*(1), 81-96. doi:10.1016/j.respol.2015.08.001

Ahrweiler, P., Pyka, A., & Gilbert, N. (2011). A New Model for University-Industry Links in Knowledge-Based Economies*. *Journal of Product Innovation Management, 28*(2), 218-235. doi:10.1111/j.1540-5885.2010.00793.x

Ahuja, G. (2000a). Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study. *Administrative Science Quarterly, 45*(3), 425. doi:10.2307/2667105

Ahuja, G. (2000b). The duality of collaboration: inducements and opportunities in the formation of interfirm linkages. *Strategic Management Journal, 21*(3), 317-343. doi:10.1002/(sici)1097-0266(200003)21:3<317::aid-smj90>3.0.co;2-b

Ahuja, G., & Katila, R. (2004). Where do resources come from? The role of idiosyncratic situations. *Strategic Management Journal, 25*(89), 887-907. doi:10.1002/smj.401

Ahuja, G., Lampert, C. M., & Tandon, V. (2014). Paradigm-Changing vs. Paradigm-Deepening Innovation: How Firm Scope Influences Firm Technological Response to Shocks. *Organization Science, 25*(3), 653-669. doi:10.1287/orsc.2013.0867

Ahuja, G., Polidoro, F., & Mitchell, W. (2009). Structural homophily or social asymmetry? The formation of alliances by poorly embedded firms. *Strategic Management Journal, 30*(9), 941-958. doi:10.1002/smj.774

Ahuja, G., Soda, G., & Zaheer, A. (2012). The Genesis and Dynamics of Organizational Networks. *Organization Science, 23*(2), 434-448. doi:10.1287/orsc.1110.0695

Albert, S., & Bell, G. G. (2002). Timing and Music. *Academy of Management Review, 27*(4), 574-593. doi:10.5465/amr.2002.7566078

Aldrich, H., & Kenworthy, A. L. (1999). The Accidental Entrepreneur. Campbellian Antinomies and Organizational Foundings. In J. A. C. Baum & B. McKelvey (Eds.), *Variations in organization science: In honor of Donald T. Campbell* (pp. 19-33). Thousand Oaks: Sage.

Aldrich, H. E., & Sasaki, T. (1995). R&D consortia in the United States and Japan. *Research Policy, 24*(2), 301-316. doi:10.1016/0048-7333(93)00768-o
Ali, A., & Gittelman, M. (2016). Research paradigms and useful inventions in medicine: Patents and licensing by teams of clinical and basic scientists in Academic Medical Centers. *Research Policy, 45*(8), 1499-1511. doi:10.1016/j.respol.2016.03.015
Alic, J. A. (1990). Cooperation in R&D. *Technovation, 10*(5), 319-332. doi:10.1016/0166-4972(90)90016-d
Alkemade, F., Heimeriks, G., Schoen, A., Villard, L., & Laurens, P. (2015). Tracking the internationalization of multinational corporate inventive activity: national and sectoral characteristics. *Research Policy, 44*(9), 1763-1772. doi:10.1016/j.respol.2015.01.007
Allarakhia, M., & Walsh, S. (2012). Analyzing and organizing nanotechnology development: Application of the institutional analysis development framework to nanotechnology consortia. *Technovation, 32*(3-4), 216-226. doi:10.1016/j.technovation.2011.11.001
Allatta, J. T., & Singh, H. (2011). Evolving communication patterns in response to an acquisition event. *Strategic Management Journal, 32*(10), 1099-1118. doi:10.1002/smj.930
Ancona, D. G., & Caldwell, D. F. (1992). Demography and Design: Predictors of New Product Team Performance. *Organization Science, 3*(3), 321-341. doi:10.1287/orsc.3.3.321
Ancona, D. G., Goodman, P. S., Lawrence, B. S., & Tushman, M. L. (2001). Time: A New Research Lens. *Academy of Management Review, 26*(4), 645-663. doi:10.5465/amr.2001.5393903
Anderson, P., & Tushman, M. L. (1990). Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. *Administrative Science Quarterly, 35*(4), 604. doi:10.2307/2393511
Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. (2010). On making causal claims: A review and recommendations. *The Leadership Quarterly, 21*(6), 1086-1120. doi:10.1016/j.leaqua.2010.10.010
Archibugi, D. (2006). Pavitt's Taxonomy Sixteen Years On: A Review Article. *Economics of Innovation and New Technology, 10*(5), 415-425. doi:10.1080/10438590100000016
Argyres, N., Bigelow, L., & Nickerson, J. A. (2015). Dominant designs, innovation shocks, and the follower's dilemma. *Strategic Management Journal, 36*(2), 216-234. doi:10.1002/smj.2207
Ata, B., & Van Mieghem, J. A. (2009). The Value of Partial Resource Pooling: Should a Service Network Be Integrated or Product-Focused? *Management Science, 55*(1), 115-131. doi:10.1287/mnsc.1080.0918
Audia, P. G., Freeman, J. H., & Reynolds, P. D. (2006). Organizational Foundings in Community Context: Instruments Manufacturers and Their Interrelationship with Other Organizations. *Administrative Science Quarterly, 51*(3), 381-419. doi:10.2189/asqu.51.3.381
Audretsch, D. B. (1997). Technological Regimes, Industrial Demography and the Evolution of Industrial Structures. *Industrial and Corporate Change, 6*(1), 49-82. doi:10.1093/icc/6.1.49
Autant-Bernard, C. (2001). Science and knowledge flows: evidence from the French case. *Research Policy, 30*(7), 1069-1078. doi:10.1016/s0048-7333(00)00131-1
Aven, B. L. (2015). The Paradox of Corrupt Networks: An Analysis of Organizational Crime at Enron. *Organization Science, 26*(4), 980-996. doi:10.1287/orsc.2015.0983
Bakker, R. M. (2016). Stepping in and stepping out: Strategic alliance partner reconfiguration and the unplanned termination of complex projects. *Strategic Management Journal, 37*(9), 1919-1941. doi:10.1002/smj.2429
Bakker, R. M., DeFillippi, R. J., Schwab, A., & Sydow, J. (2016). Temporary Organizing: Promises, Processes, Problems. *Organization Studies*. doi:10.1177/0170840616655982
Bakker, S., van Lente, H., & Meeus, M. T. H. (2012). Dominance in the prototyping phase—The case of hydrogen passenger cars. *Research Policy, 41*(5), 871-883. doi:10.1016/j.respol.2012.01.007
Barabási, A.-L., & Bonabeau, E. (2003). Scale-free networks. *Scientific American, 288*(5), 60-69. doi:10.1038/scientificamerican0503-60

Barnett, W. P., & Burgelman, R. A. (2007). Evolutionary perspectives on strategy. *Strategic Management Journal, 17*(S1), 5-19. doi:10.1002/smj.4250171003

Bartmess, A., & Cerny, K. (1993). Building Competitive Advantage through a Global Network of Capabilities. *California Management Review, 35*(2), 78-103. doi:10.2307/41166723

Battilana, J., & Casciaro, T. (2012). Change Agents, Networks, and Institutions: A Contingency Theory of Organizational Change. *Academy of Management Journal, 55*(2), 381-398. doi:10.5465/amj.2009.0891

Baum, J. A. C., Calabrese, T., & Silverman, B. S. (2000). Don't go it alone: alliance network composition and startups' performance in Canadian biotechnology. *Strategic Management Journal, 21*(3), 267-294. doi:10.1002/(sici)1097-0266(200003)21:3<267::aid-smj89>3.0.co;2-8

Baum, J. A. C., Cowan, R., & Jonard, N. (2014). Does evidence of network effects on firm performance in pooled cross-section support prescriptions for network strategy? *Strategic Management Journal, 35*(5), 652-667. doi:10.1002/smj.2133

Baum, J. A. C., & McKelvey, B. (1999). *Variations in organization science: In honor of Donald T. Campbell*. Thousand Oaks: Sage.

Baum, J. A. C., Rowley, T. J., & Shipilov, A. V. (2005). Dancing with Strangers: Aspiration Performance and the Search for Underwriting Syndicate Partners. *Administrative Science Quarterly, 50*(4), 536-575. doi:10.2189/asqu.50.4.536

Baumann, O., & Siggelkow, N. (2013). Dealing with Complexity: Integrated vs. Chunky Search Processes. *Organization Science, 24*(1), 116-132. doi:10.1287/orsc.1110.0729

Becker, M. C., & Lillemark, M. (2006). Marketing/R&D integration in the pharmaceutical industry. *Research Policy, 35*(1), 105-120. doi:10.1016/j.respol.2005.09.005

Beckman, C. M., Haunschild, P. R., & Phillips, D. J. (2004). Friends or Strangers? Firm-Specific Uncertainty, Market Uncertainty, and Network Partner Selection. *Organization Science, 15*(3), 259-275. doi:10.1287/orsc.1040.0065

Bekkers, R., Duysters, G., & Verspagen, B. (2002). Intellectual property rights, strategic technology agreements and market structure. *Research Policy, 31*(7), 1141-1161. doi:10.1016/s0048-7333(01)00189-5

Bensaou, B. M., Galunic, C., & Jonczyk-Sédès, C. (2014). Players and Purists: Networking Strategies and Agency of Service Professionals. *Organization Science, 25*(1), 29-56. doi:10.1287/orsc.2013.0826

Bercovitz, J., & Feldman, M. (2011). The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. *Research Policy, 40*(1), 81-93. doi:10.1016/j.respol.2010.09.008

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. doi:10.1287/orsc.1100.0578

Bernal, J. D. (1939). *The Social Function of Science*. London: G. Routledge & Sons Ltd.

Berthod, O., Grothe-Hammer, M., Müller-Seitz, G., Raab, J., & Sydow, J. (2016). From High-Reliability Organizations to High-Reliability Networks: The Dynamics of Network Governance in the Face of Emergency. *Journal of Public Administration Research and Theory*. doi:10.1093/jopart/muw050

Bertolotti, F., Mattarelli, E., Vignoli, M., & Macrì, D. M. (2015). Exploring the relationship between multiple team membership and team performance: The role of social networks and collaborative technology. *Research Policy, 44*(4), 911-924. doi:10.1016/j.respol.2015.01.019

Bickhard, M. H., & Campbell, D. T. (2003). Variations in Variation and Selection: The Ubiquity of the Variation-and-Selective-Retention Ratchet in Emergent Organizational Complexity. *Foundations of Science, 8*(3), 215-282. doi:10.1023/a:1025046917589

Bidwell, M., & Fernandez-Mateo, I. (2010). Relationship Duration and Returns to Brokerage in the Staffing Sector. *Organization Science, 21*(6), 1141-1158. doi:10.1287/orsc.1090.0509

Biemann, T., & Kearney, E. (2009). Size Does Matter: How Varying Group Sizes in a Sample Affect the Most Common Measures of Group Diversity. *Organizational Research Methods, 13*(3), 582-599. doi:10.1177/1094428109338875

Biggart, N. W., & Delbridge, R. (2004). Systems of Exchange. *Academy of Management Review, 29*(1), 28-49. doi:10.5465/amr.2004.11851707

Birkinshaw, J., Bessant, J., & Delbridge, R. (2007). Finding, Forming, and Performing: Creating Networks for Discontinuous Innovation. *California Management Review, 49*(3), 67-84. doi:10.2307/41166395

Birkinshaw, J., Hood, N., & Jonsson, S. (1998). Building firm-specific advantages in multinational corporations: the role of subsidiary initiative. *Strategic Management Journal, 19*(3), 221-242. doi:10.1002/(sici)1097-0266(199803)19:3<221::aid-smj948>3.0.co;2-p

Bishop, K., D'Este, P., & Neely, A. (2011). Gaining from interactions with universities: Multiple methods for nurturing absorptive capacity. *Research Policy, 40*(1), 30-40. doi:10.1016/j.respol.2010.09.009

Boardman, P. C., & Corley, E. A. (2008). University research centers and the composition of research collaborations. *Research Policy, 37*(5), 900-913. doi:10.1016/j.respol.2008.01.012

Bodas Freitas, I. M., Marques, R. A., & Silva, E. M. d. P. e. (2013). University–industry collaboration and innovation in emergent and mature industries in new industrialized countries. *Research Policy, 42*(2), 443-453. doi:10.1016/j.respol.2012.06.006

Bogers, M., Afuah, A., & Bastian, B. (2010). Users as Innovators: A Review, Critique, and Future Research Directions. *Journal of Management, 36*(4), 857-875. doi:10.1177/0149206309353944

Bogliacino, F., & Pianta, M. (2016). The Pavitt Taxonomy, revisited: patterns of innovation in manufacturing and services. *Economia Politica, 33*(2), 153-180. doi:10.1007/s40888-016-0035-1

Bond, E. U., Walker, B. A., Hutt, M. D., & Reingen, P. H. (2004). Reputational Effectiveness in Cross-Functional Working Relationships. *Journal of Product Innovation Management, 21*(1), 44-60. doi:10.1111/j.0737-6782.2004.00053.x

Bonesso, S., Comacchio, A., & Pizzi, C. (2011). Technology sourcing decisions in exploratory projects. *Technovation, 31*(10-11), 573-585. doi:10.1016/j.technovation.2011.06.001

Borgatti, S. P. (1997). Structural Holes: Unpacking Burt's Redundancy Measures. *Connections, 20*(1), 35-38.

Borgatti, S. P., & Foster, P. C. (2003). The Network Paradigm in Organizational Research: A Review and Typology. *Journal of Management, 29*(6), 991-1013. doi:10.1016/s0149-2063_03_00087-4

Boschma, R. (2005). Proximity and Innovation: A Critical Assessment. *Regional Studies, 39*(1), 61-74. doi:10.1080/0034340052000320887

Bramwell, A., & Wolfe, D. A. (2008). Universities and regional economic development: The entrepreneurial University of Waterloo. *Research Policy, 37*(8), 1175-1187. doi:10.1016/j.respol.2008.04.016

Branstetter, L. G., & Sakakibara, M. (2002). When Do Research Consortia Work Well and Why? Evidence from Japanese Panel Data. *American Economic Review, 92*(1), 143-159. doi:10.1257/000282802760015649

Brass, D. J., Galaskiewicz, J., & Greve, H. R. (2004). Taking Stock of Networks and Organizations: A Multilevel Perspective. *Academy of Management Journal, 47*(6), 795-817. doi:10.2307/20159624

Breschi, S., & Catalini, C. (2010). Tracing the links between science and technology: An exploratory analysis of scientists' and inventors' networks. *Research Policy, 39*(1), 14-26. doi:10.1016/j.respol.2009.11.004

Bridoux, F., Coeurderoy, R., & Durand, R. (2016). Heterogeneous social motives and interactions: The three predictable paths of capability development. *Strategic Management Journal*. doi:10.1002/smj.2605

Broström, A. (2010). Working with distant researchers—Distance and content in university–industry interaction. *Research Policy, 39*(10), 1311-1320. doi:10.1016/j.respol.2010.09.002

Brown, S. L., & Eisenhardt, K. M. (1995). Product Development: Past Research, Present Findings, and Future Directions. *Academy of Management Review, 20*(2), 343-378. doi:10.5465/amr.1995.9507312922

Browning, L. D., Beyer, J. M., & Shetler, J. C. (1995). Building Cooperation in a Competitive Industry: Sematech and the Semiconductor Industry. *Academy of Management Journal, 38*(1), 113-151. doi:10.2307/256730

Bruggeman, J. (2008). *Social Networks: An Introduction*. New York: Routledge.

Bunderson, J. S., & Sutcliffe, K. M. (2002). Comparing Alternative Conceptualizations of Functional Diversity in Management Teams: Process and Performance Effects. *Academy of Management Journal, 45*(5), 875-893. doi:10.2307/3069319

Burt, R. S. (1992). *Structural Holes: The Social Structure of Competition*. Cambridge: Harvard University Press.

Burt, R. S. (2000). The Network Structure of Social Capital. In B. M. Staw & R. I. Sutton (Eds.), *Research In Organizational Behavior* (pp. 345-423). Greenwich CT: JAI Press.

Burt, R. S. (2004). Structural Holes and Good Ideas. *American Journal of Sociology, 110*(2), 349-399. doi:10.1086/421787

Burt, R. S. (2005). *Brokerage and Closure*. Oxford: Oxford University Press.

Burt, R. S. (2007). Secondhand Brokerage: Evidence on the Importance of Local Structure for Managers, Bankers, and Analysts. *Academy of Management Journal, 50*(1), 119-148. doi:10.5465/amj.2007.24162082

Burt, R. S., Hogarth, R. M., & Michaud, C. (2000). The Social Capital of French and American Managers. *Organization Science, 11*(2), 123-147. doi:10.1287/orsc.11.2.123.12506

Buskens, V., & van de Rijt, A. (2008). Dynamics of Networks if Everyone Strives for Structural Holes. *American Journal of Sociology, 114*(2), 371-407. doi:10.1086/590674

Butts, C. T. (2008). A Relational Event Framework for Social Action. *Sociological Methodology*, 155-200. doi:10.1111/j.1467-9531.2008.00203.x

Calori, R., Baden-Fuller, C., & Hunt, B. (2000). Managing Change at Novotel: Back to the Future. *Long Range Planning, 33*(6), 779-804. doi:10.1016/s0024-6301(00)00090-x

Campbell, D. T. (1960). Blind variation and selective retentions in creative thought as in other knowledge processes. *Psychological Review, 67*(6), 380-400. doi:10.1037/h0040373

Caner, T., Cohen, S. K., & Pil, F. (2016). Firm heterogeneity in complex problem solving: A knowledge-based look at invention. *Strategic Management Journal*. doi:10.1002/smj.2615

Caner, T., Sun, J., & Prescott, J. E. (2014). When a firm's centrality in R&D alliance network is (not) the answer for invention: The interaction of centrality, inward and outward knowledge transfer. *Journal of Engineering and Technology Management, 33*, 193-209. doi:10.1016/j.jengtecman.2014.07.001

Cantwell, J., & Vertova, G. (2004). Historical evolution of technological diversification. *Research Policy, 33*(3), 511-529. doi:10.1016/j.respol.2003.10.003

Capaldo, A. (2007). Network structure and innovation: The leveraging of a dual network as a distinctive relational capability. *Strategic Management Journal, 28*(6), 585-608. doi:10.1002/smj.621

Capone, G., Malerba, F., & Orsenigo, L. (2013). Are Switching Costs Always Effective in Creating First-Mover Advantage? The Moderating Role of Demand and Technological Regimes. *Long Range Planning, 46*(4-5), 348-368. doi:10.1016/j.lrp.2013.06.001

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. doi:10.1002/smj.2084

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. doi:10.1177/0149206312440119

Carroll, G. R., Delacroix, J., & Goodstein, J. (1988). The political environments of organizations: an ecological view. In B. M. Staw & L. L. Cummings (Eds.), *Research In Organizational Behavior, Volume 8* (Vol. 8). Greenwich CN: JAI Press.

Casper, S. (2007). How do technology clusters emerge and become sustainable? Social network formation and inter-firm mobility within the San Diego biotechnology cluster. *Research Policy, 36*(4), 438-455. doi:10.1016/j.respol.2007.02.018

Castellacci, F. (2008). Technological paradigms, regimes and trajectories: Manufacturing and service industries in a new taxonomy of sectoral patterns of innovation. *Research Policy, 37*(6-7), 978-994. doi:10.1016/j.respol.2008.03.011

Cattani, G., & Ferriani, S. (2008). A Core/Periphery Perspective on Individual Creative Performance: Social Networks and Cinematic Achievements in the Hollywood Film Industry. *Organization Science, 19*(6), 824-844. doi:10.1287/orsc.1070.0350

Cattani, G., Ferriani, S., & Lanza, A. (2017). Deconstructing the Outsider Puzzle: The Legitimation Journey of Novelty. *Organization Science, 28*(6), 965-992. doi:10.1287/orsc.2017.1161

Cefis, E., & Orsenigo, L. (2001). The persistence of innovative activities. *Research Policy, 30*(7), 1139-1158. doi:10.1016/s0048-7333(00)00139-6

Chang, M.-H., & Harrington, J. E. (2007). Innovators, Imitators, and the Evolving Architecture of Problem-Solving Networks. *Organization Science, 18*(4), 648-666. doi:10.1287/orsc.1060.0245

Chappin, M. M. H. (2008). *Opening the black box of environmental innovation.* (Dissertation), Utrecht University, Utrecht.

Chiaroni, D., Chiesa, V., & Frattini, F. (2011). The Open Innovation Journey: How firms dynamically implement the emerging innovation management paradigm. *Technovation, 31*(1), 34-43. doi:10.1016/j.technovation.2009.08.007

Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine, 357*(4), 370-379. doi:10.1056/NEJMsa066082

Christakis, N. A., & Fowler, J. H. (2008). The collective dynamics of smoking in a large social network. *New England Journal of Medicine, 358*(21), 2249-2258. doi:10.1056/NEJMsa0706154

Christensen, R. H. B. (Producer). (2011). Regression Models for Ordinal Data - Introducing R-package ordinal. [PowerPoint slides]

Ciabuschi, F., Forsgren, M., & Martín, O. M. (2011). Rationality vs ignorance: The role of MNE headquarters in subsidiaries' innovation processes. *Journal of International Business Studies, 42*(7), 958-970. doi:10.1057/jibs.2011.24

Clark, N. (2006). The Airbus saga: Crossed wires and a multibillion-euro delay. *The New York Times*. Retrieved from http://www.nytimes.com/2006/12/11/business/worldbusiness/11iht-airbus.3860198.html

Clegg, S., Josserand, E., Mehra, A., & Pitsis, T. S. (2016). The Transformative Power of Network Dynamics: A Research Agenda. *Organization Studies, 37*(3), 277-291. doi:10.1177/0170840616629047

Clement, J., Shipilov, A. V., & Galunic, C. (2017). Brokerage as a Public Good: The Externalities of Network Hubs for Different Formal Roles in Creative Organizations. *Administrative Science Quarterly*. doi:10.1177/0001839217708984

Coenen, L., Benneworth, P., & Truffer, B. (2012). Toward a spatial perspective on sustainability transitions. *Research Policy, 41*(6), 968-979. doi:10.1016/j.respol.2012.02.014

Coenen, L., Hansen, T., & Rekers, J. V. (2015). Innovation Policy for Grand Challenges. An Economic Geography Perspective. *Geography Compass, 9*(9), 483-496. doi:10.1111/gec3.12231

Cohen, S. G., & Bailey, D. E. (1997). What Makes Teams Work: Group Effectiveness Research from the Shop Floor to the Executive Suite. *Journal of Management, 23*(3), 239-290. doi:10.1177/014920639702300303

Coleman, J. S. (1988). Social Capital in the Creation of Human Capital. *American Journal of Sociology, 94*(Supplement), S95-S120. doi:10.1086/228943

Collins-Dogrul, J. (2012). Tertius Iungens Brokerage and Transnational Intersectoral Cooperation. *Organization Studies, 33*(8), 989-1014. doi:10.1177/0170840612445118

Compagni, A., Mele, V., & Ravasi, D. (2014). How Early Implementations Influence Later Adoptions of Innovation: Social Positioning and Skill Reproduction in the Diffusion of Robotic Surgery. *Academy of Management Journal, 58*(1), 242-278. doi:10.5465/amj.2011.1184

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. doi:10.5465/amr.2006.21318925

Corey, E. R. (1997). *Technology Fountainheads: The Management Challenge of R&D Consortia*. Boston, MA: Harvard Business School Press.

Cowan, R., & Jonard, N. (2009). Knowledge Portfolios and The Organization of Innovation Networks. *Academy of Management Review, 34*(2), 320-342. doi:10.5465/amr.2008.0052

Crescenzi, R., Nathan, M., & Rodríguez-Pose, A. (2016). Do inventors talk to strangers? On proximity and collaborative knowledge creation. *Research Policy, 45*(1), 177-194. doi:10.1016/j.respol.2015.07.003

Cribari-Neto, F., & Zeileis, A. (2010). Beta Regression in R. *Journal of Statistical Software, 34*(2). doi:10.18637/jss.v034.i02

Cronin, M. A., & Weingart, L. R. (2007). Representational Gaps, Information Processing, and Conflict in Functionally Diverse Teams. *Academy of Management Review, 32*(3), 761-773. doi:10.5465/amr.2007.25275511

Cropper, S., Ebers, M., Huxham, C., & Ring, P. S. (2009). Introducing Inter-Organizational Relations. In S. Cropper, M. Ebers, C. Huxham, & P. S. Ring (Eds.), *Oxford Handbook of Inter-Organizational Relations*. New York: Oxford University Press.

Crossan, M. M., & Apaydin, M. (2010). A Multi-Dimensional Framework of Organizational Innovation: A Systematic Review of the Literature. *Journal of Management Studies, 47*(6), 1154-1191. doi:10.1111/j.1467-6486.2009.00880.x

Csárdi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal, Complex Systems*, 1695.

Cummings, J. N., & Kiesler, S. (2007). Coordination costs and project outcomes in multi-university collaborations. *Research Policy, 36*(10), 1620-1634. doi:10.1016/j.respol.2007.09.001

Dagnino, G. B., Chiara Cantù, D. D. C. a. D., Levanti, G., Minà, A., & Picone, P. M. (2015). Interorganizational network and innovation: a bibliometric study and proposed research agenda. *Journal of Business & Industrial Marketing, 30*(3/4), 354-377. doi:10.1108/jbim-02-2013-0032

Dagnino, G. B., Levanti, G., & Mocciaro Li Destri, A. (2016). Structural Dynamics and Intentional Governance in Strategic Interorganizational Network Evolution: A Multilevel Approach. *Organization Studies, 37*(3), 349-373. doi:10.1177/0170840615625706

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. doi:10.1177/0001839212474272

Dahlander, L., O'Mahony, S., & Gann, D. M. (2016). One foot in, one foot out: how does individuals' external search breadth affect innovation outcomes? *Strategic Management Journal, 37*(2), 280-302. doi:10.1002/smj.2342

Dahlin, K. B., Weingart, L. R., & Hinds, P. J. (2005). Team Diversity and Information Use. *Academy of Management Journal, 48*(6), 1107-1123. doi:10.5465/amj.2005.19573112

Damanpour, F. (1991). Organizational Innovation: A Meta-Analysis of Effects of Determinants and Moderators. *Academy of Management Journal, 34*(3), 555-590. doi:10.2307/256406

Das, T. K., & Teng, B.-S. (2002). Alliance Constellations: A Social Exchange Perspective. *Academy of Management Review, 27*(3), 445-456. doi:10.5465/amr.2002.7389937

Daskalaki, M. (2010). Building 'Bonds' and 'Bridges': Linking Tie Evolution and Network Identity in the Creative Industries. *Organization Studies, 31*(12), 1649-1666. doi:10.1177/0170840610380805

Davis, J. P. (2016). The Group Dynamics of Interorganizational Relationships. *Administrative Science Quarterly, 61*(4), 621-661. doi:10.1177/0001839216649350

Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2007). Developing Theory through Simulation Methods. *Academy of Management Review, 32*(2), 480-499. doi:10.5465/amr.2007.24351453

de Man, A.-P., & Duysters, G. (2005). Collaboration and innovation: a review of the effects of mergers, acquisitions and alliances on innovation. *Technovation, 25*(12), 1377-1387. doi:10.1016/j.technovation.2004.07.021

de Man, A.-P., & Roijakkers, N. (2009). Alliance Governance: Balancing Control and Trust in Dealing with Risk. *Long Range Planning, 42*(1), 75-95. doi:10.1016/j.lrp.2008.10.006

de Nooy, W., Mrvar, A., & Batagelj, V. (2005). *Exploratory Social Network Analysis with Pajek*. Cambridge: Cambridge University Press.

de Vaan, M., Vedres, B., & Stark, D. (2015). Game Changer: The Topology of Creativity. *American Journal of Sociology, 120*(4), 1144-1194. doi:10.1086/681213

de Vries, H. J., & Verhagen, W. P. (2016). Impact of changes in regulatory performance standards on innovation: A case of energy performance standards for newly-built houses. *Technovation, 48-49*, 56-68. doi:10.1016/j.technovation.2016.01.008

Defazio, D., Lockett, A., & Wright, M. (2009). Funding incentives, collaborative dynamics and scientific productivity: Evidence from the EU framework program. *Research Policy, 38*(2), 293-305. doi:10.1016/j.respol.2008.11.008

Dercole, F., Dieckmann, U., Obersteiner, M., & Rinaldi, S. (2008). Adaptive dynamics and technological change. *Technovation, 28*(6), 335-348. doi:10.1016/j.technovation.2007.11.004

Dess, G. G., & Shaw, J. D. (2001). Voluntary Turnover, Social Capital, and Organizational Performance. *Academy of Management Review, 26*(3), 446. doi:10.2307/259187

Dhanaraj, C., & Parkhe, A. (2006). Orchestrating Innovation Networks. *Academy of Management Review, 31*(3), 659-669. doi:10.5465/amr.2006.21318923

Díez-Vial, I., & Montoro-Sánchez, Á. (2016). How knowledge links with universities may foster innovation: The case of a science park. *Technovation, 50-51*, 41-52. doi:10.1016/j.technovation.2015.09.001

Dimaggio, P., & Powell, W. W. (1983). The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. *American Sociological Review, 48*(2), 147-160.

Dornbusch, F., & Neuhäusler, P. (2015). Composition of inventor teams and technological progress – The role of collaboration between academia and industry. *Research Policy, 44*(7), 1360-1375. doi:10.1016/j.respol.2015.04.003

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. doi:10.1016/0048-7333(82)90016-6

Dosi, G., Faillo, M., & Marengo, L. (2008). Organizational Capabilities, Patterns of Knowledge Accumulation and Governance Structures in Business Firms: An Introduction. *Organization Studies, 29*(8-9), 1165-1185. doi:10.1177/0170840608094775

Doz, Y., Olk, P., & Ring, P. S. (2000). Formation processes of R&D consortia: which path to take? Where does it lead? *Strategic Management Journal, 21*(3), 239-266. doi:10.1002/(sici)1097-0266(200003)21:3<239::aid-smj97>3.0.co;2-k

Drazin, R., & Schoonhoven, C. B. (1996). Community, Population, and Organization Effects on Innovation: A Multilevel Perspective. *Academy of Management Journal, 39*(5), 1065-1083. doi:10.2307/256992

Drejer, I., & Jørgensen, B. H. (2005). The dynamic creation of knowledge: Analysing public–private collaborations. *Technovation, 25*(2), 83-94. doi:10.1016/s0166-4972(03)00075-0

Dyer, J. H., & Nobeoka, K. (2000). Creating and managing a high-performance knowledge-sharing network: the Toyota case. *Strategic Management Journal, 21*(3), 345-367. doi:10.1002/(sici)1097-0266(200003)21:3<345::aid-smj96>3.0.co;2-n

Ebers, M., & Oerlemans, L. (2013). The Variety of Governance Structures Beyond Market and Hierarchy. *Journal of Management, 42*(6), 1491-1529. doi:10.1177/0149206313506938

Edmondson, A. C., & Nembhard, I. M. (2009). Product Development and Learning in Project Teams: The Challenges Are the Benefits. *Journal of Product Innovation Management, 26*(2), 123-138. doi:10.1111/j.1540-5885.2009.00341.x

Edquist, C. (1997). *Systems of Innovation. Technologies, Institutions and Organizations*. London: Routledge.

Edquist, C., & Hommen, L. (1999). Systems of innovation: theory and policy for the demand side. *Technology in Society, 21*(1), 63-79. doi:10.1016/s0160-791x(98)00037-2

Ehrnberg, E. (1995). On the definition and measurement of technological discontinuities. *Technovation, 15*(7), 437-452. doi:10.1016/0166-4972(95)96593-i

Eisenhardt, K. M., Graebner, M. E., & Sonenshein, S. (2016). Grand Challenges and Inductive Methods: Rigor without Rigor Mortis. *Academy of Management Journal, 59*(4), 1113-1123. doi:10.5465/amj.2016.4004

Emirbayer, M. (1997). Manifesto for a Relational Sociology. *American Journal of Sociology, 103*(2), 281-317. doi:10.1086/231209

Engelsman, E. C., & van Raan, A. F. J. (1994). A patent-based cartography of technology. *Research Policy, 23*(1), 1-26. doi:10.1016/0048-7333(94)90024-8

Erikson, E., & Bearman, P. (2006). Malfeasance and the Foundations for Global Trade: The Structure of English Trade in the East Indies, 1601–1833. *American Journal of Sociology, 112*(1), 195-230. doi:10.1086/502694

Ettlie, J. E., & Reza, E. M. (1992). Organizational Integration and Process Innovation. *Academy of Management Journal, 35*(4), 795-827. doi:10.2307/256316

Evan, W. M., & Olk, P. (1990). R&D Consortia: A New U.S. Organizational Form. *Sloan Management Review, 31*(3), 37-46.

Everett, M., & Borgatti, S. P. (2005). Ego network betweenness. *Social Networks, 27*(1), 31-38. doi:10.1016/j.socnet.2004.11.007

Fabrizio, K. R., & Thomas, L. G. (2012). The Impact of Local Demand on Innovation in a Global Industry. *Strategic Management Journal, 33*(1), 42-64. doi:10.1002/smj.942

Faems, D., & Subramanian, A. M. (2013). R&D manpower and technological performance: The impact of demographic and task-related diversity. *Research Policy, 42*(9), 1624-1633. doi:10.1016/j.respol.2013.06.001

Faems, D., Van Looy, B., & Debackere, K. (2005). Interorganizational Collaboration and Innovation: Toward a Portfolio Approach*. *Journal of Product Innovation Management, 22*(3), 238-250. doi:10.1111/j.0737-6782.2005.00120.x

Fagerberg, J., Fosaas, M., & Sapprasert, K. (2012). Innovation: Exploring the knowledge base. *Research Policy, 41*(7), 1132-1153. doi:10.1016/j.respol.2012.03.008

Fagerberg, J., & Verspagen, B. (2009). Innovation studies—The emerging structure of a new scientific field. *Research Policy, 38*(2), 218-233. doi:10.1016/j.respol.2008.12.006

Farjoun, M. (2010). Beyond Dualism: Stability and Change as a Duality. *Academy of Management Review, 35*(2), 202-225. doi:10.5465/amr.2010.48463331

Faust, K., & Skvoretz, J. (2002). Comparing Networks Across Space and Time, Size and Species. *Sociological Methodology, 32*(1), 267-299. doi:10.1111/1467-9531.00118

Feldman, M. S. (2000). Organizational Routines as a Source of Continuous Change. *Organization Science, 11*(6), 611-629. doi:10.1287/orsc.11.6.611.12529
Ferrari, S., & Cribari-Neto, F. (2004). Beta Regression for Modelling Rates and Proportions. *Journal of Applied Statistics, 31*(7), 799-815. doi:10.1080/0266476042000214501
Ferriani, S., Cattani, G., & Baden-Fuller, C. (2009). The relational antecedents of project-entrepreneurship: Network centrality, team composition and project performance. *Research Policy, 38*(10), 1545-1558. doi:10.1016/j.respol.2009.09.001
Filzmoser, P., & Gschwandtner, M. (2017). Package 'mvoutlier'. Retrieved from https://CRAN.R-project.org/package=mvoutlier
Filzmoser, P., Maronna, R., & Werner, M. (2008). Outlier identification in high dimensions. *Computational Statistics & Data Analysis, 52*(3), 1694-1711. doi:10.1016/j.csda.2007.05.018
Flammer, C., & Bansal, P. (2017). Does a long-term orientation create value? Evidence from a regression discontinuity. *Strategic Management Journal*. doi:10.1002/smj.2629
Fleming, L. (2001). Recombinant Uncertainty in Technological Search. *Management Science, 47*(1), 117-132. doi:10.1287/mnsc.47.1.117.10671
Fleming, L., Mingo, S., & Chen, D. (2007). Collaborative Brokerage, Generative Creativity, and Creative Success. *Administrative Science Quarterly, 52*(3), 443-475. doi:doi: 10.2189/asqu.52.3.443
Fleming, L., & Sorenson, O. (2001). Technology as a complex adaptive system: evidence from patent data. *Research Policy, 30*(7), 1019-1039. doi:Doi 10.1016/S0048-7333(00)00135-9
Fleming, L., & Sorenson, O. (2004). Science as a map in technological search. *Strategic Management Journal, 25*(89), 909-928. doi:10.1002/smj.384
Flynn, F. J., & Wiltermuth, S. S. (2010). Who's with Me? False Consensus, Brokerage, and Ethical Decision Making in Organizations. *Academy of Management Journal, 53*(5), 1074-1089. doi:10.5465/amj.2010.54533202
Fonti, F., Maoret, M., & Whitbred, R. (2015). Free-riding in multi-party alliances: The role of perceived alliance effectiveness and peers' collaboration in a research consortium. *Strategic Management Journal*, n/a-n/a. doi:10.1002/smj.2470
Foray, D., Mowery, D. C., & Nelson, R. R. (2012). Public R&D and social challenges: What lessons from mission R&D programs? *Research Policy, 41*(10), 1697-1702. doi:10.1016/j.respol.2012.07.011
Forti, E., Franzoni, C., & Sobrero, M. (2013). Bridges or isolates? Investigating the social networks of academic inventors. *Research Policy, 42*(8), 1378-1388. doi:10.1016/j.respol.2013.05.003
Foss, N. J., Frederiksen, L., & Rullani, F. (2015). Problem-formulation and problem-solving in self-organized communities: How modes of communication shape project behaviors in the free open source software community. *Strategic Management Journal*, n/a-n/a. doi:10.1002/smj.2439
Fowler, J. H., & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *British Medical Journal, 337*, a2338. doi:10.1136/bmj.a2338
Fox, J. (2003). Effect Displays in R for Generalised Linear Models. *Journal of Statistical Software, 8*(15). doi:10.18637/jss.v008.i15
Freeman, C. (1991). Networks of innovators: A synthesis of research issues. *Research Policy, 20*(5), 499-514. doi:10.1016/0048-7333(91)90072-x
Freeman, L. C. (1978). Centrality in social networks. Conceptual clarification. *Social Networks, 1*(3), 215-239. doi:10.1016/0378-8733(78)90021-7
Freeman, L. C., Borgatti, S. P., & White, D. R. (1991). Centrality in valued graphs: A measure of betweenness based on network flow. *Social Networks, 13*(2), 141-154. doi:10.1016/0378-8733(91)90017-n
Frenken, K. (2006). *Innovation, Evolution and Complexity Theory*. Cheltenham: Edward Elgar.

Friedkin, N. E. (1991). Theoretical Foundations for Centrality Measures. *American Journal of Sociology, 96*(6), 1478-1504. doi:10.1086/229694

Funk, R. J. (2013). Making the Most of Where You Are: Geography, Networks, and Innovation in Organizations. *Academy of Management Journal, 57*(1), 193-222. doi:10.5465/amj.2012.0585

Galunic, C., Ertug, G., & Gargiulo, M. (2012). The Positive Externalities of Social Capital: Benefiting from Senior Brokers. *Academy of Management Journal, 55*(5), 1213-1231. doi:10.5465/amj.2010.0827

García-Canal, E., Valdés-Llaneza, A., & Ariño, A. (2003). Effectiveness of Dyadic and Multi-Party Joint Ventures. *Organization Studies, 24*(5), 743-770. doi:10.1177/0170840603024005004

Garcia-Pont, C., & Nohria, N. (2002). Local versus global mimetism: the dynamics of alliance formation in the automobile industry. *Strategic Management Journal, 23*(4), 307-321. doi:10.1002/smj.225

Gardner, H. K., Gino, F., & Staats, B. R. (2011). Dynamically Integrating Knowledge in Teams: Transforming Resources into Performance. *Academy of Management Journal, 55*(4), 998-1022. doi:10.5465/amj.2010.0604

Gargiulo, M., & Sosa, M. E. (2016). Common Third Parties and Coordination Disruptions in New Product Development Organizations. *Journal of Product Innovation Management, 33*(2), 132-140. doi:10.1111/jpim.12288

Garriga, H., von Krogh, G., & Spaeth, S. (2013). How constraints and knowledge impact open innovation. *Strategic Management Journal, 34*(9), 1134-1144. doi:10.1002/smj.2049

Gay, B., & Dousset, B. (2005). Innovation and network structural dynamics: Study of the alliance network of a major sector of the biotechnology industry. *Research Policy, 34*(10), 1457-1475. doi:10.1016/j.respol.2005.07.001

Geels, F. W. (2010). Ontologies, socio-technical transitions (to sustainability), and the multi-level perspective. *Research Policy, 39*(4), 495-510. doi:10.1016/j.respol.2010.01.022

Geels, F. W., Kern, F., Fuchs, G., Hinderer, N., Kungl, G., Mylan, J., . . . Wassermann, S. (2016). The enactment of socio-technical transition pathways: A reformulated typology and a comparative multi-level analysis of the German and UK low-carbon electricity transitions (1990–2014). *Research Policy, 45*(4), 896-913. doi:10.1016/j.respol.2016.01.015

Geerts, A., Leten, B., Belderbos, R., & Van Looy, B. (2017). Does Spatial Ambidexterity Pay Off? On the Benefits of Geographic Proximity Between Technology Exploitation and Exploration. *Journal of Product Innovation Management, in print*. doi:10.1111/jpim.12380

Geletkanycz, M. A., Boyd, B. K., & Finkelstein, S. (2001). The strategic value of CEO external directorate networks: implications for CEO compensation. *Strategic Management Journal, 22*(9), 889-898. doi:10.1002/smj.172

Gelman, A., & Hill, J. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge: Cambridge University Press.

Gemser, G., & Leenders, M. A. A. M. (2011). Managing Cross-Functional Cooperation for New Product Development Success. *Long Range Planning, 44*(1), 26-41. doi:10.1016/j.lrp.2010.11.001

George, G., Howard-Grenville, J., Joshi, A., & Tihanyi, L. (2016). Understanding and Tackling Societal Grand Challenges through Management Research. *Academy of Management Journal, 59*(6), 1880-1895. doi:10.5465/amj.2016.4007

George, J. M., & Jones, G. R. (2000). The Role of Time in Theory and Theory Building. *Journal of Management, 26*(4), 657-684. doi:10.1177/014920630002600404

Ghosh, A., & Rosenkopf, L. (2015). PERSPECTIVE—Shrouded in Structure: Challenges and Opportunities for a Friction-Based View of Network Research. *Organization Science, 26*(2), 622-631. doi:10.1287/orsc.2014.0922

Gibson, C. B., & Gibbs, J. L. (2006). Unpacking the Concept of Virtuality: The Effects of Geographic Dispersion, Electronic Dependence, Dynamic Structure, and National

Diversity on Team Innovation. *Administrative Science Quarterly, 51*(3), 451-495. doi:10.2189/asqu.51.3.451
Gil, N. (2007). On the value of project safeguards: Embedding real options in complex products and systems. *Research Policy, 36*(7), 980-999. doi:10.1016/j.respol.2007.03.004
Gilbert, B. A., & Campbell, J. T. (2015). The geographic origins of radical technological paradigms: A configurational study. *Research Policy, 44*(2), 311-327. doi:10.1016/j.respol.2014.08.006
Gilsing, V. A., Cloodt, M., & Roijakkers, N. (2016). From Birth through Transition to Maturation: The Evolution of Technology-Based Alliance Networks. *Journal of Product Innovation Management, 33*(2), 181-200. doi:10.1111/jpim.12289
Gilsing, V. A., & Duysters, G. M. (2008). Understanding novelty creation in exploration networks—Structural and relational embeddedness jointly considered. *Technovation, 28*(10), 693-708. doi:10.1016/j.technovation.2008.03.004
Gilsing, V. A., Nooteboom, B., Vanhaverbeke, W., Duysters, G., & van den Oord, A. (2008). Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. *Research Policy, 37*(10), 1717-1731. doi:10.1016/j.respol.2008.08.010
Gimeno, J. (2004). Competition within and between Networks: The Contingent Effect of Competitive Embeddedness on Alliance Formation. *Academy of Management Journal, 47*(6), 820-842. doi:10.2307/20159625
Gittell, J. H., & Weiss, L. (2004). Coordination Networks Within and Across Organizations: A Multi-level Framework*. *Journal of Management Studies, 41*(1), 127-153. doi:10.1111/j.1467-6486.2004.00424.x
Giuliani, E. (2013). Network dynamics in regional clusters: Evidence from Chile. *Research Policy, 42*(8), 1406-1419. doi:10.1016/j.respol.2013.04.002
Goerzen, A. (2007). Alliance networks and firm performance: The impact of repeated partnerships. *Strategic Management Journal, 28*(5), 487-509. doi:10.1002/smj.588
Goes, J. B., & Park, S. H. (1997). Interorganizational Links and Innovation: The Case of Hospital Services. *Academy of Management Journal, 40*(3), 673-696. doi:10.2307/257058
Goodreau, S. M., Handcock, M. S., Hunter, D. R., Butts, C. T., & Morris, M. (2008). A statnet Tutorial. *Journal of Statistical Software, 24*(9). doi:10.18637/jss.v024.i09
Gopalakrishnan, S., & Damanpour, F. (1997). A review of innovation research in economics, sociology and technology management. *Omega, 25*(1), 15-28. doi:10.1016/s0305-0483(96)00043-6
Gort, M., & Klepper, S. (1982). Time Paths in the Diffusion of Product Innovations. *The Economic Journal, 92*(367). doi:10.2307/2232554
Grabher, G. (1993). The weakness of strong ties: the lock-in of regional development in the Ruhr area. In H. Hakanson, J. Johanson, & G. Grabher (Eds.), *The embedded firm: On the socioeconomics of industrial networks* (pp. 255-277). London: Routledge.
Grabher, G., & Stark, D. (1997). Organizing Diversity: Evolutionary Theory, Network Analysis and Postsocialism. *Regional Studies, 31*(5), 533-544. doi:10.1080/00343409750132315
Granovetter, M. S. (1973). The Strength of Weak Ties. *American Journal of Sociology, 78*(6), 1360-1380. doi:10.1086/225469
Granstrand, O., & Holgersson, M. (2013). Managing the Intellectual Property Disassembly Problem. *California Management Review, 55*(4), 184-210. doi:10.1525/cmr.2013.55.4.184
Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal, 17*(S2), 109-122. doi:10.1002/smj.4250171110
Greiner, L. (1972). Evolution and revolution as organizations grow. *Harvard Business Review, 50*(4), 37-46.
Greve, H. R. (1999). The Effect of Core Change on Performance: Inertia and Regression toward the Mean. *Administrative Science Quarterly, 44*(3). doi:10.2307/2666963

Greve, H. R., Baum, J. A. C., Mitsuhashi, H., & Rowley, T. J. (2010). Built to Last but Falling Apart: Cohesion, Friction, and Withdrawal from Interfirm Alliances. *Academy of Management Journal, 53*(2), 302-322. doi:10.5465/amj.2010.49388955

Greve, H. R., Mitsuhashi, H., & Baum, J. A. C. (2013). Greener Pastures: Outside Options and Strategic Alliance Withdrawal. *Organization Science, 24*(1), 79-98. doi:10.1287/orsc.1110.0733

Griliches, Z. (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth. *The Bell Journal of Economics, 10*(1). doi:10.2307/3003321

Grodal, S., Gotsopoulos, A., & Suarez, F. F. (2014). The Coevolution of Technologies and Categories During Industry Emergence. *Academy of Management Review, 40*(3), 423-445. doi:10.5465/amr.2013.0359

Groh, M. R., Stockman, J. C., Powell, G., Prague, C. N., Irwin, M. R., & Reardon, J. (2007). *Access™ 2007 Bible*. Indianapolis, IN: Wiley Publishing, Inc.

Gruber, M., MacMillan, I. C., & Thompson, J. D. (2008). Look Before You Leap: Market Opportunity Identification in Emerging Technology Firms. *Management Science, 54*(9), 1652-1665. doi:10.1287/mnsc.1080.0877

Guan, J., Zuo, K., Chen, K., & Yam, R. C. M. (2016). Does country-level R&D efficiency benefit from the collaboration network structure? *Research Policy, 45*(4), 770-784. doi:10.1016/j.respol.2016.01.003

Guennif, S., & Ramani, S. V. (2012). Explaining divergence in catching-up in pharma between India and Brazil using the NSI framework. *Research Policy, 41*(2), 430-441. doi:10.1016/j.respol.2011.09.005

Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics* (4th ed.). Columbus, OH: McGraw-Hill Education.

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. doi:10.2307/256729

Gulati, R. (1998). Alliances and networks. *Strategic Management Journal, 19*(4), 293-317. doi:10.1002/(sici)1097-0266(199804)19:4<293::aid-smj982>3.0.co;2-m

Gulati, R. (1999). Network location and learning: the influence of network resources and firm capabilities on alliance formation. *Strategic Management Journal, 20*(5), 397-420. doi:10.1002/(sici)1097-0266(199905)20:5<397::aid-smj35>3.0.co;2-k

Gulati, R., & Gargiulo, M. (1999). Where Do Interorganizational Networks Come From? *American Journal of Sociology, 104*(5), 1439-1493. doi:10.1086/210179

Gulati, R., Sytch, M., & Tatarynowicz, A. (2012). The Rise and Fall of Small Worlds: Exploring the Dynamics of Social Structure. *Organization Science, 23*(2), 449-471. doi:10.1287/orsc.1100.0592

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. doi:10.1002/smj.957

Haans, R. F. J., Pieters, C., & He, Z.-L. (2016). Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. *Strategic Management Journal, 37*(7), 1177-1195. doi:10.1002/smj.2399

Hagedoorn, J. (2002). Inter-firm R&D partnerships: an overview of major trends and patterns since 1960. *Research Policy, 31*(4), 477-492. doi:10.1016/s0048-7333(01)00120-2

Hagenaars, J. A., & McCutcheon, A. L. (2002). *Applied latent class analysis*. Cambridge, UK: Cambridge University Press.

Hakansson, H. (1992). *Evolution process in industrial networks*. London: Routledge.

Hall, B., Griliches, Z., & Hausman, J. (1984). Patents and R and D: Is there a lag? *International Economic Review, 27*(2), 265-283. doi:10.3386/w1454

Hallen, B. L. (2008). The Causes and Consequences of the Initial Network Positions of New Organizations: From Whom Do Entrepreneurs Receive Investments? *Administrative Science Quarterly, 53*(4), 685-718. doi:10.2189/asqu.53.4.685

Ham, R. M., Linden, G., & Appleyard, M. M. (1998). The Evolving Role of Semiconductor Consortia in the United States and Japan. *California Management Review, 41*(1), 137-163. doi:10.2307/41165979

Ham, R. M., & Mowery, D. C. (1998). Improving the effectiveness of public–private R&D collaboration: case studies at a US weapons laboratory. *Research Policy, 26*(6), 661-675. doi:10.1016/s0048-7333(97)00041-3

Hameri, A.-P. (1996). Technology transfer between basic research and industry. *Technovation, 16*(2), 51-92. doi:10.1016/0166-4972(95)00030-5

Hanaki, N., Nakajima, R., & Ogura, Y. (2010). The dynamics of R&D network in the IT industry. *Research Policy, 39*(3), 386-399. doi:10.1016/j.respol.2010.01.001

Hannan, M. T., & Carroll, G. R. (1992). *Dynamics of Organizational Populations: Density, Competition, and Legitimation*. New York NY: Oxford University Press.

Hansen, M. T. (2002). Knowledge Networks: Explaining Effective Knowledge Sharing in Multiunit Companies. *Organization Science, 13*(3), 232-248. doi:10.1287/orsc.13.3.232.2771

Hargadon, A., & Sutton, R. I. (1997). Technology Brokering and Innovation in a Product Development Firm. *Administrative Science Quarterly, 42*(4). doi:10.2307/2393655

Harrell, F. E., Jr. (2001). *Regression Modelling Strategies - With Applications to Linear Models, Logistic Regression, and Survival Analysis*. New York: Springer-Verlag.

Harrison, D. A., & Klein, K. J. (2007). What's the Difference? Diversity Constructs as Separation, Variety, or Disparity in Organizations. *Academy of Management Review, 32*(4), 1199-1228. doi:10.5465/amr.2007.26586096

Hasan, S., & Bagde, S. (2015). Peers and Network Growth: Evidence from a Natural Experiment. *Management Science, 61*(10), 2536-2547. doi:10.1287/mnsc.2014.2109

Haughton, D., Legrand, P., & Woolford, S. (2009). Review of Three Latent Class Cluster Analysis Packages: Latent Gold, poLCA, and MCLUST. *The American Statistician, 63*(1), 81-91. doi:10.1198/tast.2009.0016

Hayashi, T. (2003). Effect of R&D programmes on the formation of university–industry–government networks: comparative analysis of Japanese R&D programmes. *Research Policy, 32*(8), 1421-1442. doi:10.1016/s0048-7333(02)00158-0

Heidenreich, S., Landsperger, J., & Spieth, P. (2016). Are Innovation Networks in Need of a Conductor? Examining the Contribution of Network Managers in Low and High Complexity Settings. *Long Range Planning, 49*(1), 55-71. doi:10.1016/j.lrp.2014.03.003

Heidl, R. A., Steensma, H. K., & Phelps, C. (2014). Divisive Faultlines and the Unplanned Dissolutions of Multipartner Alliances. *Organization Science, 25*(5), 1351-1371. doi:10.1287/orsc.2014.0898

Hellsmark, H., Frishammar, J., Söderholm, P., & Ylinenpää, H. (2016). The role of pilot and demonstration plants in technology development and innovation policy. *Research Policy, 45*(9), 1743-1761. doi:10.1016/j.respol.2016.05.005

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. doi:10.2307/2393549

Henisz, W. J., & Macher, J. T. (2004). Firm- and Country-Level Trade-offs and Contingencies in the Evaluation of Foreign Investment: The Semiconductor Industry, 1994–2002. *Organization Science, 15*(5), 537-554. doi:10.1287/orsc.1040.0091

Henn, S., & Bathelt, H. (2015). Knowledge generation and field reproduction in temporary clusters and the role of business conferences. *Geoforum, 58*, 104-113. doi:10.1016/j.geoforum.2014.10.015

Hermelo, F. D., & Vassolo, R. (2010). Institutional development and hypercompetition in emerging economies. *Strategic Management Journal, 31*(13), 1457-1473. doi:10.1002/smj.898

Hernandez, E., Sanders, W. G., & Tuschke, A. (2014). Network Defense: Pruning, Grafting, and Closing to Prevent Leakage of Strategic Knowledge to Rivals. *Academy of Management Journal, 58*(4), 1233-1260. doi:10.5465/amj.2012.0773

Hinds, P. J., & Bailey, D. E. (2003). Out of Sight, Out of Sync: Understanding Conflict in Distributed Teams. *Organization Science, 14*(6), 615-632. doi:10.1287/orsc.14.6.615.24872

Hite, J. M., & Hesterly, W. S. (2001). The evolution of firm networks: from emergence to early growth of the firm. *Strategic Management Journal, 22*(3), 275-286. doi:10.1002/smj.156

Ho, V. T., & Pollack, J. M. (2014). Passion Isn't Always a Good Thing: Examining Entrepreneurs' Network Centrality and Financial Performance with a Dualistic Model of Passion. *Journal of Management Studies, 51*(3), 433-459. doi:10.1111/joms.12062

Hoang, H., & Rothaermel, F. T. (2005). The Effect of General and Partner-Specific Alliance Experience on Joint R&D Project Performance. *Academy of Management Journal, 48*(2), 332-345. doi:10.5465/amj.2005.16928417

Hoffmann, W. H., & Schlosser, R. (2001). Success Factors of Strategic Alliances in Small and Medium-sized Enterprises—An Empirical Survey. *Long Range Planning, 34*(3), 357-381. doi:10.1016/s0024-6301(01)00041-3

Holcomb, T. R., Combs, J. G., Sirmon, D. G., & Sexton, J. (2009). Modeling Levels and Time in Entrepreneurship Research: An Illustration With Growth Strategies and Post-IPO Performance. *Organizational Research Methods, 13*(2), 348-389. doi:10.1177/1094428109338401

Hollenstein, H. (2003). Innovation modes in the Swiss service sector: a cluster analysis based on firm-level data. *Research Policy, 32*(5), 845-863. doi:10.1016/s0048-7333(02)00091-4

Horner, D. S. (1992). Frameworks for technology analysis and classification. *Journal of Information Science, 18*(1), 57-68. doi:10.1177/016555159201800107

Howard, M. D., Withers, M. C., Carnes, C. M., & Hillman, A. J. (2016). Friends or strangers? It all depends on context: A replication and extension of Beckman, Haunschild, and Phillips (2004). *Strategic Management Journal*. doi:10.1002/smj.2573

Hox, J. J. (2010). *Multilevel Analysis - Techniques and Applications* (2nd ed.). New York: Routledge.

Hoye, K., & Pries, F. (2009). 'Repeat commercializers,' the 'habitual entrepreneurs' of university–industry technology transfer. *Technovation, 29*(10), 682-689. doi:10.1016/j.technovation.2009.05.008

Hsu, D. H., & Lim, K. (2014). Knowledge Brokering and Organizational Innovation: Founder Imprinting Effects. *Organization Science, 25*(4), 1134-1153. doi:10.1287/orsc.2013.0863

Hu, Y., McNamara, P., & Piaskowska, D. (2017). Project Suspensions and Failures in New Product Development: Returns for Entrepreneurial Firms in Co-Development Alliances. *Journal of Product Innovation Management, 34*(1), 35-59. doi:10.1111/jpim.12322

Huisman, M., & Snijders, T. A. B. (2003). Statistical Analysis of Longitudinal Network Data With Changing Composition. *Sociological Methods & Research, 32*(2), 253-287. doi:10.1177/0049124103256096

Human, S. E., & Provan, K. G. (1997). An Emergent Theory of Structure and Outcomes in Small-Firm Strategic Manufacturing Networks. *Academy of Management Journal, 40*(2), 368-403. doi:10.2307/256887

Hung, C.-L. (2017). Social networks, technology ties, and gatekeeper functionality: Implications for the performance management of R&D projects. *Research Policy, 46*(1), 305-315. doi:10.1016/j.respol.2016.11.009

Hung, S.-C., & Tu, M.-F. (2014). Is small actually big? The chaos of technological change. *Research Policy, 43*(7), 1227-1238. doi:10.1016/j.respol.2014.03.003

Hwang, P., & Burgers, W. P. (1997). The Many Faces of Multi-Firm Alliances: Lessons for Managers. *California Management Review, 39*(3), 101-117. doi:10.2307/41165901

Hyytinen, A., & Toivanen, O. (2005). Do financial constraints hold back innovation and growth? *Research Policy, 34*(9), 1385-1403. doi:10.1016/j.respol.2005.06.004

Ibarra, H., Kilduff, M., & Tsai, W. (2005). Zooming In and Out: Connecting Individuals and Collectivities at the Frontiers of Organizational Network Research. *Organization Science, 16*(4), 359-371. doi:10.1287/orsc.1050.0129

Ibert, O., & Müller, F. C. (2015). Network dynamics in constellations of cultural differences: Relational distance in innovation processes in legal services and biotechnology. *Research Policy, 44*(1), 181-194. doi:10.1016/j.respol.2014.07.016

Ingram, P., & Torfason, M. T. (2010). Organizing the In-between: The Population Dynamics of Network-weaving Organizations in the Global Interstate Network. *Administrative Science Quarterly, 55*(4), 577-605. doi:10.2189/asqu.2010.55.4.577

Jarvenpaa, S. L., & Välikangas, L. (2014). Opportunity Creation in Innovation Networks: Interactive Revealing Practices. *California Management Review, 57*(1), 67-87. doi:10.1525/cmr.2014.57.1.67

Jiang, H., Jun, X., Cannella, A. A., & Xiao, T. (2017). Do Ongoing Networks Block Out New Friends? Reconciling The Embeddedness Constraint Dilemma on New Alliance Partner Addition. *Strategic Management Journal*. doi:10.1002/smj.2695

Jiang, R. J., Tao, Q. T., & Santoro, M. D. (2010). Alliance portfolio diversity and firm performance. *Strategic Management Journal, 31*(10), 1136-1144. doi:10.1002/smj.869

Johnston, W. J., Peters, L. D., & Gassenheimer, J. (2006). Questions about network dynamics: Characteristics, structures, and interactions. *Journal of Business Research, 59*(8), 945-954. doi:10.1016/j.jbusres.2006.03.002

Jones, C., Hesterly, W. S., Fladmoe-Lindquist, K., & Borgatti, S. P. (1998). Professional Service Constellations: How Strategies and Capabilities Influence Collaborative Stability and Change. *Organization Science, 9*(3), 396-410. doi:10.1287/orsc.9.3.396

Jung, H. J., & Lee, J. J. (2015). The Quest for Originality: A New Typology of Knowledge Search and Breakthrough Inventions. *Academy of Management Journal, 59*(5), 1725-1753. doi:10.5465/amj.2014.0756

Kaiser, U., & Kuhn, J. M. (2012). Long-run effects of public–private research joint ventures: The case of the Danish Innovation Consortia support scheme. *Research Policy, 41*(5), 913-927. doi:10.1016/j.respol.2012.01.009

Kajikawa, Y., Takeda, Y., Sakata, I., & Matsushima, K. (2010). Multiscale analysis of interfirm networks in regional clusters. *Technovation, 30*(3), 168-180. doi:10.1016/j.technovation.2009.12.004

Kale, P., & Singh, H. (2009). Managing Strategic Alliances: What Do We Know Now, and Where Do We Go From Here? *Academy of Management Perspectives, 23*(3), 45-62. doi:10.5465/amp.2009.43479263

Kash, D. E., & Rycoft, R. W. (2000). Patterns of innovating complex technologies: a framework for adaptive network strategies. *Research Policy, 29*(7-8), 819-831. doi:10.1016/s0048-7333(00)00107-4

Kassambara, A. (2017). *Practical Guide to Cluster Analysis in R*. North Charleston SC: CreateSpace Independent Publishing Platform.

Katila, R. (2002). New Product Search over Time: Past Ideas in Their Prime? *Academy of Management Journal, 45*(5), 995-1010. doi:10.2307/3069326

Katila, R., & Ahuja, G. (2002). Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction. *Academy of Management Journal, 45*(6), 1183-1194. doi:10.2307/3069433

Kato, M., & Odagiri, H. (2012). Development of university life-science programs and university–industry joint research in Japan. *Research Policy, 41*(5), 939-952. doi:10.1016/j.respol.2012.02.011

Kauffman, R. G., & Oliva, T. A. (1994). Multivariate Catastrophe Model Estimation: Method and Application. *Academy of Management Journal, 37*(1), 206-221. doi:10.2307/256778

Kauffman, S. A. (1993). *The Origins of Order. Self-Organization and Selection in Evolution*. New York and Oxford: Oxford University Press.
Kauffman, S. A., Lobo, J., & Macready, W. G. (2000). Optimal search on a technology landscape. *Journal of Economic Behavior & Organization, 43*(2), 141-166. doi:10.1016/s0167-2681(00)00114-1
Kavanagh, D., & Araujo, L. (1995). Chronigami: Folding and unfolding time. *Accounting, Management and Information Technologies, 5*(2), 103-121. doi:10.1016/0959-8022(95)00010-7
Kavusan, K., Noorderhaven, N. G., & Duysters, G. M. (2016). Knowledge acquisition and complementary specialization in alliances: The impact of technological overlap and alliance experience. *Research Policy, 45*(10), 2153-2165. doi:10.1016/j.respol.2016.09.013
Keller, R. T. (2001). Cross-Functional Project Groups in Research and New Product Development: Diversity, Communications, Job Stress, and Outcomes. *Academy of Management Journal, 44*(3), 547-555. doi:10.2307/3069369
Kelley, D. J., Ali, A., & Zahra, S. A. (2013). Where Do Breakthroughs Come From? Characteristics of High-Potential Inventions. *Journal of Product Innovation Management, 30*(6), 1212-1226. doi:10.1111/jpim.12055
Kenis, P., & Knoke, D. (2002). How Organizational Field Networks Shape Interorganizational Tie-Formation Rates. *Academy of Management Review, 27*(2), 275-293. doi:10.5465/amr.2002.6588029
Kilduff, M., & Brass, D. J. (2010). Organizational Social Network Research: Core Ideas and Key Debates. *Academy of Management Annals, 4*(1), 317-357. doi:10.1080/19416520.2010.494827
Kilduff, M., & Tsai, W. (2003). *Social Networks and Organizations*. Thousand Oaks CA: Sage.
Kilduff, M., Tsai, W., & Hanke, R. (2006). A Paradigm Too Far? A Dynamic Stability Reconsideration of the Social Network Research Program. *Academy of Management Review, 31*(4), 1031-1048. doi:10.5465/amr.2006.22528168
Kim, T. Y., Oh, H., & Swaminathan, A. (2006). Framing Interorganizational Network Change: A Network Inertia Perspective. *Academy of Management Review, 31*(3), 704-720. doi:10.5465/amr.2006.21318926
Kivimaa, P., & Kern, F. (2016). Creative destruction or mere niche support? Innovation policy mixes for sustainability transitions. *Research Policy, 45*(1), 205-217. doi:10.1016/j.respol.2015.09.008
Kivimaa, P., & Virkamäki, V. (2014). Policy Mixes, Policy Interplay and Low Carbon Transitions: The Case of Passenger Transport in Finland. *Environmental Policy and Governance, 24*(1), 28-41. doi:10.1002/eet.1629
Klein Woolthuis, R., Lankhuizen, M., & Gilsing, V. A. (2005). A system failure framework for innovation policy design. *Technovation, 25*(6), 609-619. doi:10.1016/j.technovation.2003.11.002
Kleinbaum, A. M., Stuart, T. E., & Tushman, M. L. (2013). Discretion Within Constraint: Homophily and Structure in a Formal Organization. *Organization Science, 24*(5), 1316-1336. doi:10.1287/orsc.1120.0804
Klerkx, L., & Aarts, N. (2013). The interaction of multiple champions in orchestrating innovation networks: Conflicts and complementarities. *Technovation, 33*(6-7), 193-210. doi:10.1016/j.technovation.2013.03.002
Knights, D., Murray, F., & Willmott, H. (1993). Networking as Knowledge Work: A Study of Strategic Interorganizational Development in the Financial Services Industry*. *Journal of Management Studies, 30*(6), 975-995. doi:10.1111/j.1467-6486.1993.tb00475.x
Knoben, J., & Oerlemans, L. A. G. (2006). Proximity and inter-organizational collaboration: A literature review. *International Journal of Management Reviews, 8*(2), 71-89. doi:10.1111/j.1468-2370.2006.00121.x

Knudsen, T., & Srikanth, K. (2014). Coordinated Exploration: Organizing Joint Search by Multiple Specialists to Overcome Mutual Confusion and Joint Myopia. *Administrative Science Quarterly, 59*(3), 409-441. doi:10.1177/0001839214538021

Kogut, B. (2000). The network as knowledge: generative rules and the emergence of structure. *Strategic Management Journal, 21*(3), 405-425. doi:10.1002/(sici)1097-0266(200003)21:3<405::aid-smj103>3.0.co;2-5

Kogut, B., Urso, P., & Walker, G. (2007). Emergent Properties of a New Financial Market: American Venture Capital Syndication, 1960–2005. *Management Science, 53*(7), 1181-1198. doi:10.1287/mnsc.1060.0620

Kogut, B., Walker, G., & Kim, D.-J. (1995). Cooperation and entry induction as an extension of technological rivalry. *Research Policy, 24*(1), 77-95. doi:10.1016/0048-7333(93)00750-n

Kogut, B., & Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science, 3*(3), 383-397. doi:10.1287/orsc.3.3.383

Kolodny, H. F. (1979). Evolution to a Matrix Organization. *Academy of Management Review, 4*(4), 543-553. doi:10.5465/amr.1979.4498362

Koschmann, M. A., Kuhn, T. R., & Pfarrer, M. D. (2012). A Communicative Framework of Value in Cross-Sector Partnerships. *Academy of Management Review, 37*(3), 332-354. doi:10.5465/amr.2010.0314

Kotabe, M., & Scott Swan, K. (1995). The role of strategic alliances in high-technology new product development. *Strategic Management Journal, 16*(8), 621-636. doi:10.1002/smj.4250160804

Kotha, R., George, G., & Srikanth, K. (2012). Bridging the Mutual Knowledge Gap: Coordination and the Commercialization of University Science. *Academy of Management Journal, 56*(2), 498-524. doi:10.5465/amj.2010.0948

Koza, M. P., & Lewin, A. Y. (1999). The Coevolution of Network Alliances: A Longitudinal Analysis of an International Professional Service Network. *Organization Science, 10*(5), 638-653. doi:10.1287/orsc.10.5.638

Kozlowski, S. W. J., 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. doi:10.1177/1094428113493119

Krackhardt, D. (1994). Constraints on the Interactive Organization as an Ideal Type. In C. Heckscher & A. Donnellan (Eds.), *The Post Bureaucratic Organization* (pp. 211-222). Beverly Hills CA: SAGE.

Krackhardt, D. (1999). The Ties that Torture: Simmelian Tie Analysis in Organizations. In S. B. Bacharach (Ed.), *Research in the Sociology of Organizations* (pp. 183-210). Stanford, CT: JAI Press Inc.

Krackhardt, D., & Kilduff, M. (1999). Whether close or far: Social distance effects on perceived balance in friendship networks. *Journal of Personality and Social Psychology, 76*(5), 770-782. doi:10.1037/0022-3514.76.5.770

Kreiner, K., & Schultz, M. (1993). Informal Collaboration in R & D. The formation of Networks Across Organizations. *Organization Studies, 14*(2), 189-209. doi:10.1177/017084069301400202

Krivitsky, P. N., Handcock, M. S., & Morris, M. (2011). Adjusting for Network Size and Composition Effects in Exponential-Family Random Graph Models. *Stat Methodol, 8*(4), 319-339. doi:10.1016/j.stamet.2011.01.005

Kuemmerle, W. (1998). Optimal scale for research and development in foreign environments—an investigation into size and performance of research and development laboratories abroad. *Research Policy, 27*(2), 111-126. doi:10.1016/s0048-7333(98)00030-4

Kuhlmann, S. (2001). Future governance of innovation policy in Europe — three scenarios. *Research Policy, 30*(6), 953-976. doi:10.1016/s0048-7333(00)00167-0

Kulve, H. t., & Smit, W. A. (2003). Civilian–military co-operation strategies in developing new technologies. *Research Policy, 32*(6), 955-970. doi:10.1016/s0048-7333(02)00105-1

Landini, F., Lee, K., & Malerba, F. (2017). A history-friendly model of the successive changes in industrial leadership and the catch-up by latecomers. *Research Policy, 46*(2), 431-446. doi:10.1016/j.respol.2016.09.005

Lanzolla, G., & Suarez, F. F. (2012). Closing the Technology Adoption–Use Divide. *Journal of Management, 38*(3), 836-859. doi:10.1177/0149206310369938

Larson, J. R. (2007). Deep Diversity and Strong Synergy. *Small Group Research, 38*(3), 413-436. doi:10.1177/1046496407301972

Laumann, E. O., Marsden, P. V., & Prensky, D. (1983). The boundary specification problem in network analysis. In R. S. Burt & M. J. Minor (Eds.), *Applied Network Analysis: A Methodological Introduction*. Beverly Hills: Sage Publications.

Laursen, K., Masciarelli, F., & Prencipe, A. (2012). Regions Matter: How Localized Social Capital Affects Innovation and External Knowledge Acquisition. *Organization Science, 23*(1), 177-193. doi:10.1287/orsc.1110.0650

Laursen, K., & Salter, A. (2006). Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms. *Strategic Management Journal, 27*(2), 131-150. doi:10.1002/smj.507

Lavie, D. (2006a). Capability Reconfiguration: An Analysis of Incumbent Responses to Technological Change. *Academy of Management Review, 31*(1), 153-174. doi:10.5465/amr.2006.19379629

Lavie, D. (2006b). The Competitive Advantage of Interconnected Firms: An Extension of the Resource-Based View. *Academy of Management Review, 31*(3), 638-658. doi:10.5465/amr.2006.21318922

Lavie, D. (2007). Alliance portfolios and firm performance: A study of value creation and appropriation in the U.S. software industry. *Strategic Management Journal, 28*(12), 1187-1212. doi:10.1002/smj.637

Lavie, D., Lechner, C., & Singh, H. (2007). The Performance Implications of Timing of Entry and Involvement in Multipartner Alliances. *Academy of Management Journal, 50*(3), 578-604. doi:10.5465/amj.2007.25525906

Lazzarini, S. G. (2015). Strategizing by the government: Can industrial policy create firm-level competitive advantage? *Strategic Management Journal, 36*(1), 97-112. doi:10.1002/smj.2204

Leana, C. R., & Van Buren, H. J. (1999). Organizational Social Capital and Employment Practices. *Academy of Management Review, 24*(3), 538-555. doi:10.5465/amr.1999.2202136

Lechevalier, S., Nishimura, J., & Storz, C. (2014). Diversity in patterns of industry evolution: How an intrapreneurial regime contributed to the emergence of the service robot industry. *Research Policy, 43*(10), 1716-1729. doi:10.1016/j.respol.2014.07.012

Lee, C., & Chen, W.-J. (2007). Cross-functionality and charged behavior of the new product development teams in Taiwan's information technology industries. *Technovation, 27*(10), 605-615. doi:10.1016/j.technovation.2007.02.012

Lee, D., Kirkpatrick-Husk, K., & Madhavan, R. (2014). Diversity in Alliance Portfolios and Performance Outcomes: A Meta-Analysis. *Journal of Management*. doi:10.1177/0149206314556316

Lee, G. K. (2007). The significance of network resources in the race to enter emerging product markets: the convergence of telephony communications and computer networking, 1989–2001. *Strategic Management Journal, 28*(1), 17-37. doi:10.1002/smj.566

Lee, J. J. (2010). Heterogeneity, Brokerage, and Innovative Performance: Endogenous Formation of Collaborative Inventor Networks. *Organization Science, 21*(4), 804-822. doi:10.1287/orsc.1090.0488

Leiponen, A. (2006). Managing Knowledge for Innovation: The Case of Business-to-Business Services*. *Journal of Product Innovation Management, 23*(3), 238-258. doi:10.1111/j.1540-5885.2006.00196.x

Leiponen, A., & Drejer, I. (2007). What exactly are technological regimes? *Research Policy, 36*(8), 1221-1238. doi:10.1016/j.respol.2007.04.008
Leiponen, A., & Helfat, C. E. (2010). Innovation objectives, knowledge sources, and the benefits of breadth. *Strategic Management Journal, 31*(2), 224-236. doi:10.1002/smj.807
Levén, P., Holmström, J., & Mathiassen, L. (2014). Managing research and innovation networks: Evidence from a government sponsored cross-industry program. *Research Policy, 43*(1), 156-168. doi:10.1016/j.respol.2013.08.004
Lévesque, M., Minniti, M., & Shepherd, D. (2013). How Late Should Johnny-Come-Lately Come? *Long Range Planning, 46*(4-5), 369-386. doi:10.1016/j.lrp.2013.06.004
Levinthal, D., & Posen, H. E. (2007). Myopia of Selection: Does Organizational Adaptation Limit the Efficacy of Population Selection? *Administrative Science Quarterly, 52*(4), 586-620. doi:10.2189/asqu.52.4.586
Lewin, A. Y., Massini, S., & Peeters, C. (2011). Microfoundations of Internal and External Absorptive Capacity Routines. *Organization Science, 22*(1), 81-98. doi:10.1287/orsc.1100.0525
Lewis, K., & Herndon, B. (2011). Transactive Memory Systems: Current Issues and Future Research Directions. *Organization Science, 22*(5), 1254-1265. doi:10.1287/orsc.1110.0647
Li, D., Eden, L., Hitt, M. A., Ireland, R. D., & Garrett, R. P. (2012). Governance in Multilateral R&D Alliances. *Organization Science, 23*(4), 1191-1210. doi:10.1287/orsc.1110.0671
Li, S. X., & Rowley, T. J. (2002). Inertia and Evaluation Mechanisms in Interorganizational Partner Selection: Syndicate Formation among U.S. Investment Banks. *Academy of Management Journal, 45*(6), 1104-1119. doi:10.2307/3069427
Lin, H.-M., Chen, H., Sher, P. J., & Mei, H.-C. (2010). Inter-Network Co-evolution: Reversing the Fortunes of Declining Industrial Networks. *Long Range Planning, 43*(5-6), 611-638. doi:10.1016/j.lrp.2010.02.007
Lin, J. L., Fang, S.-C., Fang, S.-R., & Tsai, F.-S. (2009). Network embeddedness and technology transfer performance in R&D consortia in Taiwan. *Technovation, 29*(11), 763-774. doi:10.1016/j.technovation.2009.05.001
Lin, Z., Peng, M. W., Yang, H., & Sun, S. L. (2009). How do networks and learning drive M&As? An institutional comparison between China and the United States. *Strategic Management Journal, 30*(10), 1113-1132. doi:10.1002/smj.777
Lincoln, J. R., Gerlach, M. L., & Ahmadjian, C. L. (1996). Keiretsu networks and corporate performance in Japan. *American Sociological Review, 61*(1), 67-88.
Lindblom, C. E. (1959). The Science of "Muddling Through". *Public Administration Review, 19*(2), 79-88.
Lindenberg, S., & Foss, N. J. (2011). Managing Joint Production Motivation: The Role of Goal Framing and Governance Mechanisms. *Academy of Management Review, 36*(3), 500-525. doi:10.5465/amr.2010.0021
Lingo, E. L., & O'Mahony, S. (2010). Nexus Work: Brokerage on Creative Projects. *Administrative Science Quarterly, 55*(1), 47-81. doi:10.2189/asqu.2010.55.1.47
Linzer, D. A., & Lewis, J. B. (2011). poLCA: An R Package for Polytomous Variable Latent Class Analysis. *Journal of Statistical Software, 42*(10). doi:10.18637/jss.v042.i10
lo Storto, C. (2006). A method based on patent analysis for the investigation of technological innovation strategies: The European medical prostheses industry. *Technovation, 26*(8), 932-942. doi:10.1016/j.technovation.2005.10.005
Lomi, A., & Pattison, P. (2006). Manufacturing Relations: An Empirical Study of the Organization of Production Across Multiple Networks. *Organization Science, 17*(3), 313-332. doi:10.1287/orsc.1060.0190
Lomnitz, L. (1983). The Scientific Meeting: An Anthropologist's Point of View. *4S Review, 1*(2), 2-7. doi:10.2307/690361

Lopez-Vega, H., Tell, F., & Vanhaverbeke, W. (2016). Where and how to search? Search paths in open innovation. *Research Policy, 45*(1), 125-136. doi:10.1016/j.respol.2015.08.003

Lounamaa, P. H., & March, J. G. (1987). Adaptive Coordination of a Learning Team. *Management Science, 33*(1), 107-123. doi:10.1287/mnsc.33.1.107

Lounsbury, M. (2000). Book review. *Administrative Science Quarterly, 45*(4), 837-840. doi:10.2307/2667021

Lovelace, K., Shapiro, D. L., & Weingart, L. R. (2001). Maximizing Cross-Functional New Product Teams' Innovativeness and Constraint Adherence: A Conflict Communications Perspective. *Academy of Management Journal, 44*(4), 779-793. doi:10.2307/3069415

Luiten, E., van Lente, H., & Blok, K. (2006). Slow technologies and government intervention: Energy efficiency in industrial process technologies. *Technovation, 26*(9), 1029-1044. doi:10.1016/j.technovation.2005.10.004

Lundvall, B. Å. (1992). *National Systems of Innovation: Toward a Theory of Innovation and Interactive Learning*. London: Anthem Press.

Luo, Y. (2003). Industrial dynamics and managerial networking in an emerging market: the case of China. *Strategic Management Journal, 24*(13), 1315-1327. doi:10.1002/smj.363

Lusher, D., Koskinen, J., & Robins, G. (2013). *Exponential Random Graph Models for Social Networks* (Vol. 35). New York: Cambridge University Press.

M'Chirgui, Z. (2009). Dynamics of R&D networked relationships and mergers and acquisitions in the smart card field. *Research Policy, 38*(9), 1453-1467. doi:10.1016/j.respol.2009.07.002

Macher, J. T. (2006). Technological Development and the Boundaries of the Firm: A Knowledge-Based Examination in Semiconductor Manufacturing. *Management Science, 52*(6), 826-843. doi:10.1287/mnsc.1060.0511

MacKay, R. B., & Chia, R. (2012). Choice, Chance, and Unintended Consequences in Strategic Change: A Process Understanding of the Rise and Fall of NorthCo Automotive. *Academy of Management Journal, 56*(1), 208-230. doi:10.5465/amj.2010.0734

Maclean, M., & Harvey, C. (2015). 'Give It Back, George': Network Dynamics in the Philanthropic Field. *Organization Studies, 37*(3), 399-423. doi:10.1177/0170840615613368

Madhavan, R., Koka, B. R., & Prescott, J. E. (1998). Networks in transition: how industry events (re)shape interfirm relationships. *Strategic Management Journal, 19*(5), 439-459. doi:10.1002/(sici)1097-0266(199805)19:5<439::aid-dia952>3.0.co;2-2

Magro, E., & Wilson, J. R. (2013). Complex innovation policy systems: Towards an evaluation mix. *Research Policy, 42*(9), 1647-1656. doi:10.1016/j.respol.2013.06.005

Maietta, O. W. (2015). Determinants of university–firm R&D collaboration and its impact on innovation: A perspective from a low-tech industry. *Research Policy, 44*(7), 1341-1359. doi:10.1016/j.respol.2015.03.006

Maine, E., Probert, D., & Ashby, M. (2005). Investing in new materials: a tool for technology managers. *Technovation, 25*(1), 15-23. doi:10.1016/s0166-4972(03)00070-1

Makadok, R., & Walker, G. (2007). Search and selection in the money market fund industry. *Strategic Management Journal, 17*(S1), 39-54. doi:10.1002/smj.4250171005

Malerba, F. (2002). Sectoral systems of innovation and production. *Research Policy, 31*(2), 247-264. doi:10.1016/s0048-7333(01)00139-1

Malerba, F., & Orsenigo, L. (1996). Schumpeterian patterns of innovation are technology-specific. *Research Policy, 25*(3), 451-478. doi:10.1016/0048-7333(95)00840-3

Malerba, F., & Orsenigo, L. (1997). Technological Regimes and Sectoral Patterns of Innovative Activities. *Industrial and Corporate Change, 6*(1), 83-118. doi:10.1093/icc/6.1.83

Malerba, F., & Orsenigo, L. (1999). Technological entry, exit and survival: an empirical analysis of patent data. *Research Policy, 28*(6), 643-660. doi:10.1016/s0048-7333(99)00005-0

Mannak, R. S. (2015). *To repeat or not to repeat: A temporal perspective on repeated collaboration in R&D consortia.* (Dissertation), Ridderprint, Ridderkerk.

Mannak, R. S., Raab, J., & Smit, A. C. (2012). Repeated ties in Multi-Partner R&D-consortia: Temporal Dynamic Effects of Embeddedness. *Academy of Management Proceedings, 2012*(1), 1-1. doi:10.5465/ambpp.2012.199

Manning, S. (2017). The rise of project network organizations: Building core teams and flexible partner pools for interorganizational projects. *Research Policy, 46*(8), 1399-1415. doi:10.1016/j.respol.2017.06.005

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies, 60*(3), 531. doi:10.2307/2298123

March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science, 2*(1), 71-87. doi:10.1287/orsc.2.1.71

Marchington, M., & Vincent, S. (2004). Analysing the Influence of Institutional, Organizational and Interpersonal Forces in Shaping Inter-Organizational Relations*. *Journal of Management Studies, 41*(6), 1029-1056. doi:10.1111/j.1467-6486.2004.00465.x

Martin, B. R. (2012). The evolution of science policy and innovation studies. *Research Policy, 41*(7), 1219-1239. doi:10.1016/j.respol.2012.03.012

Martin, J. L. (2003). What Is Field Theory? *American Journal of Sociology, 109*(1), 1-49. doi:10.1086/375201

Maskell, P., Bathelt, H., & Malmberg, A. (2006). Building global knowledge pipelines: The role of temporary clusters. *European Planning Studies, 14*(8), 997-1013. doi:10.1080/09654310600852332

Mathews, J. A. (2002). The origins and dynamics of Taiwan's R&D consortia. *Research Policy, 31*(4), 633-651. doi:10.1016/s0048-7333(01)00131-7

Mathieu, J. E., Marks, M. A., & Zaccaro, S. J. (2001). Multiteam Systems. In N. Anderson, D. S. Ones, H. K. Sinangil, & C. Viswesvaran (Eds.), *Handbook of Industrial, Work and Organizational Psychology. Volume 2: Organizational Psychology* (pp. 289-313). London: Sage Publications.

Mathieu, J. E., Maynard, M. T., Rapp, T., & Gilson, L. (2008). Team Effectiveness 1997-2007: A Review of Recent Advancements and a Glimpse Into the Future. *Journal of Management, 34*(3), 410-476. doi:10.1177/0149206308316061

McCarter, M. W., Mahoney, J. T., & Northcraft, G. B. (2011). Testing the Waters: Using Collective Real Options to Manage the Social Dilemma of Strategic Alliances. *Academy of Management Review, 36*(4), 621-640. doi:10.5465/amr.2009.0481

McDermott, G. A., Corredoira, R. A., & Kruse, G. (2009). Public-Private Institutions as Catalysts of Upgrading in Emerging Market Societies. *Academy of Management Journal, 52*(6), 1270-1296. doi:10.5465/amj.2009.47084929

McEvily, B., & Zaheer, A. (1999). Bridging ties: a source of firm heterogeneity in competitive capabilities. *Strategic Management Journal, 20*(12), 1133-1156. doi:10.1002/(sici)1097-0266(199912)20:12<1133::aid-smj74>3.0.co;2-7

McGrath, C. H., Horvath, V., Baruch, B., Gunashekar, S., Lu, H., Culbertson, S., . . . Chataway, J. (2014). *The international dimension of research and innovation cooperation addressing grand challenges in the global context - Final Policy Brief.* Retrieved from Santa Monica, CA: http://www.rand.org/pubs/research_reports/RR725.html

McGrath, R. G., Macmillan, I. C., & Tushman, M. L. (1992). The role of executive team actions in shaping dominant designs: Towards the strategic shaping of technological progress. *Strategic Management Journal, 13*(S2), 137-161. doi:10.1002/smj.4250130910

McKendrick, D. G. (2001). Global strategy and population-level learning: the case of hard disk drives. *Strategic Management Journal, 22*(4), 307-334. doi:10.1002/smj.161

Meeus, M. T. H., Oerlemans, L. A. G., & Hage, J. (2001). Patterns of Interactive Learning in a High-tech Region. *Organization Studies, 22*(1), 145-172. doi:10.1177/0170840601022001006

Meeus, M. T. H., Oerlemans, L. A. G., & Kenis, P. (2008). Inter-organisational networks and innovation. In B. Nooteboom & E. Stam (Eds.), *Micro-foundations for Innovation Policy* (pp. 273-314). Amsterdam: Amsterdam University Press.

Mehra, A., Dixon, A. L., Brass, D. J., & Robertson, B. (2006). The Social Network Ties of Group Leaders: Implications for Group Performance and Leader Reputation. *Organization Science, 17*(1), 64-79. doi:10.1287/orsc.1050.0158

Meyer-Krahmer, F. (1992). The German R & D system in transition: Empirical results and prospects of future development. *Research Policy, 21*(5), 423-436. doi:10.1016/0048-7333(92)90003-m

Michelfelder, I., & Kratzer, J. (2013). Why and How Combining Strong and Weak Ties within a Single Interorganizational R&D Collaboration Outperforms Other Collaboration Structures. *Journal of Product Innovation Management, 30*(6), 1159-1177. doi:10.1111/jpim.12052

Mihm, J., Sting, F. J., & Wang, T. (2015). On the Effectiveness of Patenting Strategies in Innovation Races. *Management Science, 61*(11), 2662-2684. doi:10.1287/mnsc.2014.2128

Miller, D. (1999). Selection Processes Inside Organizations. The Self-Reinforcing Consequences of Success. In J. A. C. Baum & B. McKelvey (Eds.), *Variations in organization science: In honor of Donald T. Campbell* (pp. 93-109). Thousand Oaks: Sage.

Milliken, F. J., & Martins, L. L. (1996). Searching for Common Threads: Understanding the Multiple Effects of Diversity in Organizational Groups. *Academy of Management Review, 21*(2), 402-433. doi:10.5465/amr.1996.9605060217

Mindruta, D. (2013). Value creation in university-firm research collaborations: A matching approach. *Strategic Management Journal, 34*(6), 644-665. doi:10.1002/smj.2036

Miner, A., & Raghavan, S. V. (1999). Interorganizational Imitation: A Hidden Engine of Selection. In J. A. C. Baum & B. McKelvey (Eds.), *Variations in organization science: In honor of Donald T. Campbell*. Thousand Oaks: Sage.

Mitchell, W., & Singh, K. (1996). Survival of Businesses Using Collaborative Relationships to Commercialize Complex Goods. *Strategic Management Journal, 17*(3), 169-195. doi:10.1002/(sici)1097-0266(199603)17:3<169::aid-smj801>3.0.co;2-#

Mitsuhashi, H., & Greve, H. R. (2009). A Matching Theory of Alliance Formation and Organizational Success: Complementarity and Compatibility. *Academy of Management Journal, 52*(5), 975-995. doi:10.5465/amj.2009.44634482

Mohr, A. T., & Puck, J. F. (2005). Managing Functional Diversity to Improve the Performance of International Joint Ventures. *Long Range Planning, 38*(2), 163-182. doi:10.1016/j.lrp.2005.02.004

Mohrman, S. A., Gailbrath, J. R., & Monge, P. (2006). Network attributes impacting the generation and flow of knowledge with and from the basic science community. In J. Hage & M. T. H. Meeus (Eds.), *Innovation, Science, and Institutional Change - A Research Handbook* (pp. 196-216). Oxford: Oxford University Press.

Molina-Morales, F. X., Martínez-Fernández, M. T., & Torlò, V. J. (2011). The Dark Side of Trust: The Benefits, Costs and Optimal Levels of Trust for Innovation Performance. *Long Range Planning, 44*(2), 118-133. doi:10.1016/j.lrp.2011.01.001

Monge, P. R. (1990). Theoretical and Analytical Issues in Studying Organizational Processes. *Organization Science, 1*(4), 406-430. doi:10.1287/orsc.1.4.406

Monge, P. R., Fulk, J., Kalman, M. E., Flanagin, A. J., Parnassa, C., & Rumsey, S. (1998). Production of Collective Action in Alliance-Based Interorganizational Communication and Information Systems. *Organization Science, 9*(3), 411-433. doi:10.1287/orsc.9.3.411

Montoya-Weiss, M. M., Massey, A. P., & Song, M. (2001). Getting It Together: Temporal Coordination and Conflict Management in Global Virtual Teams. *Academy of Management Journal, 44*(6), 1251-1262. doi:10.2307/3069399

Mooney, A. C., Holahan, P. J., & Amason, A. C. (2007). Don't Take It Personally: Exploring Cognitive Conflict as a Mediator of Affective Conflict. *Journal of Management Studies, 44*(5), 733-758. doi:10.1111/j.1467-6486.2006.00674.x

Moretti, A., & Zirpoli, F. (2016). A Dynamic Theory of Network Failure: The Case of the Venice Film Festival and the Local Hospitality System. *Organization Studies, 37*(5), 607-633. doi:10.1177/0170840615613369

Morris, S. S., & Snell, S. A. (2007). Relational Archetypes, Organizational Learning, and Value Creation: Extending the Human Resource Architecture. *Academy of Management Review, 32*(1), 236-256. doi:10.5465/amr.2007.23464060

Mors, M. L. (2010). Innovation in a global consulting firm: when the problem is too much diversity. *Strategic Management Journal*, n/a-n/a. doi:10.1002/smj.837

Mowery, D. C. (1988). Assessing the effects of divestiture on Bell telephone laboratories. *Technovation, 7*(4), 353-375. doi:10.1016/0166-4972(88)90007-7

Murmann, J. P. (2013). The Coevolution of Industries and Important Features of Their Environments. *Organization Science, 24*(1), 58-78. doi:10.1287/orsc.1110.0718

Murmann, J. P., & Frenken, K. (2006). Toward a systematic framework for research on dominant designs, technological innovations, and industrial change. *Research Policy, 35*(7), 925-952. doi:10.1016/j.respol.2006.04.011

Nahapiet, J., & Ghoshal, S. (1998). Social Capital, Intellectual Capital, and the Organizational Advantage. *Academy of Management Review, 23*(2), 242. doi:10.2307/259373

Nelson, R. R., & Winter, S. (1982). *An Evolutionary Theory of Economic Change*. Cambridge, MA: The Belknap Press of Harvard University Press.

Nerkar, A., & Paruchuri, S. (2005). Evolution of R&D Capabilities: The Role of Knowledge Networks Within a Firm. *Management Science, 51*(5), 771-785. doi:10.1287/mnsc.1040.0354

Newcomb, T. M. (1961). *The acquaintance process*. New York NY: Holt, Rinehart and Winston.

Nishimura, J., & Okada, Y. (2014). R&D portfolios and pharmaceutical licensing. *Research Policy, 43*(7), 1250-1263. doi:10.1016/j.respol.2014.03.008

O'Connor, G. C., & DeMartino, R. (2006). Organizing for Radical Innovation: An Exploratory Study of the Structural Aspects of RI Management Systems in Large Established Firms. *Journal of Product Innovation Management, 23*(6), 475-497. doi:10.1111/j.1540-5885.2006.00219.x

O'Leary, M. B., Mortensen, M., & Woolley, A. W. (2011). Multiple Team Membership: A Theoretical Model of its Effects on Productivity and Learning for Individuals and Teams. *Academy of Management Review, 36*(3), 461-478. doi:10.5465/amr.2011.61031807

O'Reilly, C. A., Harreld, J. B., & Tushman, M. L. (2009). Organizational Ambidexterity: IBM and Emerging Business Opportunities. *California Management Review, 51*(4), 75-99. doi:10.2307/41166506

Oberski, D. (2016). Mixture Models: Latent Profile and Latent Class Analysis. In *Modern Statistical Methods for HCI* (pp. 275-287).

Obstfeld, D. (2005). Social Networks, the Tertius Iungens Orientation, and Involvement in Innovation. *Administrative Science Quarterly, 50*(1), 100-130. doi:doi: 10.2189/asqu.2005.50.1.100

Odagiri, H., Nakamura, Y., & Shibuya, M. (1997). Research consortia as a vehicle for basic research: The case of a fifth generation computer project in Japan. *Research Policy, 26*(2), 191-207. doi:10.1016/s0048-7333(97)00008-5

Oh, W., & Jeon, S. (2007). Membership Herding and Network Stability in the Open Source Community: The Ising Perspective. *Management Science, 53*(7), 1086-1101. doi:10.1287/mnsc.1060.0623

Oliver, C. (1990). Determinants of Interorganizational Relationships: Integration and Future Directions. *Academy of Management Review, 15*(2), 241. doi:10.2307/258156

Olk, P., & Young, C. (1997). Why members stay in or leave an R&D consortium: performance and conditions of membership as determinants of continuity. *Strategic Management Journal, 18*(11), 855-877. doi:10.1002/(sici)1097-0266(199712)18:11<855::aid-smj923>3.0.co;2-q
Olsen, A. O., Sofka, W., & Grimpe, C. (2016). Coordinated Exploration for Grand Challenges: The Role of Advocacy Groups in Search Consortia. *Academy of Management Journal, 59*(6), 2232-2255. doi:10.5465/amj.2015.0730
Orsenigo, L., Pammolli, F., & Riccaboni, M. (2001). Technological change and network dynamics: Lessons from the pharmaceutical industry. *Research Policy, 30*(3), 485-508. doi:10.1016/s0048-7333(00)00094-9
Ouchi, W. G., & Bolton, M. K. (1988). The Logic of Joint Research and Development. *California Management Review, 30*(3), 9-33. doi:10.2307/41166512
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. doi:10.1287/orsc.1030.0054
Owen-Smith, J., Riccaboni, M., Pammolli, F., & Powell, W. W. (2002). A Comparison of U.S. and European University-Industry Relations in the Life Sciences. *Management Science, 48*(1), 24-43. doi:10.1287/mnsc.48.1.24.14275
Pakes, A., & Schankerman, M. (1984). The Rate of Obsolence of Patents, Research Gestation Lags, and the Private Rate of Return to Research Resources. In Z. Griliches (Ed.), *R&D, Patents, and Productivity* (pp. 73-88). Chicago: University of Chicago Press.
Pallant, J. F. (2005). *SPSS survival manual: a step by step guide to data analysis using SPSS* (2nd ed.). Crows Nest: Alex & Unwin.
Pallotti, F., Tubaro, P., & Lomi, A. (2015). How Far do Network Effects Spill Over? Evidence from an Empirical Study of Performance Differentials in Interorganizational Networks. *European Management Review, 12*(3), 189-208. doi:10.1111/emre.12052
Pampel, F. C. (2000). *Logistic Regression - A Primer*. Thousand Oaks, CA: SAGE Publications, Inc.
Pangarkar, N. (2009). Do Firms Learn from Alliance Terminations? An Empirical Examination. *Journal of Management Studies, 46*(6), 982-1004. doi:10.1111/j.1467-6486.2009.00844.x
Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometrics, 11*(6), 619-632. doi:10.1002/(sici)1099-1255(199611)11:6<619::Aid-jae418>3.0.Co;2-1
Park, H. W., & Leydesdorff, L. (2010). Longitudinal trends in networks of university–industry–government relations in South Korea: The role of programmatic incentives. *Research Policy, 39*(5), 640-649. doi:10.1016/j.respol.2010.02.009
Park, S. H. (1996). Managing an Interorganizational Network: A Framework of the Institutional Mechanism for Network Control. *Organization Studies, 17*(5), 795-824. doi:10.1177/017084069601700505
Park, S. H., & Zhou, D. (2005). Firm Heterogeneity and Competitive Dynamics in Alliance Formation. *Academy of Management Review, 30*(3), 531-554. doi:10.5465/amr.2005.17293697
Parkhe, A., Wasserman, S., & Ralston, D. A. (2006). New Frontiers in Network Theory Development. *Academy of Management Review, 31*(3), 560-568. doi:10.5465/amr.2006.21318917
Parmigiani, A., & Rivera-Santos, M. (2011). Clearing a Path Through the Forest: A Meta-Review of Interorganizational Relationships. *Journal of Management, 37*(4), 1108-1136. doi:10.1177/0149206311407507
Paruchuri, S., & Awate, S. (2016). Organizational knowledge networks and local search: The role of intra-organizational inventor networks. *Strategic Management Journal*, n/a-n/a. doi:10.1002/smj.2516
Patel, P. C., Kohtamäki, M., Parida, V., & Wincent, J. (2015). Entrepreneurial orientation-as-experimentation and firm performance: The enabling role of absorptive capacity. *Strategic Management Journal, 36*(11), 1739-1749. doi:10.1002/smj.2310

Patzelt, H., Lechner, C., & Klaukien, A. (2011). Networks and the Decision to Persist with Underperforming R&D Projects. *Journal of Product Innovation Management*, no-no. doi:10.1111/j.1540-5885.2011.00840.x

Pavitt, K. (1984). Sectoral patterns of technical change: Towards a taxonomy and a theory. *Research Policy, 13*(6), 343-373. doi:10.1016/0048-7333(84)90018-0

Peine, A. (2006). Technological paradigms revisited - how they contribute to the understanding of open systems of technology. *Working paper, Technical University Technology Studies*(TUTS-WP-2-2006), 1-27.

Pena, E. A., & Slate, E. H. (2006). Global Validation of Linear Model Assumptions. *Journal of the American Statistical Association, 101*(473), 341. doi:10.1198/016214505000000637

Pentland, B. T., Feldman, M. S., Becker, M. C., & Liu, P. (2012). Dynamics of Organizational Routines: A Generative Model. *Journal of Management Studies, 49*(8), 1484-1508. doi:10.1111/j.1467-6486.2012.01064.x

Peri, G. (2005). Determinants of Knowledge Flows and Their Effect on Innovation. *Review of Economics and Statistics, 87*(2), 308-322. doi:10.1162/0034653053970258

Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'Este, P., . . . Sobrero, M. (2013). Academic engagement and commercialisation: A review of the literature on university–industry relations. *Research Policy, 42*(2), 423-442. doi:10.1016/j.respol.2012.09.007

Perry-Smith, J. E., & Mannucci, P. V. (2017). From Creativity to Innovation: The Social Network Drivers of the Four Phases of the Idea Journey. *Academy of Management Review, 42*(1), 53-79. doi:10.5465/amr.2014.0462

Peterman, A., Kourula, A., & Levitt, R. (2014). Balancing act: Government roles in an energy conservation network. *Research Policy, 43*(6), 1067-1082. doi:10.1016/j.respol.2013.12.007

Peterson, B., & Harrell, F. E. (1990). Partial Proportional Odds Models for Ordinal Response Variables. *Applied Statistics, 39*(2). doi:10.2307/2347760

Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, Networks, and Knowledge Networks: A Review and Research Agenda. *Journal of Management, 38*(4), 1115-1166. doi:10.1177/0149206311432640

Pitt, L., Merwe, R. v. d., Berthon, P., Salehi-Sangari, E., & Barnes, B. R. (2006). Swedish BioTech SMEs: The veiled values in online networks. *Technovation, 26*(5-6), 553-560. doi:10.1016/j.technovation.2005.09.009

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, 5-6*(3-4), 137-168. doi:10.1111/j.1460-8545.2004.00101.x

Podolny, J. M. (2001). Networks as the Pipes and Prisms of the Market. *American Journal of Sociology, 107*(1), 33-60. doi:10.1086/323038

Podolny, J. M., & Page, K. L. (1998). Network Forms of Organization. *Annual Review of Sociology, 24*(1), 57-76. doi:10.1146/annurev.soc.24.1.57

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903. doi:10.1037/0021-9010.88.5.879

Pollock, T. G., Porac, J. F., & Wade, J. B. (2004). Constructing Deal Networks: Brokers as Network "Architects" in the U.S. Ipo Market and Other Examples. *Academy of Management Review, 29*(1), 50-72. doi:10.5465/amr.2004.11851710

Postrel, S. (2002). Islands of Shared Knowledge: Specialization and Mutual Understanding in Problem-Solving Teams. *Organization Science, 13*(3), 303-320. doi:10.1287/orsc.13.3.303.2773

Pouder, R., & John, C. H. S. (1996). Hot Spots and Blind Spots: Geographical Clusters of Firms and Innovation. *Academy of Management Review, 21*(4), 1192. doi:10.2307/259168

Powell, W. W. (1990). Neither Market Nor Hierarchy: Network Forms of Organization. *Research In Organizational Behavior, 12*, 295-336.
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. doi:10.2307/2393988
Powell, W. W., White, Douglas R., Koput, Kenneth W., & Owen-Smith, J. (2005). Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences. *American Journal of Sociology, 110*(4), 1132-1205. doi:10.1086/421508
Prettner, K., & Werner, K. (2016). Why it pays off to pay us well: The impact of basic research on economic growth and welfare. *Research Policy, 45*(5), 1075-1090. doi:10.1016/j.respol.2016.03.001
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. doi:10.1177/0149206307302554
Provan, K. G., & Kenis, P. (2008). Modes of Network Governance: Structure, Management, and Effectiveness. *Journal of Public Administration Research and Theory, 18*(2), 229-252. doi:10.1093/jopart/mum015
Provan, K. G., & Lemaire, R. (2012). Core Concepts and Key Ideas for Understanding Public Sector Organizational Networks: Using Research to Inform Scholarship and Practice. *Public Administration Review, 72*(5), 638-648. doi:10.2307/41687977
Provan, K. G., & Milward, H. B. (1995). A Preliminary Theory of Interorganizational Network Effectiveness: A Comparative Study of Four Community Mental Health Systems. *Administrative Science Quarterly, 40*(1), 1. doi:10.2307/2393698
Provan, K. G., & Milward, H. B. (2001). Do Networks Really Work? A Framework for Evaluating Public-Sector Organizational Networks. *Public Administration Review, 61*(4), 414-423. doi:10.1111/0033-3352.00045
Provan, K. G., & Sebastian, J. G. (1998). Networks within Networks: Service Link Overlap, Organizational Cliques, and Network Effectiveness. *Academy of Management Journal, 41*(4), 453-463. doi:10.2307/257084
Puranam, P., Alexy, O., & Reitzig, M. (2013). What's "New" About New Forms of Organizing? *Academy of Management Review, 39*(2), 162-180. doi:10.5465/amr.2011.0436
Quintana-García, C., & Benavides-Velasco, C. A. (2004). Cooperation, competition, and innovative capability: a panel data of European dedicated biotechnology firms. *Technovation, 24*(12), 927-938. doi:10.1016/s0166-4972(03)00060-9
Quintane, E., & Carnabuci, G. (2016). How Do Brokers Broker? Tertius Gaudens, Tertius Iungens, and the Temporality of Structural Holes. *Organization Science, 27*(6), 1343-1360. doi:10.1287/orsc.2016.1091
R Development Core team. (2016). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-project.org/
Raab, J. (1998). *Differentiation and Integration as General Dimensions for the Analysis of Interorganizational Networks*. Paper presented at the 14th EGOS Colloquium, Maastricht.
Raab, J., & Kenis, P. (2009). Heading Toward a Society of Networks: Empirical Developments and Theoretical Challenges. *Journal of Management Inquiry*. doi:10.1177/1056492609337493
Ranganathan, R., & Rosenkopf, L. (2013). Do Ties Really Bind? The Effect of Knowledge and Commercialization Networks on Opposition to Standards. *Academy of Management Journal, 57*(2), 515-540. doi:10.5465/amj.2011.1064
Rao, H., & Singh, J. V. (1999). Types of Variation in Organizational Populations: The Specification of New Organizational Forms. In J. A. C. Baum & B. McKelvey (Eds.), *Variations in organization science: In honor of Donald T. Campbell*. Thousand Oaks: Sage.

Reagans, R., & McEvily, B. (2003). Network Structure and Knowledge Transfer: The Effects of Cohesion and Range. *Administrative Science Quarterly, 48*(2), 240. doi:10.2307/3556658

Reagans, R., Zuckerman, E. W., McEvily, B., & Stuart, T. E. (2004). How to Make the Team: Social Networks vs. Demography as Criteria for Designing Effective Teams. *Administrative Science Quarterly, 49*(1), 101-133. doi:10.2307/4131457

Reagans, R. E., & Zuckerman, E. W. (2008). Why knowledge does not equal power: the network redundancy trade-off. *Industrial and Corporate Change, 17*(5), 903-944. doi:10.1093/icc/dtn036

Reger, G. (2003). Building Innovation: Complex Constructs in a Changing World. *Research Policy, 32*(3), 528-529. doi:10.1016/s0048-7333(02)00014-8

Reitzig, M., & Sorenson, O. (2013). Biases in the selection stage of bottom-up strategy formulation. *Strategic Management Journal, 34*(7), 782-799. doi:10.1002/smj.2047

Rhisiart, M., & Carabias, V. (2013). Foresight and "grand challenges" within research and innovation policies. *Foresight, 15*(1), 29-39. doi:10.1108/14636681311310123

Ring, P. S., & van de Ven, A. H. (1994). Developmental Processes of Cooperative Interorganizational Relationships. *Academy of Management Review, 19*(1), 90. doi:10.2307/258836

Rodan, S., & Galunic, C. (2004). More than network structure: how knowledge heterogeneity influences managerial performance and innovativeness. *Strategic Management Journal, 25*(6), 541-562. doi:10.1002/smj.398

Roelofsen, A., Boon, W. P. C., Kloet, R. R., & Broerse, J. E. W. (2011). Stakeholder interaction within research consortia on emerging technologies: Learning how and what? *Research Policy, 40*(3), 341-354. doi:10.1016/j.respol.2010.10.015

Rogan, M. (2014). Too Close for Comfort? The Effect of Embeddedness and Competitive Overlap on Client Relationship Retention Following an Acquisition. *Organization Science, 25*(1), 185-203. doi:10.1287/orsc.2013.0833

Rogers, E. M. (2003). *Diffusion of innovations* (5th edition ed.). New York (NY): Free Press.

Roijakkers, N., & Hagedoorn, J. (2006). Inter-firm R&D partnering in pharmaceutical biotechnology since 1975: Trends, patterns, and networks. *Research Policy, 35*(3), 431-446. doi:10.1016/j.respol.2006.01.006

Romanelli, E. (1999). Blind (But Not Unconditioned) Variation: Problems of Copying in Sociocultural Evolution. In J. A. C. Baum & B. McKelvey (Eds.), *Variations in organization science: In honor of Donald T. Campbell.* Thousand Oaks: Sage.

Rondé, P. (2001). Technological clusters with a knowledge-based principle: evidence from a Delphi investigation in the French case of the life sciences. *Research Policy, 30*(7), 1041-1057. doi:10.1016/s0048-7333(00)00134-7

Ropohl, G. (1999). Philosophy of Socio-Technical Systems. *Techné: Research in Philosophy and Technology, 4*(3), 186-194. doi:10.5840/techne19994311

Rose Kim, J. Y., Howard, M. D., Cox Pahnke, E., & Boeker, W. (2016). Understanding network formation in strategy research: Exponential random graph models. *Strategic Management Journal, 37*(1), 22-44. doi:10.1002/smj.2454

Rosenberg, N. (1990). Why do firms do basic research (with their own money)? *Research Policy, 19*(2), 165-174. doi:10.1016/0048-7333(90)90046-9

Rosenkopf, L., Metiu, A., & George, V. P. (2001). From the Bottom Up? Technical Committee Activity and Alliance Formation. *Administrative Science Quarterly, 46*(4), 748-772. doi:10.2307/3094830

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. doi:10.1002/smj.160

Rosenkopf, L., & Schilling, M. A. (2007). Comparing alliance network structure across industries: observations and explanations. *Strategic Entrepreneurship Journal, 1*(3-4), 191-209. doi:10.1002/sej.33

Rosenkopf, L., & Tushman, M. L. (1998). The Coevolution of Community Networks and Technology: Lessons from the Flight Simulation Industry. *Industrial and Corporate Change, 7*(2), 311-346. doi:10.1093/icc/7.2.311

Rost, K. (2011). The strength of strong ties in the creation of innovation. *Research Policy, 40*(4), 588-604. doi:10.1016/j.respol.2010.12.001

Rothaermel, F. T., & Hill, C. W. L. (2005). Technological Discontinuities and Complementary Assets: A Longitudinal Study of Industry and Firm Performance. *Organization Science, 16*(1), 52-70. doi:10.1287/orsc.1040.0100

Rowley, T., Behrens, D., & Krackhardt, D. (2000). Redundant governance structures: an analysis of structural and relational embeddedness in the steel and semiconductor industries. *Strategic Management Journal, 21*(3), 369-386. doi:10.1002/(sici)1097-0266(200003)21:3<369::aid-smj93>3.0.co;2-m

Safarzyńska, K., Frenken, K., & van den Bergh, J. C. J. M. (2012). Evolutionary theorizing and modeling of sustainability transitions. *Research Policy, 41*(6), 1011-1024. doi:10.1016/j.respol.2011.10.014

Sakakibara, M. (1997). Evaluating government-sponsored R&D consortia in Japan: who benefits and how? *Research Policy, 26*(4-5), 447-473. doi:10.1016/s0048-7333(97)00018-8

Sakakibara, M. (2002). Formation of R&D consortia: industry and company effects. *Strategic Management Journal, 23*(11), 1033-1050. doi:10.1002/smj.272

Sakakibara, M. (2003). The Diversity of R&D Consortia and Firm Behavior: Evidence from Japanese Data. *The Journal of Industrial Economics, 49*(2), 181-196. doi:10.1111/1467-6451.00145

Sakakibara, M., & Cho, D.-S. (2002). Cooperative R&D in Japan and Korea: a comparison of industrial policy. *Research Policy, 31*(5), 673-692. doi:10.1016/s0048-7333(01)00150-0

Salavisa, I., Sousa, C., & Fontes, M. (2012). Topologies of innovation networks in knowledge-intensive sectors: Sectoral differences in the access to knowledge and complementary assets through formal and informal ties. *Technovation, 32*(6), 380-399. doi:10.1016/j.technovation.2012.02.003

Salman, N., & Saives, A.-L. (2005). Indirect networks: an intangible resource for biotechnology innovation. *R&D Management, 35*(2), 203-215. doi:10.1111/j.1467-9310.2005.00383.x

Salter, A. J., & Martin, B. R. (2001). The economic benefits of publicly funded basic research: a critical review. *Research Policy, 30*(3), 509-532. doi:10.1016/s0048-7333(00)00091-3

Sammarra, A., & Biggiero, L. (2008). Heterogeneity and Specificity of Inter-Firm Knowledge Flows in Innovation Networks. *Journal of Management Studies, 45*(4), 800-829. doi:10.1111/j.1467-6486.2008.00770.x

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. doi:10.2189/asqu.2010.55.4.639

Sasson, A. (2008). Exploring Mediators: Effects of the Composition of Organizational Affiliation on Organization Survival and Mediator Performance. *Organization Science, 19*(6), 891-906. doi:10.1287/orsc.1080.0363

Saxton, T. (1997). The Effects of Partner and Relationship Characteristics on Alliance Outcomes. *Academy of Management Journal, 40*(2), 443-461. doi:10.2307/256890

Schilling, M. A. (2009). Understanding the alliance data. *Strategic Management Journal, 30*(3), 233-260. doi:10.1002/smj.731

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. doi:10.1287/mnsc.1060.0624

Schmoch, U. (2008). *Concept of a Technology Classification for Country Comparisons - Final Report to the World Intellectual Property Organisation (WIPO)*. Retrieved from Karlsruhe, Germany:
Schoenmakers, W., & Duysters, G. (2010). The technological origins of radical inventions. *Research Policy, 39*(8), 1051-1059. doi:10.1016/j.respol.2010.05.013
Schreyögg, G., & Sydow, J. (2010). CROSSROADS—Organizing for Fluidity? Dilemmas of New Organizational Forms. *Organization Science, 21*(6), 1251-1262. doi:10.1287/orsc.1100.0561
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.
Schwartz, M., & Hornych, C. (2008). Specialization as strategy for business incubators: An assessment of the Central German Multimedia Center. *Technovation, 28*(7), 436-449. doi:10.1016/j.technovation.2008.02.003
Scott, J. (2000). *Social Network Analysis - A Handbook* (2nd edition ed.). London: SAGE Publications.
Scrucca, L., Fop, M., Murphy, T. B., & Raftery, A. E. (2016). mclust 5: Clustering, Classification and Density Estimation Using Gaussian Finite Mixture Models. *The R Journal, 8*(1), 289-317.
Shane, S., & Venkataraman, S. (2003). Guest editors' introduction to the special issue on technology entrepreneurship. *Research Policy, 32*(2), 181-184. doi:10.1016/s0048-7333(02)00104-x
Shipilov, A. V. (2006). Network Strategies and Performance of Canadian Investment Banks. *Academy of Management Journal, 49*(3), 590-604. doi:10.5465/amj.2006.21794676
Shipilov, A. V., & Li, S. X. (2008). Can You Have Your Cake and Eat It Too? Structural Holes' Influence on Status Accumulation and Market Performance in Collaborative Networks. *Administrative Science Quarterly, 53*(1), 73-108. doi:10.2189/asqu.53.1.73
Shipilov, A. V., & Li, S. X. (2012). The Missing Link: The Effect of Customers on the Formation of Relationships Among Producers in the Multiplex Triads. *Organization Science, 23*(2), 472-491. doi:10.1287/orsc.1100.0568
Shipilov, A. V., Li, S. X., & Greve, H. R. (2011). The Prince and the Pauper: Search and Brokerage in the Initiation of Status-Heterophilous Ties. *Organization Science, 22*(6), 1418-1434. doi:10.1287/orsc.1100.0594
Shore, J., Bernstein, E., & Lazer, D. (2015). Facts and Figuring: An Experimental Investigation of Network Structure and Performance in Information and Solution Spaces. *Organization Science, 26*(5), 1432-1446. doi:10.1287/orsc.2015.0980
Short, J. C., Ketchen Jr., D. J., Bennett, D., & Toit, M. d. (2006). An Examination of Firm, Industry, and Time Effects on Performance Using Random Coefficients Modeling. *Organizational Research Methods, 9*(3), 259-284. doi:10.1177/1094428106287572
Short, J. C., Payne, G. T., & Ketchen, D. J. (2008). Research on Organizational Configurations: Past Accomplishments and Future Challenges. *Journal of Management, 34*(6), 1053-1079. doi:10.1177/0149206308324324
Silverberg, G., & Verspagen, B. (2005). A percolation model of innovation in complex technology spaces. *Journal of Economic Dynamics and Control, 29*(1-2), 225-244. doi:10.1016/j.jedc.2003.05.005
Silvestre, B. d. S., & Dalcol, P. R. T. (2009). Geographical proximity and innovation: Evidences from the Campos Basin oil & gas industrial agglomeration—Brazil. *Technovation, 29*(8), 546-561. doi:10.1016/j.technovation.2009.01.003
Siu, W.-s., & Bao, Q. (2008). Network Strategies of Small Chinese High-Technology Firms: A Qualitative Study. *Journal of Product Innovation Management, 25*(1), 79-102.
Sivasubramaniam, N., Liebowitz, S. J., & Lackman, C. L. (2012). Determinants of New Product Development Team Performance: A Meta-analytic Review. *Journal of Product Innovation Management, 29*(5), 803-820. doi:10.1111/j.1540-5885.2012.00940.x
Slotte-Kock, S., & Coviello, N. (2010). Entrepreneurship Research on Network Processes: A Review and Ways Forward. *Entrepreneurship Theory and Practice, 34*(1), 31-57. doi:10.1111/j.1540-6520.2009.00311.x

Smith, K. (2000). Innovation as a Systemic Phenomenon: Rethinking the Role of Policy. *Enterprise and Innovation Management Studies, 1*(1), 73-102. doi:10.1080/146324400363536

Smithson, M., & Verkuilen, J. (2006). A better lemon squeezer? Maximum-likelihood regression with beta-distributed dependent variables. *Psychol Methods, 11*(1), 54-71. doi:10.1037/1082-989X.11.1.54

Snijders, T. A. B. (2001). The Statistical Evaluation of Social Network Dynamics. *Sociological Methodology, 31*(1), 361-395. doi:10.1111/0081-1750.00099

Snijders, T. A. B., & Bosker, R. J. (1999). *Multilevel Analysis - An introduction to basic and advanced multilevel modeling*. London: SAGE Publications Ltd.

Soda, G., Stea, D., & Pedersen, T. (2017). Network Structure, Collaborative Context, and Individual Creativity. *Journal of Management*. doi:10.1177/0149206317724509

Soda, G., Tortoriello, M., & Iorio, A. (2017). Harvesting Value from Brokerage: Individual Strategic Orientation, Structural Holes, and Performance. *Academy of Management Journal*. doi:10.5465/amj.2016.0123

Soda, G., Usai, A., & Zaheer, A. (2004). Network Memory: The Influence of Past and Current Networks on Performance. *Academy of Management Journal, 47*(6), 893-906. doi:10.2307/20159629

Soh, P.-H. (2010). Network patterns and competitive advantage before the emergence of a dominant design. *Strategic Management Journal, 31*(4), 438-461. doi:10.1002/smj.819

Solanas, A., Selvam, R. M., Navarro, J., & Leiva, D. (2012). Some common indices of group diversity: upper boundaries. *Psychological Reports, 111*(3), 777-796. doi:10.2466/01.09.21.PR0.111.6.777-796

Song, M., & Montoya-Weiss, M. M. (2001). The Effect of Perceived Technological Uncertainty on Japanese New Product Development. *Academy of Management Journal, 44*(1), 61-80. doi:10.2307/3069337

Sorenson, O., & Fleming, L. (2004). Science and the diffusion of knowledge. *Research Policy, 33*(10), 1615-1634. doi:10.1016/j.respol.2004.09.008

Sosa, M. E. (2011). Where Do Creative Interactions Come From? The Role of Tie Content and Social Networks. *Organization Science, 22*(1), 1-21. doi:10.1287/orsc.1090.0519

Souder, W. E. (1983). Organizing for modern technology and innovation: A review and synthesis. *Technovation, 2*(1), 27-44. doi:10.1016/0166-4972(83)90005-6

Sparrowe, R. T., & Liden, R. C. (1997). Process and Structure in Leader-Member Exchange. *Academy of Management Review, 22*(2), 522-552. doi:10.5465/amr.1997.9707154068

Sparrowe, R. T., & Liden, R. C. (2005). Two Routes to Influence: Integrating Leader-Member Exchange and Social Network Perspectives. *Administrative Science Quarterly, 50*(4), 505-535. doi:10.2189/asqu.50.4.505

Spencer, J. W., Murtha, T. P., & Lenway, S. A. (2005). How Governments Matter to New Industry Creation. *Academy of Management Review, 30*(2), 321-337. doi:10.5465/amr.2005.16387889

Spithoven, A., Frantzen, D., & Clarysse, B. (2010). Heterogeneous Firm-Level Effects of Knowledge Exchanges on Product Innovation: Differences between Dynamic and Lagging Product Innovators. *Journal of Product Innovation Management, 27*(3), 362-381. doi:10.1111/j.1540-5885.2010.00722.x

Staber, U. (1998). Inter-firm Co-operation and Competition in Industrial Districts. *Organization Studies, 19*(4), 701-724. doi:10.1177/017084069801900407

Stam, W. (2010). Industry Event Participation and Network Brokerage among Entrepreneurial Ventures. *Journal of Management Studies, 47*(4), 625-653. doi:10.1111/j.1467-6486.2009.00909.x

Stokes, P. D. (2014). Crossing Disciplines: A Constraint-Based Model of the Creative/Innovative Process. *Journal of Product Innovation Management, 31*(2), 247-258. doi:10.1111/jpim.12093

Stokman, F. N., & Doreian, P. (1996). Concluding remarks. *The Journal of Mathematical Sociology, 21*(1-2), 197-199. doi:10.1080/0022250x.1996.9990180

Stuart, T. E. (1998). Network Positions and Propensities to Collaborate: An Investigation of Strategic Alliance Formation in a High-Technology Industry. *Administrative Science Quarterly, 43*(3). doi:10.2307/2393679

Stuart, T. E. (2000). Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high-technology industry. *Strategic Management Journal, 21*(8), 791-811. doi:10.1002/1097-0266(200008)21:8<791::aid-smj121>3.0.co;2-k

Stuart, T. E., Ozdemir, S. Z., & Ding, W. W. (2007). Vertical alliance networks: The case of university–biotechnology–pharmaceutical alliance chains. *Research Policy, 36*(4), 477-498. doi:10.1016/j.respol.2007.02.016

Stuart, T. E., & Podolny, J. M. (1996). Local search and the evolution of technological capabilities. *Strategic Management Journal, 17*(S1), 21-38. doi:10.1002/smj.4250171004

Stuart, T. E., & Sorenson, O. (2003). The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms. *Research Policy, 32*(2), 229-253. doi:10.1016/s0048-7333(02)00098-7

STW. (2005). *Wetenschap in Bedrijf*. Utrecht: Technologiestichting STW.

STW. (2016). *Wetenschap waar anderen op zitten te wachten - Emancipatie van de technische wetenschappen in Nederland*. Utrecht: Technologiestichting STW.

STW, T. (2009). *Utilisatierapport 2009*. Amsterdam: Technologiestichting STW.

STW, T. (2010). *Utilisatierapport 2010*. Amsterdam: Technologiestichting STW.

Suarez, F. F. (2005). Network Effects Revisited: The Role of Strong Ties in Technology Selection. *Academy of Management Journal, 48*(4), 710-720. doi:10.5465/amj.2005.17843947

Swan, J., Bresnen, M., Robertson, M., Newell, S., & Dopson, S. (2010). When Policy meets Practice: Colliding Logics and the Challenges of 'Mode 2' Initiatives in the Translation of Academic Knowledge. *Organization Studies, 31*(9-10), 1311-1340. doi:10.1177/0170840610374402

Sydow, J., & Windeler, A. (1998). Organizing and Evaluating Interfirm Networks: A Structurationist Perspective on Network Processes and Effectiveness. *Organization Science, 9*(3), 265-284. doi:10.1287/orsc.9.3.265

Sydow, J., Windeler, A., Schubert, C., & Möllering, G. (2012). Organizing R&D Consortia for Path Creation and Extension: The Case of Semiconductor Manufacturing Technologies. *Organization Studies, 33*(7), 907-936. doi:10.1177/0170840612448029

Sytch, M., & Tatarynowicz, A. (2013a). Exploring the Locus of Invention: The Dynamics of Network Communities and Firms' Invention Productivity. *Academy of Management Journal, 57*(1), 249-279. doi:10.5465/amj.2011.0655

Sytch, M., & Tatarynowicz, A. (2013b). Friends and Foes: The Dynamics of Dual Social Structures. *Academy of Management Journal, 57*(2), 585-613. doi:10.5465/amj.2011.0979

Tamada, S., Naito, Y., Kodama, F., Gemba, K., & Suzuki, J. (2006). Significant difference of dependence upon scientific knowledge among different technologies. *Scientometrics, 68*(2), 289-302. doi:10.1007/s11192-006-0112-2

Tang, F., Mu, J., & Maclachlan, D. (2008). Implication of network size and structure on organizations' knowledge transfer. *Expert Systems with Applications, 34*(2), 1109-1114. doi:10.1016/j.eswa.2006.12.020

Tanskanen, K., Ahola, T., Aminoff, A., Bragge, J., Kaipia, R., & Kauppi, K. (2017). Towards evidence-based management of external resources: Developing design propositions and future research avenues through research synthesis. *Research Policy, 46*(6), 1087-1105. doi:10.1016/j.respol.2017.04.002

Tasselli, S., Kilduff, M., & Menges, J. I. (2015). The Microfoundations of Organizational Social Networks: A Review and an Agenda for Future Research. *Journal of Management, 41*(5), 1361-1387. doi:10.1177/0149206315573996

Teece, D. J. (1992). Competition, cooperation, and innovation. *Journal of Economic Behavior & Organization, 18*(1), 1-25. doi:10.1016/0167-2681(92)90050-l

Teece, D. J. (2008). Dosi's technological paradigms and trajectories: insights for economics and management. *Industrial and Corporate Change, 17*(3), 507-512. doi:10.1093/icc/dtn014

Teichmann, D. (1974). On the classification of the technical sciences. In F. Rapp (Ed.), *Contributions to a Philosophy of Technology* (pp. 134-139). Dordrecht: D. Reidel Publishing Company.

Thieme, J. (2007). PERSPECTIVE: The World's Top Innovation Management Scholars and Their Social Capital. *Journal of Product Innovation Management, 24*(3), 214-229. doi:10.1111/j.1540-5885.2007.00246.x

Thorelli, H. B. (1986). Networks: Between markets and hierarchies. *Strategic Management Journal, 7*(1), 37-51. doi:10.1002/smj.4250070105

Tidd, J., Bessant, J., & Pavitt, K. (2005). *Managing Innovation - Integrating Technological, Market and Organizational Change* (Third Edition ed.). West Sussex: John Wiley & Sons Ltd.

Tijssen, R. J. W., & van Wijk, E. (1999). In search of the European Paradox: an international comparison of Europe's scientific performance and knowledge flows in information and communication technologies research. *Research Policy, 28*(5), 519-543. doi:10.1016/s0048-7333(99)00011-6

Tiwana, A. (2008). Do bridging ties complement strong ties? An empirical examination of alliance ambidexterity. *Strategic Management Journal, 29*(3), 251-272. doi:10.1002/smj.666

Todo, Y., Matous, P., & Inoue, H. (2016). The strength of long ties and the weakness of strong ties: Knowledge diffusion through supply chain networks. *Research Policy, 45*(9), 1890-1906. doi:10.1016/j.respol.2016.06.008

Triguero, Á., & Córcoles, D. (2013). Understanding innovation: An analysis of persistence for Spanish manufacturing firms. *Research Policy, 42*(2), 340-352. doi:10.1016/j.respol.2012.08.003

Tsai, W. (2000). Social capital, strategic relatedness and the formation of intraorganizational linkages. *Strategic Management Journal, 21*(9), 925-939. doi:10.1002/1097-0266(200009)21:9<925::aid-smj129>3.0.co;2-i

Turner, W. A., Michelet, B., & Courtial, J. P. (1990). Scientific and Technological Information Banks for the network management of research. *Research Policy, 19*(5), 467-475. doi:10.1016/0048-7333(90)90054-a

Turrini, A., Cristofoli, D., Frosini, F., & Nasi, G. (2009). Networking Literature About Determinants of Network Effectiveness. *Public Administration, 88*(2), 528-550. doi:10.1111/j.1467-9299.2009.01791.x

Tushman, M., & Nadler, D. (1986). Organizing for Innovation. *California Management Review, 28*(3), 74-92. doi:10.2307/41165203

Tushman, M. L., & Anderson, P. (1986). Technological Discontinuities and Organizational Environments. *Administrative Science Quarterly, 31*(3), 439. doi:10.2307/2392832

Uzunca, B. (2017). A Competence-Based View of Industry Evolution: The Impact of Submarket Convergence on Incumbent-Entrant Dynamics. *Academy of Management Journal*. doi:10.5465/amj.2015.1080

Uzzi, B. (1996). The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect. *American Sociological Review, 61*(4), 674. doi:10.2307/2096399

Uzzi, B. (1997). Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness. *Administrative Science Quarterly, 42*(1), 35. doi:10.2307/2393808

Uzzi, B., & Spiro, J. (2005). Collaboration and Creativity: The Small World Problem. *American Journal of Sociology, 111*(2), 447-504. doi:10.186/432782

Vaara, E., Kleymann, B., & Seristo, H. (2004). Strategies as Discursive Constructions: The Case of Airline Alliances. *Journal of Management Studies, 41*(1), 1-35. doi:10.1111/j.1467-6486.2004.00419.x

Vaarst Andersen, K. (2013). The problem of embeddedness revisited: Collaboration and market types. *Research Policy, 42*(1), 139-148. doi:10.1016/j.respol.2012.05.005

van Beers, C., & Zand, F. (2014). R&D Cooperation, Partner Diversity, and Innovation Performance: An Empirical Analysis. *Journal of Product Innovation Management, 31*(2), 292-312. doi:10.1111/jpim.12096

van de Ven, A. H. (1992). Suggestions for studying strategy process: A research note. *Strategic Management Journal, 13*(S1), 169-188. doi:10.1002/smj.4250131013

van de Ven, A. H., & Poole, M. S. (1995). Explaining Development and Change in Organizations. *Academy of Management Review, 20*(3), 510-540. doi:10.2307/258786

van den Ende, J., van de Kaa, G., den Uijl, S., & de Vries, H. J. (2012). The Paradox of Standard Flexibility: The Effects of Co-evolution between Standard and Interorganizational Network. *Organization Studies, 33*(5-6), 705-736. doi:10.1177/0170840612443625

van der Valk, T., Moors, E. H. M., & Meeus, M. T. H. (2009). Conceptualizing patterns in the dynamics of emerging technologies: The case of biotechnology developments in the Netherlands. *Technovation, 29*(4), 247-264. doi:10.1016/j.technovation.2008.09.005

van Dijk, M. (2000). Technological regimes and industrial dynamics: the evidence from Dutch manufacturing. *Industrial and Corporate Change, 9*(2), 173-194. doi:10.1093/icc/9.2.173

van Wijk, R., Jansen, J. J. P., & 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. doi:10.1111/j.1467-6486.2008.00771.x

Van Wyk, R. J. (2002). Technology: A fundamental structure? *Knowledge, Technology & Policy, 15*(3), 14-35. doi:10.1007/s12130-002-1002-4

Van Wyk, R. J. (2017). *Technology: Its Fundamental Nature. To Explore Further Ahead and Farther Afield.* Beau Bassin: LAP LAMBERT Academic Publishing.

Vanhaverbeke, W., Gilsing, V. A., Beerkens, B., & Duysters, G. (2009). The Role of Alliance Network Redundancy in the Creation of Core and Non-core Technologies. *Journal of Management Studies, 46*(2), 215-244. doi:10.1111/j.1467-6486.2008.00801.x

Vanhaverbeke, W., Gilsing, V. A., & Duysters, G. (2012). Competence and Governance in Strategic Collaboration: The Differential Effect of Network Structure on the Creation of Core and Noncore Technology. *Journal of Product Innovation Management, 29*(5), 784-802. doi:10.1111/j.1540-5885.2012.00941.x

Vásquez-Urriago, Á. R., Barge-Gil, A., & Modrego Rico, A. (2016). Science and Technology Parks and cooperation for innovation: Empirical evidence from Spain. *Research Policy, 45*(1), 137-147. doi:10.1016/j.respol.2015.07.006

Vedovello, C. (1997). Science parks and university-industry interaction: Geographical proximity between the agents as a driving force. *Technovation, 17*(9), 491-531. doi:10.1016/s0166-4972(97)00027-8

Velzing, E.-J. (2013). *Innovatiepolitiek - Een reconstructie van het innovatiebeleid van het ministerie van Economische Zaken van 1976-2010*. Eburon, Delft.

Vermunt, J. K., & Magidson, J. (2016). *Technical Guide for Latent GOLD 5.1: Basic, Advanced, and Syntax*. Belmont MA: Statistical Innovations Inc.

Vlasov, S. A., Bahlmann, M. D., & Knoben, J. (2017). A study of how diversity in conference participation relates to SMEs' innovative performance. *Journal of Economic Geography, 17*(1), 191-216. doi:10.1093/jeg/lbw004

Vlot, A. (2001). *Glare: History of the Development of a New Aircraft Material*. Dordrecht: Kluwer Academic Publishers.

Vlot, A., Vogelesang, L. B., & de Vries, T. J. (1999). Towards application of fibre metal laminates in large aircraft. *Aircraft Engineering and Aerospace Technology, 71*(6), 558-570. doi:10.1108/00022669910303711

Vogelesang, L. B. (2001). *The integration of academic education and research and development*. Delft: Delft University of Technology, Faculty of Aerospace Engineering.

Vogelesang, L. B., & Gunnink, J. W. (1986). ARALL: A materials challenge for the next generation of aircraft. *Materials & Design, 7*(6), 287-300. doi:10.1016/0261-3069(86)90098-1

Volberda, H. W., & Lewin, A. Y. (2003). Co-evolutionary Dynamics Within and Between Firms: From Evolution to Co-evolution. *Journal of Management Studies, 40*(8), 2111-2136. doi:10.1046/j.1467-6486.2003.00414.x
Volberda, H. W., Van Den Bosch, F. A. J., & Mihalache, O. R. (2014). Advancing Management Innovation: Synthesizing Processes, Levels of Analysis, and Change Agents. *Organization Studies, 35*(9), 1245-1264. doi:10.1177/0170840614546155
von Hippel, E. (1988). *The Sources of Innovation*. New York: Oxford University Press.
Wade, J. (1995). Dynamics of organizational communities and technological bandwagons: An empirical investigation of community evolution in the microprocessor market. *Strategic Management Journal, 16*(S1), 111-133. doi:10.1002/smj.4250160920
Wade, J. (1996). A Community-Level Analysis of Sources and Rates of Technological Variation in the Microprocessor Market. *Academy of Management Journal, 39*(5), 1218-1244. doi:10.2307/256997
Waguespack, D. M., & Fleming, L. (2009). Scanning the Commons? Evidence on the Benefits to Startups Participating in Open Standards Development. *Management Science, 55*(2), 210-223. doi:10.1287/mnsc.1080.0944
Walker, G., Kogut, B., & Shan, W. (1997). Social Capital, Structural Holes and the Formation of an Industry Network. *Organization Science, 8*(2), 109-125. doi:10.1287/orsc.8.2.109
Wang, C., Rodan, S., Fruin, M., & Xu, X. (2013). Knowledge Networks, Collaboration Networks, and Exploratory Innovation. *Academy of Management Journal, 57*(2), 484-514. doi:10.5465/amj.2011.0917
Wang, D. J., & Soule, S. A. (2012). Social Movement Organizational Collaboration: Networks of Learning and the Diffusion of Protest Tactics, 1960–1995. *American Journal of Sociology, 117*(6), 1674-1722. doi:10.1086/664685
Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. New York NY: Cambridge University Press.
Wassmer, U., & Dussauge, P. (2012). Network resource stocks and flows: how do alliance portfolios affect the value of new alliance formations? *Strategic Management Journal, 33*(7), 871-883. doi:10.1002/smj.973
Watanabe, C., Asgari, B., & Nagamatsu, A. (2003). Virtuous cycle between R&D, functionality development and assimilation capacity for competitive strategy in Japan's high-technology industry. *Technovation, 23*(11), 879-900. doi:10.1016/s0166-4972(02)00041-x
Watanabe, C., Kishioka, M., & Nagamatsu, A. (2004). Effect and limit of the government role in spurring technology spillover — a case of R&D consortia by the Japanese government. *Technovation, 24*(5), 403-420. doi:10.1016/s0166-4972(02)00075-5
Watkins, T. A. (1991). A technological communications costs model of R&D consortia as public policy. *Research Policy, 20*(2), 87-107. doi:10.1016/0048-7333(91)90073-y
Whetten, D. A. (1989). What Constitutes a Theoretical Contribution? *Academy of Management Review, 14*(4), 490-495. doi:10.5465/amr.1989.4308371
Whittington, K. B., Owen-Smith, J., & Powell, W. W. (2009). Networks, Propinquity, and Innovation in Knowledge-intensive Industries. *Administrative Science Quarterly, 54*(1), 90-122. doi:10.2189/asqu.2009.54.1.90
Wicaksono, D. H. B., Zhang, L. J., Pandraud, G., French, P. J., & Vincent, J. F. V. (2006). Fly's proprioception-inspired micromachined strain-sensing structure: idea, design, modeling and simulation, and comparison with experimental results. *Journal of Physics: Conference Series, 34*, 336-341. doi:10.1088/1742-6596/34/1/055
Wickham, H. (2009). *ggplot2: Elegant Graphics for Data Analysis*. New York: Springer-Verlag.
Wiegmann, P. M., de Vries, H. J., & Blind, K. (2017). Multi-mode standardisation: A critical review and a research agenda. *Research Policy, 46*(8), 1370-1386. doi:10.1016/j.respol.2017.06.002

Wooldridge, B., Schmid, T., & Floyd, S. W. (2008). The Middle Management Perspective on Strategy Process: Contributions, Synthesis, and Future Research. *Journal of Management, 34*(6), 1190-1221. doi:10.1177/0149206308324326

Yayavaram, S., & Ahuja, G. (2008). Decomposability in Knowledge Structures and Its Impact on the Usefulness of Inventions and Knowledge-base Malleability. *Administrative Science Quarterly, 53*(2), 333-362. doi:10.2189/asqu.53.2.333

Yayavaram, S., & Chen, W.-R. (2015). Changes in firm knowledge couplings and firm innovation performance: The moderating role of technological complexity. *Strategic Management Journal, 36*(3), 377-396. doi:10.1002/smj.2218

Yin, X., & Shanley, M. (2008). Industry Determinants of the "Merger Versus Alliance" Decision. *Academy of Management Review, 33*(2), 473-491. doi:10.5465/amr.2008.31193515

Yu, J., Gilbert, B. A., & Oviatt, B. M. (2011). Effects of alliances, time, and network cohesion on the initiation of foreign sales by new ventures. *Strategic Management Journal, 32*(4), 424-446. doi:10.1002/smj.884

Yue, L. Q. (2012). Asymmetric Effects of Fashions on the Formation and Dissolution of Networks: Board Interlocks with Internet Companies, 1996–2006. *Organization Science, 23*(4), 1114-1134. doi:10.1287/orsc.1110.0683

Zaheer, A., & Bell, G. (2005). Benefiting from network position: firm capabilities, structural holes, and performance. *Strategic Management Journal, 26*(9), 809-825. doi:10.1002/smj.482

Zaheer, A., Gozubuyuk, R., & Milanov, H. (2010). It's the connections: The network perspective in interorganizational research. *Academy of Management Perspectives, 24*(1), 62-77.

Zaheer, S., Albert, S., & Zaheer, A. (1999). Time Scales and Organizational Theory. *Academy of Management Review, 24*(4), 725. doi:10.2307/259351

Zappa, P., & Lomi, A. (2015). The Analysis of Multilevel Networks in Organizations: Models and Empirical Tests. *Organizational Research Methods, 18*(3), 542-569. doi:10.1177/1094428115579225

Zeng, M., & Chen, X. P. (2003). Achieving Cooperation in Multiparty Alliances: A Social Dilemma Approach to Partnership Management. *Academy of Management Review, 28*(4), 587-605. doi:10.5465/amr.2003.10899383

Zhang, & Shaw, J. D. (2012). Publishing in AMJ--Part 5: Crafting the Methods and Results. *Academy of Management Journal, 55*(1), 8-12. doi:10.5465/amj.2012.4001

Zhang, L., Gupta, A., & Hallen, B. (2016). The Conditional Importance of Prior Ties: A Group-Level Analysis of Venture Capital Syndication. *Academy of Management Journal*. doi:10.5465/amj.2013.1088

Ziedonis, R. H. (2004). Don't Fence Me In: Fragmented Markets for Technology and the Patent Acquisition Strategies of Firms. *Management Science, 50*(6), 804-820. doi:10.1287/mnsc.1040.0208

Zollo, M., Reuer, J. J., & Singh, H. (2002). Interorganizational Routines and Performance in Strategic Alliances. *Organization Science, 13*(6), 701-713. doi:10.1287/orsc.13.6.701.503

Summary

Basic research & development (i.e. activities devoted to increasing scientific or technical knowledge and applying that knowledge in the creation of new and improved products or processes) is often seen as the first step towards the development of new technologies. Especially in the early stages of technological development, collaboration between industrial and academic actors is considered to be of key importance. In this dissertation, we focus on a specific form of organizing such joint research & development: R&D consortia. Based on the following three related research questions we explore topics related to the effects of network features on the innovative outcomes of both R&D consortia and consortium networks:

1) *To what extent does R&D consortium network structure affect innovative outcomes?*

2) *To what extent does the network position of R&D consortia affect innovative outcomes?*

3) *To what extent do network dynamics and technology field dynamics moderate the relationships explored in research question 1 and 2?*

The existing literature on R&D consortia has considered the prevalence of such consortia, as well as the role these consortia play for individual members. One of the aspects that is not explicitly considered in the current academic debate regarding the management of R&D consortia is that consortium members often are involved in multiple research collaborations simultaneously. As a result, R&D consortia are embedded in a larger collaborative network, and delineating to what extent this network affects the innovative outcomes of a consortium is important: scholars have often stressed that in addition to building internal capabilities, actively managing the external network by an organization becomes a crucial issue for effective innovation management and network orchestration. We contribute to this debate in two related ways. First, we focus on the relative effect of the complete consortium network structure compared to consortium-level features on the innovative outcomes of R&D consortia. Second, we compare the effect on innovative outcomes of the brokerage position a consortium has in the complete network structure with the effect on innovative outcomes of the level of closure of the consortium's ego network. With respect to both effects, we are especially interested in the role of time, to tease out which network position is most salient for generating innovative outcomes, and when such a position during the innovation process is most beneficial for generating such outcomes.

Through funding R&D collaborations, government has an important role in the formation and subsequent dynamics of consortium networks geared towards technological development. One of the aspects related to the public funding of R&D networks that has received scant attention in the literature is that -despite the underlined importance of such public funding- questions regarding efficient network structures for generating innovation at the network-level as well as the dynamics of such networks merits further investigation. We seek to contribute to knowledge regarding the dynamics and innovativeness of complete consortium networks in two related ways. First, we focus on the question if differences exist in the dynamics of different technology field networks. Second, we focus on predicting network-level innovative outcomes using network structural features, as well as features of the network population and the stability of the underlying technology field. Similar to our approach regarding consortium-level outcomes, we are especially interested in the role of time, for example to detect differences in developmental paces between networks, as well as time lags between network structure and the generation of network-level innovative performance.

Hence, without a thorough understanding of the constraining and enabling effects of collaboration networks for both consortium managers and innovation policy makers, management of network positions and structures remains speculative and intuitive. Answering our research questions requires the inclusion of as many consortia and consortium networks in our study as possible. For this purpose, we have built a unique database that allows us to use multi-level perspectives that incorporate the role of time and employ a unique longitudinal dataset comprising 1,928 consortia, 156 complete field networks, and 7 technology fields. This repository served as an important asset of this dissertation. The empirical chapters in this dissertation addressed the relation between networks and innovation in the following ways.

In Chapter 2, we addressed research question 1 at the level of the consortium: which antecedents determine the likelihood of an R&D consortium generating innovative outcomes. More specifically, we were interested in the role of the complete consortium network structure in the relationship between the consortium features geographical proximity and technological diversity and the likelihood of a consortium generating innovative outcomes. We tested our hypotheses using a dataset of 1,263 Dutch R&D consortia that each were active somewhere in the time frame 1989-2004. We found that consortia that are embedded in networks characterized by mutual awareness of consortium members of what members in other consortia are doing (i.e. consortium networks characterized by density-based network integration), are more likely to generate innovative outcomes compared to consortia in networks that are characterized by other types of network integration. In addition, we found an inverted U-shaped relation between technological diversity and the likelihood of a consortium generating innovation, yet this relation only occurs in those networks of which the structure can be characterized by density-based integration.

Whereas Chapter 2 considered research question 1 on the role of the complete consortium network structure in R&D consortia in generating innovative outcomes, Chapter 3 considered the role of the <u>position</u> of R&D consortia in consortium networks over time. In the existing literature on the relationship between a consortium's position in an interorganizational network and the likelihood of a consortium generating innovative outcomes, no consensus has emerged with respect to the question which network position is most advantageous. This is especially salient in the debate that focuses on the question whether network brokerage or closure provides the most efficient structure for innovation. In Chapter 3, we analysed this issue by focusing on the effect of both global and local network position on the likelihood of generating technological innovation. In addition, we considered the role of time in the salience of both effects, as we expected a link between stages in the process of R&D and the fruitfulness of occupying a certain network position. We tested our theoretical predictions with a multi-level analysis of 814 Dutch R&D consortia, each of which started somewhere in the time frame 1989-2004 and lasted for at least five years. Contrary to our expectations, we found that -although not salient across all years- global brokerage had a negative effect on the likelihood of generating technological innovation. We also found that local cohesion consistently enhanced the likelihood of innovation over time. Lastly, a time-dependent effect was found for the interaction between global brokerage and local cohesion, especially in the maiden years of consortia: here, consortia that combined being in locally embedded networks with a brokerage position in the complete network were more innovative compared to consortia that had other combinations local cohesion and global brokerage.

Chapter 2 and Chapter 3 considered the role of networks for the innovative outcomes of R&D consortia. In Chapter 4 and Chapter 5, we moved our focus to the level of the complete consortium network. In Chapter 4, we started from the observation that existing literature suggests a differentiated development of networks in different technology fields. However, Dutch innovation policy tends to approach these networks as homogeneous with respect to structure and in ways to ensure their viability. To explore the validity of this assumption in this policy approach we addressed the question if interorganizational technology field networks differ in their development in Chapter 4. By considering both network structural characteristics and the node set that comprises a network, we proposed an analytical framework that revolved around the 'network state' concept. We conceptualized this network state as a configuration of values in a five-dimensional state space: network centralization, network density, network size, the number of exiting nodes, and entrants. This model of network states was used to explore the evolution of 7 distinct technology field consortium networks over 23 years, using a latent profile analysis. This method allowed a mapping of all possible dynamics of a network through tracing a sequence of state changes over time. Our findings revealed that network dynamics unfold over sequences of changes in five distinct states: formation, growth, stagnation, stability and disintegration. Although we found a core sequence of state changes of formation, via growth, to stability, we also found considerable variations on, and extensions of this pathway. In addition to suggesting a terminology to talk about network dynamics at the complete network level, the most important findings of this chapter were that (1) field network dynamics are anything but homogeneous, and (2) the duration of states across consortium networks in different technology fields differs considerably across such fields.

In Chapter 5, our focus was on the role of knowledge in the generation of network-level innovative outcomes. Although several scholars have addressed the issue of explaining outcomes of interorganizational networks at the network level, the role of knowledge in the generation of these outcomes, especially in the case of publicly funded R&D networks is understudied. In addition, this topic is important to consider since, despite the many advantages of networks as flexible forms of organizing, several studies have shown that overall change in a network's environment can be detrimental for network outcomes. Hence, we used our insights regarding technology field network dynamics from Chapter 4 for determining technology field stability and considered the role of such stability in the generation of network-level outcomes. Building on the preliminary theory of network effectiveness as suggested by Provan and Milward (1995) and Provan and Sebastian (1998), we developed a model in which network innovative performance is explained by the level of node entry, stayers and node exit, and network integration. These acted as proxies for mechanisms of knowledge variation, selection and retention. Using a sample of 93 R&D consortium networks in the Dutch context, our analysis suggested an important role of said predictors in explaining network innovative performance. The effect of node entry (enabling knowledge variation) on innovative outcomes was found to be negative in the short run. This effect however, switches to positive in the longer run. In addition, the effect of stayers (enabling positive knowledge selection) was found to be positive on the short run. Lastly, our results suggested a crossover interaction between network integration (enabling knowledge retention) and technology field stability.

In sum, we can say that, even though our findings are not always according to what we expected theoretically, networks do matter for innovation at multiple levels of analysis, and so does a consideration of network and technology field dynamics. With this dissertation, we suggest that there is value in considering the role of higher-order network effects in the relation between networks and innovation. Doing so provides levers to move away from muddling through with respect to these effects and move towards a more targeted management of networks.

Samenvatting

Basisonderzoek en -ontwikkeling (activiteiten die zijn gericht op het vergroten van wetenschappelijke of technische kennis en de toepassing van die kennis in de creatie van nieuwe en verbeterde producten of processen) wordt vaak gezien als de eerste stap in de ontwikkeling van nieuwe technologieën. Vooral in vroege stadia van zulke technologische ontwikkeling wordt samenwerking tussen industriële en academische actoren als cruciaal beschouwd. In dit proefschrift richten we ons op een specifieke vorm van dergelijke samenwerkingen: R&D consortia. Aan de hand van de volgende drie gerelateerde onderzoeksvragen richten we ons op onderwerpen die verband houden met de effecten van netwerkkenmerken op de innovatieve resultaten van zowel R&D consortia als netwerken van R&D consortia:

1) *In hoeverre beïnvloedt de netwerkstructuur van R&D consortia innovatieve uitkomsten?*

2) *In hoeverre beïnvloedt de netwerkpositie van R&D consortia innovatieve uitkomsten?*

3) *In welke mate worden de relaties die zijn onderzocht in onderzoeksvraag 1 en 2 gemodereerd door netwerkdynamiek en de dynamiek van technologievelden?*

In de bestaande literatuur over R&D consortia is gekeken naar de prevalentie van dergelijke consortia en de rol die deze consortia spelen voor individuele leden. Één van de aspecten die niet expliciet in het huidige academische debat over het management van R&D consortia aan de orde is gesteld, is dat consortiumleden vaak gelijktijdig betrokken zijn bij meerdere consortia. Als gevolg hiervan zijn R&D consortia ingebed in een groter netwerk, en het is belangrijk om te bepalen in hoeverre dit netwerk invloed heeft op de innovatieve resultaten van een consortium: in de literatuur wordt vaak benadrukt dat naast het opbouwen van interne capaciteiten, het beheren van het externe netwerk door een organisatie een cruciaal punt is voor innovatiemanagement en het managen van netwerken. In deze dissertatie dragen we op twee manieren bij aan dit debat: allereerst richten we ons op het relatieve effect tussen de complete netwerkstructuur van het consortium en kenmerken van het consortium zelf op de innovatieve uitkomsten van R&D consortia. Ten tweede vergelijken we het effect op innovatieve uitkomsten van de positie die een consortium heeft in de complete netwerkstructuur met het effect op innovatieve resultaten van de positie die een consortium heeft in de locale netwerkstructuur. Met betrekkking tot deze effecten zijn we met name geïnteresseerd in de rol van tijd, om zo te kunnen bepalen welke netwerkpositie het meest belangrijk is voor het genereren van innovatieve resultaten, en wanneer.

De overheid speelt een belangrijke rol in de vorming en daaropvolgende dynamiek van consortiumnetwerken, met name door het verlenen van subsidies voor consortia. Één van de aspecten met betrekking tot de publieke financiering van consortiumnetwerken die in de literatuur nauwelijks aandacht heeft gekregen, is dat -ondanks het meermaals benadrukte belang van dergelijke publieke financiering- het niet duidelijk is wat nu efficiënte netwerkstructuren zijn voor het genereren van innovatie op netwerkniveau, en in hoeverre deze netwerken over de tijd onderhevig zijn aan verandering. In deze dissertatie leveren we twee bijdragen aan het verder begrijpen van de dynamiek en innovativiteit van complete consortiumnetwerken. Allereerst richten we ons op de vraag of er verschillen bestaan tussen de dynamiek van verschillende technologische veldnetwerken. Ten tweede richten we ons op het voorspellen van innovatieve resultaten op netwerkniveau. Dit doen we met behulp van netwerkstructurele kenmerken, kenmerken van de netwerkpopulatie en de stabiliteit van het onderliggende technologische veld. Net als in de hoofdstukken waarin we ons richten op het verklaren van innovatieve resultaten op consortiumniveau zijn we in deze studies met name geïnteresseerd in de rol van tijd. Zo bekijken we verschillen in de ontwikkelingssnelheid van netwerken, maar ook naar verschillende tijdsintervallen tussen het bestaan van een zekere netwerkstructuur en de generatie van innovatieve prestaties op het niveau van het complete netwerk.

Zonder een goed begrip van de beperkende en bevorderende effecten van samenwerkingsnetwerken voor zowel consortiummanagers als innovatiebeleidsmakers, blijft het beheer van netwerkposities en structuren dus speculatief en intuïtief. Het beantwoorden van onze onderzoeksvragen vereist dat zoveel mogelijk consortia en consortiumnetwerken in ons onderzoek worden betrokken. Voor dit doel hebben we een unieke database gebouwd die ons in staat stelt om multi-level perspectieven te hanteren en tijdseffecten in onze analyses mee te nemen. We hebben hiertoe een unieke longitudinale dataset ontwikkeld die 1.928 consortia, 156 complete veldnetwerken en 7 technologievelden omvat. Deze database vormt een belangrijke basis binnen deze dissertatie. Op basis van deze dataset zijn we op de volgende manieren ingegaan op de relatie tussen netwerken en innovatie in de empirische hoofdstukken van dit proefschrift.

In hoofdstuk 2 hebben we onderzoeksvraag 1 op het niveau van het consortium behandeld: welke factoren bepalen de waarschijnlijkheid waarmee R&D consortia innovatieve resultaten genereren? Meer specifiek hebben we gekeken naar de rol van de complete consortiumnetwerkstructuur, en de rol die deze structuur speelt in de relatie tussen enerzijds de geographische nabijheid van consortiumleden en hun technologische diversiteit, en anderzijds de innovatieve uitkomsten van het consortium. Onze hypothesen zijn getoetst met behulp van een dataset van 1.263 Nederlandse R&D consortia die elk een aantal jaren actief waren ergens in de periode 1989-2004. Onze resultaten suggereren dat consortia die zijn ingebed in netwerken die gekenmerkt worden door wederzijdse bekendheid van consortiumleden met wat leden binnen andere consortia doen (we noemen dit op densiteit gebaseerde netwerkintegratie), meer kans hebben om innovatieve resultaten te genereren ten opzichte van consortia in netwerken die een andere vorm van netwerkintegratie kennen. Daarnaast vonden we een omgekeerde U-vormige relatie tussen technologische diversiteit en de waarschijnlijkheid dat een consortium innovatieve resultaten genereert, maar deze relatie komt alleen voor in die netwerken waarvan de structuur kan worden gekenmerkt door op densiteit gebaseerde netwerkintegratie.

Waar we ons in hoofdstuk 2 richten op onderzoeksvraag 1 voor wat betreft de rol van de complete netwerkstructuur in de generatie van innovatie door individuele R&D consortia, wordt in hoofdstuk 3 de rol van de positie over de tijd van R&D consortia in consortiumnetwerken besproken. In de bestaande literatuur over de relatie tussen de positie in een organisatienetwerk en de waarschijnlijkheid dat een consortium innovatieve uitkomsten genereert, bestaat geen consensus over het antwoord op de vraag welke netwerkpositie het meest voordelig is. Dit is vooral een prominent punt in het debat dat zich richt op de vraag of het nu het gepositioneerd zijn in samenhangende lokale netwerken ('local cohesion') of juist het gepositioneerd zijn in open globale netwerken ('global brokerage') is die de meest efficiënte positie voor innovatie biedt. In hoofdstuk 3 hebben we dit probleem geanalyseerd door ons te richten op het effect van beide netwerkposities op de waarschijnlijkheid van het genereren van technologische innovatie. Daarnaast hebben bekeken hoe beide effecten over de tijd veranderden, omdat we een verband verwachtten tussen de fasen in het proces van R&D en de mate waarin het bezetten van een bepaalde netwerkpositie tot innovatieve uitkomsten leidt. We hebben onze theoretische voorspellingen getest met een multilevel analyse van 814 Nederlandse R&D consortia, die elk ergens in het tijdsbestek 1989-2004 begonnen en minstens vijf jaar duurden. In tegenstelling tot onze theoretische verwachtingen wijzen onze resultaten erop dat global brokerage -hoewel niet in alle jaren- een negatief effect heeft op de waarschijnlijkheid dat een consortium innovatieve resultaten levert. Ook vonden we dat local cohesion consistent over de jaren heen een positief effect heeft op het genereren van die innovatieve resultaten. Tot slot vonden we dat vooral in de eerste jaren van een consortium een interactie bestond tussen beide posities: consortia die een positie in een lokaal samenhangend netwerken combineren met een positie in een globaal open netwerk waren innovatiever in vergelijking met consortia die andere combinaties van beide netwerkposities hadden.

In hoofdstuk 4 en 5 hebben we onze focus verlegd naar het niveau van het complete consortiumnetwerk. Het startpunt voor hoofdstuk 4 was de observatie dat de bestaande literatuur een gedifferentieerde ontwikkeling van netwerken op verschillende technologische gebieden suggereert. Het Nederlandse innovatiebeleid benadert deze netwerken echter vaak als homogeen, zowel voor wat betreft de structuur als voor wat betreft manieren om de levensvatbaarheid te waarborgen. Om de geldigheid van deze veronderstelling in het huidige beleid te onderzoeken hebben we de vraag beantwoord of er verschillen zijn in netwerkdynamiek tussen netwerken die ingebed zijn in verschillende technologievelden. We hebben een analytisch raamwerk ontwikkeld dat ons in staat stelt de staat waarin een netwerk zich bevindt te kwalificeren met behulp van zowel netwerkstructuurkenmerken als kenmerken van de netwerkpopulatie. Deze netwerkstaat is geconceptualiseerd als een configuratie van waarden in een vijfdimensionale ruimte: netwerkcentralisatie, netwerkdichtheid, netwerkgrootte, het aantal uitgaande consortia en nieuwkomers. Dit model van 'network states' is gebruikt om de evolutie van 7 verschillende consortiumnetwerken over 23 jaar te onderzoeken met behulp van een latente profielanalyse. De voorgestelde methode maakt het mogelijk om dynamieken van een netwerk in kaart te brengen door een reeks van verschillende netwerkstaten over de tijd in kaart te brengen. Onze bevindingen lieten zien dat de dynamiek van een netwerk zich kan ontvouwen aan de hand van vijf verschillende netwerkstaten: vorming, groei, stagnatie, stabiliteit en desintegratie. Weliswaar vonden we een basissequentie van veranderingen die liep van formatie, via groei, naar stabiliteit, we vonden ook aanzienlijke variaties op, en uitbreidingen van deze sequentie. Niet alleen doen we met de gehanteerde methode een voorstel voor een terminologie waarmee gesproken kan worden over de dynamiek van complete netwerken, we hebben ook laten zien dat (1) de dynamiek van technologieveldnetwerken allesbehalve homogeen is en (2) er tussen velden aanzienlijke verschillen bestaan in de duur van de verschillende staten waarin consortiumnetwerken zich kunnen bevinden.

In hoofdstuk 5 lag onze focus op de rol van kennis bij het genereren van innovatieve resultaten op netwerkniveau. Hoewel verschillende academici de kwestie van het verklaren van uitkomsten van interorganisatorische netwerken op netwerkniveau hebben aangepakt, is de rol van kennis in het genereren van deze uitkomsten in het geval van publiek-private R&D netwerken niet inzichtelijk gemaakt. Bovendien is dit onderwerp belangrijk om bekijken omdat, ondanks de vele voordelen van netwerken als flexibele organisatievormen, verschillende onderzoeken hebben aangetoond dat verandering in de omgeving van een netwerk nadelig kan zijn voor netwerkresultaten. Daarom hebben we onze inzichten met betrekking tot de dynamiek van het technologienetwerk uit hoofdstuk 4 gebruikt voor het bepalen van technologische veldstabiliteit en de rol van dergelijke stabiliteit in de generatie van uitkomsten op netwerkniveau. Voortbouwend op de voorgestelde theorie van netwerkeffectiviteit door Provan en Milward (1995) en Provan en Sebastian (1998) hebben we een model ontwikkeld waarin innovatieve netwerkprestaties worden verklaard aan de hand van het niveau van nieuwe consortia die een netwerk binnenkomen, consortia die blijven, consortia die het netwerk verlaten en netwerkintegratie. Deze aspecten fungeerden als proxies voor mechanismen van kennisvariatie, -selectie en -retentie. Onze analyse, aan de hand van een steekproef van 93 R&D-consortiumnetwerken in de Nederlandse context, suggereert een belangrijke rol van genoemde voorspellers in het verklaren van innovatieve netwerkprestaties. Het effect van nieuwe consortia die het netwerk binnenkomen (waardoor kennisvariatie mogelijk wordt gemaakt) op innovatieve resultaten op netwerkniveau bleek negatief te zijn op korte termijn. Op de langere termijn verandert dit echter in een positief effect. Daarnaast blijkt het effect van consortia die in het netwerk blijven (waardoor positieve kennisselectie mogelijk is) op de korte termijn positief. Ten slotte suggereerden onze resultaten een interactie tussen netwerkintegratie (waardoor kennisbehoud mogelijk is) en de stabiliteit van het onderliggende technologieveld.

Samenvattend kunnen we zeggen dat, hoewel onze bevindingen niet altijd overeenstemmen met wat theoretisch werd verwacht, netwerken van belang zijn voor innovatie op meerdere analyseniveaus, net als de dynamiek van deze netwerken en de onderliggende technologische velden. De resultaten van dit proefschrift suggereren dat het waardevol is om de rol van hogere orde netwerkeffecten in de relatie tussen netwerken en innovatie te beschouwen. Hiermee worden handvatten aangereikt om te bewegen van een 'muddling through'-benadering met betrekking tot deze effecten naar een meer gericht management van deze netweken.

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