Paper to be presented at the

DRUID Society Conference 2014, CBS, Copenhagen, June 16-18

On the evolutionary nature of innovation networks in science-driven and scale-intensive industries

Tobias Buchmann
University of Hohenheim
Innovation Economics
Buchmann@uni-hohenheim.de

Daniel S. Hain
University of Aalborg
Department of Business and Management
dsh@business.aau.dk

Muhamed Kudic
Stifterverband, a German Industry Initiative Promoting Education and Science
Department for statistical analysis
muhamed.kudic@stifterverband.de

Matthias Mueller
University of Hohenheim
Innovation Economics
m_mueller@uni-hohenheim.de

Abstract

Our primary goal is to analyse the drivers of network change processes by using a stochastic actor-based simulation approach. We combine two unique datasets, German laser and automotive industry, between 2002 and 2006 to explore whether geo-graphical, network-related, and technological determinants affect the evolution of net-works, and if so, as to what extent these determinants systematically differ for science-driven industries compared to scale-intensive industries. Our results are preliminary. The update of our database and several robustness check of our findings are currently work in progress. So far, our results indicate strong empirical evidence for the explanatory power of network-related determinants in both industries. The ?experience effect? as well as the ?transitivity effects? are significant for both industries but more pronounced for laser manufacturing firms. When it comes to ?geographical? and ?technological?

effects the picture changes considerably. While geographical proximity plays an important role in the automotive industry, firms in the laser industry seem to be less de-pended on geographical closeness to cooperation partners; instead they rather search out for cooperation opportunities in distance. Technological proximity negatively influences cooperation decisions for laser source manufacturers, yet has no impact for automotive firms. Hence, technological heterogeneity explains, at least in science-driven industries, the attractiveness of potential cooperation partners.

Jelcodes:D85,C15

1. Introduction[1]

Innovation is above all a social process not happening in isolation (Powell et al., 1996). It is not astonishing that researchers in organization science, economics and related disciplines have increasingly focused their efforts on the analysis of R&D cooperation processes and innovation networks.

In the early 1990s the knowledge-based view gained in relevance in management science (Kogut & Zander, 1992; Grant, 1996). Scholars from this school of thought argued that alliances allow firms to gain access to external knowledge stocks (Grant & Baden-Fuller, 2004),to recombine existing knowledge and learn from cooperation partners (Kale et al., 2000) in order to gain a competitive advantage (Dierickx & Cool, 1989; Coff, 2003). Almost at the same time the Neo-Schumpeterian approach to economics (Hanusch & Pyka, 2007; Winter, 2006; Pyka, 2002) came up and claimed its position. Innovations are considered to be the outcome of interactions between heterogeneous economic actors (Pyka, 2002; Pyka, 2007). Previous research in both areas provides sound empirical evidence on the relatedness between a firm's strategic network position and its innovative performance (Powell et al., 1996; Stuart, 2000; Baum et al., 2000). Not only firm-specific network positions but also the overall topologies of large-scale innovation networks have been shown to affect the innovative performance of firms (Schilling & Phelps, 2007) as well as the innovative performance of entire regions (Fleming et al., 2007).

Against this backdrop, it becomes obvious that innovation outcomes are strongly affected by evolutionary processes determining change of networks at the micro level. Ever since the seminal contribution of Barabasi & Albert (1999) we have powerful models that allow us to explain the emergence of scaling patterns in large-scale networks. Several concepts were introduced, such as the "homophily concept" (McPherson et al., 2001), "heterophily concept" (Amburgey et al., 2009), "assimilation principle" (Friedkin, 1998) and "herd behavior" (Kirman, 1993) to explain the nature of tie-formation and tie dissolution processes. These ideas have been adopted and incorpo-

[1] We especially thank xxx, xxx and the xxx Project Team Partners for providing us with proprietary raw data and other valuable information on the industry dynamics of German laser industry. Furthermore we thank xxx for reviewing the paper and providing critical comments and helpful suggestions. An early draft of the Paper has been presented and discusses in non-public internal research seminar at the xxx Institute and the xxx PhD Conference. We assume responsibility for all errors.

rated in path-breaking empirical network studies, taking as an example the U.S. Biotech industry (Powell et al., 2005). Nonetheless, we still lack an in-depth understanding of how and why innovation networks change over time (Cantner & Graf, 2011; Brenner et al., 2011).

We employ a stochastic actor-based simulation approach (SIENA), originally developed by Snijders (1996; 2001), to analyze and understand whether firm-specific, geographical, network-related, or technological determinants affect the evolution of innovation networks in science-driven and scale-intensive industries and as to what extent these determinants systematically differ across industries. Most recently, simulation techniques (Gilbert et. al., 2001; Snijders et al. 2010) have been applied to properly embrace the complexity end endogeneity of structural change processes in large-scale innovation networks. At the same time, it can be observed that researchers increasingly make use of stochastic agent-based simulation techniques in innovation studies (Giulliani, 2010; Ter Wal, 2011; Balland et. al., 2012; Mueller et al., 2013, Hain & Jurowetzki 2013).

In this paper, we combine two unique longitudinal datasets for the observation period 2002 - 2006. The first dataset provides a comprehensive picture of German laser source manufacturers (LSMs), as an example for a young science-driven industry. The second dataset compromises a set of German automotive original equipment manufacturers (AOEMs) and a larger number of suppliers, as an example for a matured scale-intensive industry. This empirical setting allows us to contrast a science-based industry (laser) with a scale-intensive (automotive) which are assumed to operate at different industry lifecycle stages.

Our study contributes to the existing body by combining sociological concepts (Doreian & Stockman, 2005), proximity concepts (Boschma, 2005; Boschma & Frenken, 2010) and Neo-Schumpeterian ideas (Hanusch & Pyka, 2007; Winter, 2006) to provide a more nuanced understanding of network dynamics. From an empirical perspective we are amongst the first to analyze in which way endogenous and exogenous determinants (e.g. various proximity dimensions) affect the structural evolution of innovation networks in scale-intensive and science-based industries. Last but not least, our findings provide the basis for more differentiated policy instruments by explicitly considering the differences among science-driven and scale-intensive industries.

Preliminary results show that many traditional firm-specific determinants such as age and size yield no explanatory contribution, indicating the somewhat limited power of traditional variables commonly utilized in static network analyses. In contrast, our findings indicate that an endogenous network determinant (the so called 'transitivity effect') matters for both industries considered. Cooperation experience (the so called 'experience effect') is significant for science-driven and scale-intensive industries, too, but it is more pronounced for the science-driven laser industry. A closer look at geographical and technological determinants provides a different picture. Geographical proximity matters in both industries, but surprisingly in different directions. Technological proximity negatively influences cooperation decisions in the laser industry, yet has no significant impact on automotive firms, reflecting the more interdisciplinary and explorative nature of science-based vis-à-vis scale-driven industries.

Section 2 provides a brief overview on the relevant literature and Section 3 introduces the two industries – the German laser industry and the German automotive industry. What follow next is the theoretical foundation and the hypotheses development. The two datasets and the variable specification are described in Section 4 and 5, respectively. The intuition behind stochastic actor-oriented approach is outlined in Section 6 and Section 7 provides a discussion of main findings. Finally, in Section 8, we give a brief conclusion and outline some fruitful avenues for further research.

2. State of the art – a brief sketch of the literature

For the purpose of this paper, we are interested in knowledge exchange and interorganisational learning processes among a well-specified population of economic actors, which brings us to the notion of innovation networks. Over the past years a number of highly interesting studies has addressed the dynamics of these types of network.[2]

The first generation of dynamic network conceptualizations, so-called linear life-cycle models, is based on the idea that one can identify ideal stages of change like initialization, growth, maturity and decline (Sydow, 2003). These models do not explicitly analyze tie-formation or tie-termination processes at the micro level. An idealized change pattern is assumed, where all stages are traversed only once. These models are predominantly growth-oriented (Lorrenzoni & Ornati, 1988; Dwyer et al., 1987) while

2 Cf. Schwerk (2000), Sydow (2003), Parkhe et al. (2006), Tiberius (2008) and Cantner & Graf (2011).

instabilities and unplanned terminations are underemphasized and length of the phase may vary arbitrarily have been often criticized (Sydow, 2003).

Non-linear process models focus predominantly on the dyadic level (Ring & Van De Ven, 1994; Doz, 1996; Kumar & Nti, 1998; Ariño & DeLaTorre, 1998). However, these models contain both forming and catalyst processes of tie formations as well as a greater consideration of tie terminations (Schwerk, 2000). The integration of feed-back loops and the explicit consideration social factors affecting micro-level network change processes are the essential differences compared to linear models. However these dyadic models do not allow explaining the structural evolution at the network level. The advanced development of these models was carried out and promoted by the IMP research group (e.g. Halinen et al., 1999). The main deficit of these models is the missing integration of the determinants that are crucial for explaining network evolution. Others have applied a more growth oriented view of network change (Gulati, 1995; Gulati & Gargiulo, 1999; Hite & Hersterly, 2001). Common to these contributions is the strong focus on tie formation processes. The emergence of networks stands in the foreground whereas fragmentation tendencies are widely neglected.

In this paper, we ground our theoretical considerations on the network evolution concept which is based on a more comprehensive understanding of how networks evolve over time. Network evolution "[…] captures the idea of conceptualizing change via some understood process […]" whereas these underlying processes can be defined as a "[…] series of events that create, sustain and dissolve […]" the network structure over time (Doreian & Stokman, 2005, pp. 3-5). It is important to note that this notion of network evolution explicitly emphasizes an in-depth understanding of the determinants and mechanism that force networks to change. Thus, network change processes at the micro level – i.e. tie formations or tie terminations – as well as changes with regard to network nodes – i.e. node entries or node exits – affect the structural configuration of networks over time. These processes of network change are clearly Schumpeterian in nature and provide the basis to explain and understand the very nature of network change (Boschma & Frenken, 2010). In this tradition, a number of excellent empirical network evolution studies have been conducted in recent years (Powell et al., 2005; Venkatraman & Lee 2004; Koka et al. 2006). Similarly, studies using stochastic agent-based methods (Van de Bunt & Groenewegen, 2007; Balland et. al., 2012; Ter Wal, 2011; Giulliani, 2010) can be assigned to this research stream.

3. The empirical setting – introducing the industries

3.1 The German laser industry

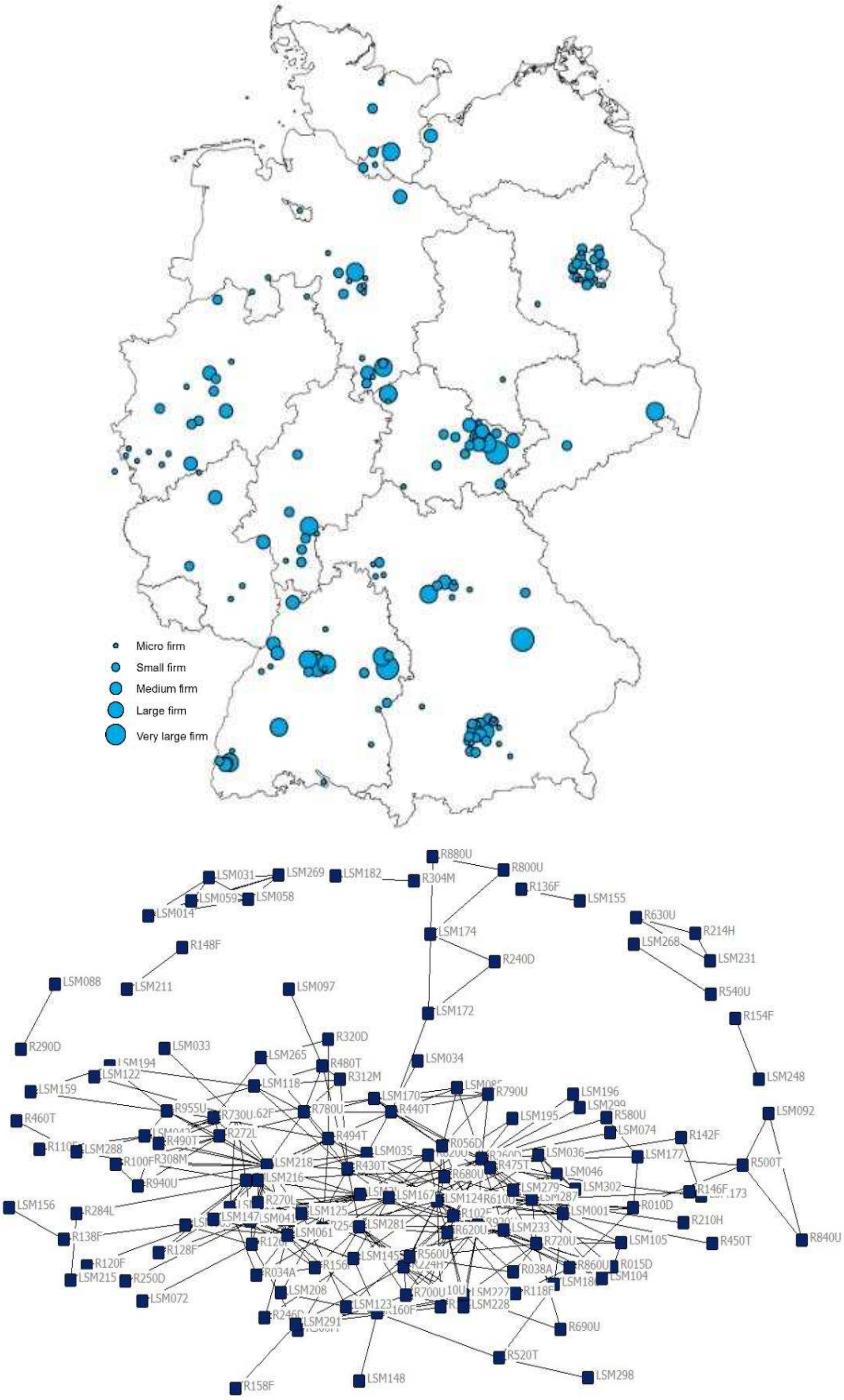
Lasers are artificial light sources that emit a coherent light beam characterized by some distinctive physical properties that make lasers useful for a broad range of technological applications (Buenstorf, 2007). The beginnings of the laser stretches back to the middle of the 20th century. Almost instantly after Theodore H. Maiman (1960) put the first stable laser device into operation, numerous laser source manufacturing firms entered the scene, not only in the U.S. but also in Germany. In the early 1960s, the Siemens Group started to play a dominant role in the development and manufacturing of lasers in Germany. Shortly afterwards, an entire industry, characterized by a high number of micro and small-sized firms, started to emerge (Buenstorf, 2007). Today, laser applications can be found in nearly every sphere of life. In 2006, the revenue of German laser sources and optical component producers reached approximately EUR 8.0 billion and about 45,000 workers were employed in the industry (Giesekus, 2007). For the purpose of this study we focus on German laser source manufacturers (LSMs).[3] The reasons for this are straightforward. LSMs are the very heart of the industry's value chain because these firms develop and produce the laser beam unit which is a core element of each laser system (cf. Kudic, 2012).

The German laser industry provides an ideal setting for studying the evolution of innovation networks for several reasons. Firstly, according to the industry topology originally proposed by Pavitt (1984), the German laser industry can be classified as a "science-based" sector. As a science-driven industry (Grupp, 2000) the development of lasers requires knowledge from various academic disciplines, such as physics, optics and electrical engineering (Fritsch & Medrano, 2010). Both, the access to basic and applied knowledge are essential to keep pace with competitors. Hence, R&D from both in-house sources and interorganisational joint research projects are a crucial success factor. Secondly, the interdisciplinary and science-based character of the industry is reflected in

3 Our sample encompasses all LSMs that were actively involved in at least one publicly funded cooperation project and showed patenting activities between 2002 and 2006. We ended up with a total number of 73 firms.

the high level of collaboration activities (Kudic, 2012). Thirdly, our data reveal a pronounced tendency towards geographical clustering in at least four regions, namely Berlin, Baden Wurttemberg, Thuringia, and Bavaria.

Figure 1: Spatial distribution and network position of German laser source manufacturer, 2006



Source: own illustration; network visualization (Borgatti, 2002).

Figure 1 illustrates the industries innovation network and the spatial distribution of firms in 2006. As outlined above, a look at the spatial dimension (cf. Figure 1, top) reveals at least four densely crowded agglomeration areas. The structural configuration of the industry's innovation network is illustrated in Figure 1, (bottom). The network visualization shows all R&D linkages among LSMs and among LSM and laser-related public research organization (PROs).

3.2 The German automotive industry

Our second dataset provides information on German original equipment manufacturers (OEM) in the automotive industry and a large number of suppliers grouped in different tiers.[4] The latter group encompasses component manufactures (often SMEs) as well as large multinational enterprises (e.g. Bosch, ZF) which assemble entire systems that are just in time supplied at the assembly lines of the OEMs. During the last decade, more and more value creation (including R&D), and with it relevant knowledge, was shifted from the OEMs to (specialized) suppliers. This organizational shift together with an increased complexity of parts and systems created new coordination and transaction problems along the value chain.

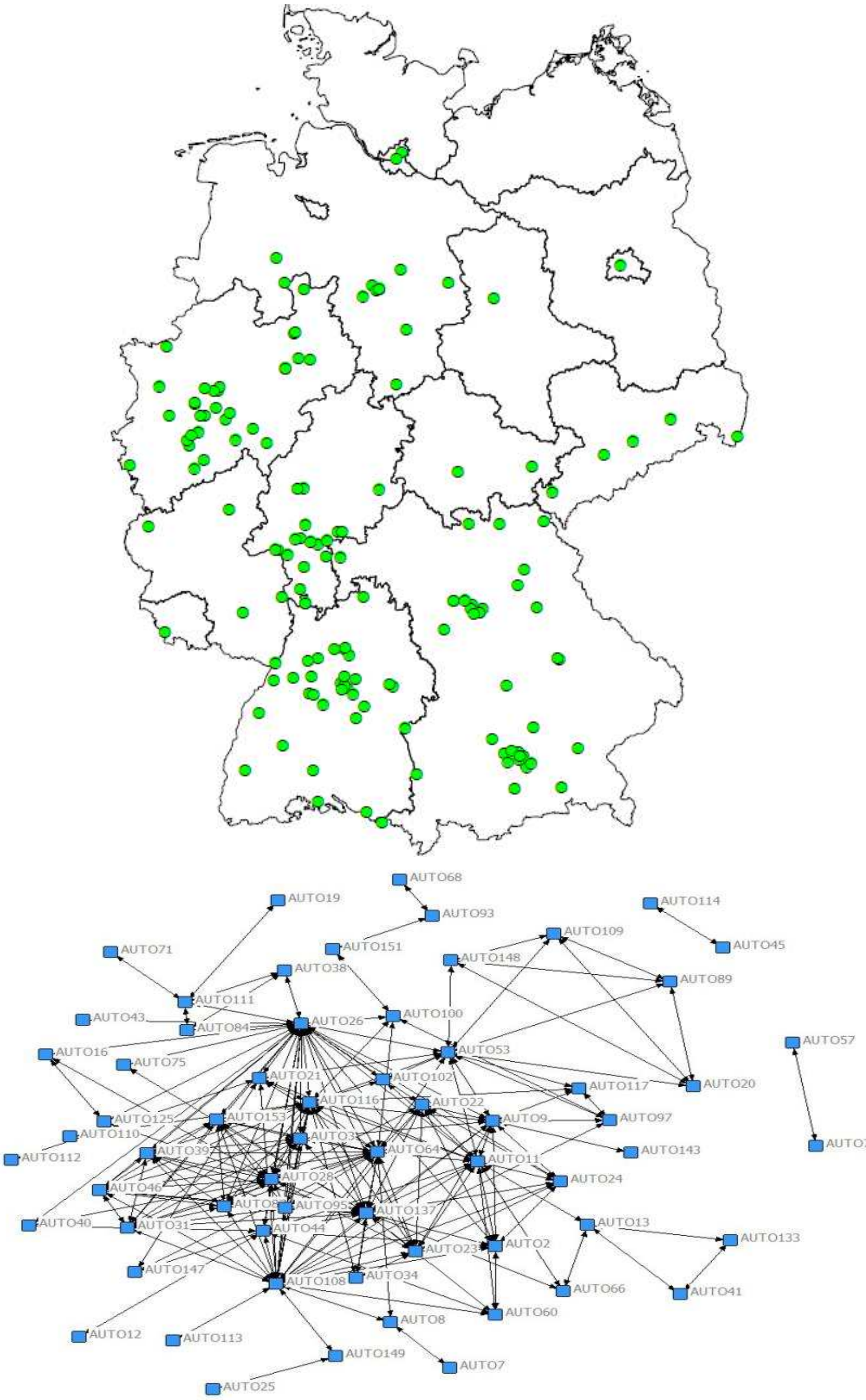
Increased complexity and new technologies, such as internet-based car solutions, amplify the pressure to form alliances with partners operating at the cutting edge of technology. The complexity of cars rises sharply, making system integration an increasingly challenging task. Stricter environmental regulation[5] requires solutions beyond the established design of the internal combustion engine fuelled with petrol. Moreover, German producers are particularly affected by regularity hurdles since their cars are known for being high comfort which went in the past hand in hand with heavy weight and high emissions. The dominant design of the internal combustion engine, as the heart of the power train, is increasingly challenged by new and supposedly more efficient technologies. With the established design being challenged, also the "masters" of this design, the incumbent car manufacturers and their suppliers, are threatened by the firms appearing now on the playing field. New technologies leverage the possibilities and

4 The dataset encompasses information on 148 firms in the German automotive industry.

5 For instance, EU Regulation 443/2009 forces car producers by 2020 to reduce CO_2 emissions of their product portfolio to a level which does not exceed the threshold of 95g CO_2/km.

lower market entrance barriers for innovative firms. New solutions lead to an erosion of the value of incumbent knowledge-bases if they are not “refilled” with new knowledge.

Figure 2: Spatial distribution and network position of German automotive original equipment manufacturers, 2006



Source: own illustration; network visualization (Borgatti, 2002).

This pushes firms to enter alliances, or more specifically, R&D alliances. Consequently, the industry is leaving a rather exploitative phase and is entering a more explorative phase. Accordingly, a new phase of the industry life-cycle takes off which is characterized by the integration and development of new knowledge. It strengthens the explorative side and requires strong absorptive capacities to acquire and process external knowledge which might even have its origins outside the automotive industry. Figure 2 illustrates the spatial distribution of AOEMs (cf. Figure 2, top) as well as R&D linkages among these AOEMs and suppliers which constitute the industries innovation network in 2006 (cf. Figure 2, bottom).

According to Pavitt's (1984) taxonomy, the automotive industry can be classified as a "scale intensive sector", where both, product and process innovation play important roles. Moreover, process innovation (e.g. production technologies yielding economies of scale) plays an important role for a continuous growth in productivity (Van Biesebroeck, 2003). German car producers and suppliers identified the realization of innovative solutions with regard to their product portfolio and their organizational structure as a successful strategy to escape the selective pressure. Thereby, intensified innovation competition and shortened product life-cycles emerge as a race for innovation.

4. Theory and Hypotheses

4.1 Innovation systems and network change

In the early 1990s Neo-Schumpeterian scholars introduced the 'systemic innovation approach' (Freeman, 1988; Lundvall, 1992; Nelson, 1992) to take account for the very nature of innovation processes. Innovations are considered to the outcome of repeated knowledge exchange and learning processes between various types of actors in socio-economic systems. An innovation system is characterized by multiple interactions and feed-backs and it allows for the reproduction of individual or collective knowledge (Lundvall, 1992). It can be defined from a national perspective (NIS; Nelson, 1992) but also along several other dimensions: regional dimension (RIS; Cooke, 2001), sectoral dimension (SIS; Malerba, 2002), or technological dimension (TIS; Carlsson, et al., 2002). However, the common denominator of all these conceptualizations is that they all involve creation, diffusion and use of knowledge and each of them can be fully described by a set of components, relationships among these components and their attributes (ibid.). Finally, innovation systems are not static but rather dynamic entities, as the elements and relations in the systems are subject to change (Lundvall, 1992; Carlsson et al., 2002). The conceptual overlaps of the innovation systems and the network theories are straightforward. An innovation system can be seen as a broader and more general concept that inherently entails innovation networks (Kudic, 2012). Innovation networks allow organizations not only to exchange existing information, knowledge and expertise but also to commonly generate new knowledge which can be embodied in new products, services or processes (Cantner & Graf, 2011).

4.2 Taking a closer look at the proximity concept

Proximity – in all its facets – can improve but also hamper a firm's ability to tap new sources of knowledge and to learn recombining existing stocks of knowledge in order to improve or create new products, processes, and services (Amin & Wilkinson, 1999; Boschma, 2005; Oerlemans et al., 2001; Knoben & Oerlemans, 2006; Visser, 2009; Whittington et al., 2009; Laursen et al. 2012). The concept acknowledges that firms are usually exposed to a variety of different proximity dimensions simultaneously, such as institutional, organizational, cultural, technological, network and geographic proximity (Boschma, 2005; Knoben & Oerlemans, 2006). In short, geographical proximity indicates the physical distance between actors in space, cognitive proximity the extent of congruence between actors knowledge stocks; social proximity their embeddedness and positioning in network structures; institutional proximity if they share common formal or informal norms or rules; organizational proximity their relationship in terms of common governance structures.

We follow the proximity concept proposed by Boschma (2005) for several reasons.[6] Firstly, the framework provides a clear definition and separation of the proximity dimensions. Secondly, the proximity dimensions can be conceptualized as orthogonal to each other. This implies that one can reduce as well as extend the list of relevant proximity dimensions without changing the meaning of each dimension (Boschma & Frenken, 2010). Thirdly, the framework lays the ground for analyzing each dimension separately and, at the same time, it allows the exploration of the interplay between selected proximity dimensions. In other words, it provides a solid theoretical foundation for analyzing both, distinct and combined proximity effects. Finally, the proximity con-

6 For an in-depth discussion see, Kudic (2012).

cept has strong conceptual overlaps with the network concept. Instead of emphasizing the structure on overall network level, however, the emphasis here lies on the dyadic characteristics of actor pairs.

It explicitly acknowledges the importance of social interaction by integrating a network proximity dimension. In a recent study, Boschma and Frenken (2010) apply the original proximity concept (Boschma 2005) to explain to what extent selected proximity dimensions affect the spatial evolution of innovation networks. For the purpose of this study three dimensions are of primary interest: geographical proximity, social (network) proximity and technological proximity.

To start with, we take a closer look at geographical proximity. Firms can benefit from geographical proximity in many ways (cf. Boschma, 2005; Boschma & Frenken, 2010). For instance, frequent direct communication and face-to-face contact facilitate the exchange of tacit knowledge (Von Hippel, 1994). Short distances simplify the exchange of information and enable interactive learning processes. Information provided via these channels may enable firms to become aware of new cooperation opportunities earlier than others. Thus, it is plausible to assume that regional environments can simplify the search for potentially new cooperation partners. Geographic proximity can also be accompanied by negative effects. Boschma (2005) argues that highly specialized regions can become inward looking due to spatial lock-in effects and a lack of openness to the outside world. As a consequence, geographic proximity may also hamper a firm's willingness to initialize new partnerships, depending regional characteristics.

The conceptualization of social proximity has its intellectual roots in the social embeddedness literature (Granovetter, 1985; Uzzi, 1996), which envisions interactions and relations in the economic sphere as always embedded in a social context. A firm's embeddedness and strategic positioning in the industry’s innovation network is likely to affect its future cooperation activities. Likewise, its cooperation history provides important signals to other firms and organizations in the industry. Connections to high-quality partners allow firms to build up reputation (Podolny, 1993; Podolny, 1994). Thus, the network structure itself can provide important signals to other market actors to judge an organization's reliability. For the purpose of this study we follow the structuralist network approach. From this perspective, social proximity can be measured by the indirect relationship through common third party ties between ego and alter (referred to as transitivity or triadic closure), which facilitates the initial creating of ties (Granovetter, 1973). However, social proximity can also have a negative effect on the innovative performance in cases when firms are too densely embedded. Uzzi (1996; 1997) has coined the term 'overembeddedness' to address this phenomenon.

Finally, we also address the technological (also referred to as cognitive) dimension of proximity. Learning theory suggests that the ability to receive and process new higher level knowledge is ultimately constrained by an actor's absorptive capacity, which is a function of related lower level knowledge (Cohen & Levinthal, 1990). As a consequence, cognitive or technological proximity becomes crucial to determine the performance of collaborative knowledge transfer and creating processes. High cognitive proximity indicates a large overlap between the interacting agents' knowledge bases and thus a high relative absorptive capacity, which facilitates collective learning and knowledge creation (Simonin, 1999). In contrast, without some basic shared knowledge and common understanding, learning processes between actors become increasingly difficult (Mowery et al., 1996). On the other hand, the more congruent the knowledge bases of actors are, the less the generic potential of collaboration to create innovative results by the means of combining formerly unrelated knowledge fragments.

4.3 Hypotheses development

Keeping in mind the preceding theoretical considerations, we develop a set of testable hypotheses. Based on Pavitt's (1984) taxonomy we differentiate between scale-intensive and science-based industries. We assume to find systematically different patterns of network dynamics of the two focal industries.

We address the relationship between various facets of social proximity on network evolution in science-driven and mature scale-intensive industries. Moreover, our line of arguments relates to a firm's cooperation experience. With each new R&D cooperation a firm passes through a learning process of how to successfully initiate, establish and manage this partnership. The firm learns how to implement cooperation routines in order to reduce costs and increase managerial efficiency (Goerzen, 2005). In other words, a firm can benefit from each cooperation event by building up what is frequently referred to as cooperation (or alliance) capabilities (Kale et al., 2000; Schilke & Goerzen, 2010). At the same time it is important to note that previous connections to high-quality partners allow firms to build up reputation and status which is an important signal for other market actors (Podolny, 1993; Podolny, 1994). We assume that both the ability to build up cooperation capabilities and gain reputation and status from preceding cooperation events is unequally pronounced in the two industries. One the one hand, LSMs in the German laser industry is on average significantly smaller and firms are on average younger compared to OEMs in the German automotive industry.[7] They have not the same resource endowment and time horizon like long-established large firm have. Small and young firms are in general known to have higher failure rates (Freeman et. al., 1983), and limited cooperation capabilities. As a consequence, reputation effects stemming from successful past cooperation can be assumed to be of higher value in science driven industries. These arguments inform our first hypothesis.

H1: ***Cooperation experience affects a firm's propensity to build new R&D ties; the effect is expected to be more pronounced in a science-driven industry.***

Next, we turn to a more structuralist oriented line of argument by focusing on transitivity in large-scale innovation networks. Transitivity is a structural effect which refers to an actor's position in a network (Davis, 1970; Buchmann & Pyka. 2013). In the most basic sense, it stipulates that two alters with direct linkages to a focal actor have a higher probability to build a tie among each other rather than with other actors. The rationales behind this connection mechanism are straightforward. The shared common alter might introduce both yet unconnected actors, and some of this actor's reputation and creditability is likely to be transferred also to her other network partners. Previous studies show that social cohesion breeds trust (Buskens & Raub, 2002). For instance, Reagans and McEvily (2003) demonstrate that strong social cohesion around a relationship reinforces the willingness to share knowledge. We argue that structural network effects are not industry specific. Instead they are first and foremost determined by the very nature of the network's structural configuration itself. Thus, we assume that transitivity is an important factor of tie formation processes for both industries. In line with previous studies (e.g. Ter Wal, 2011), we interpret the structural effect of transitivity as an operationalizable measure of social proximity.

H2: ***Social proximity (measured by 'triadic closure') affects a firm's propensity to build new R&D ties; the effect is expected to be not industry specific but rather determined by the network structure itself.***

7 For descriptive statistics on both industries, see Table 1.

According to Oerlemans & Meeus (2005, p. 94) research on geographical proximity can be grouped in two broad strands: one which focuses on spatial (or face-to-face) interaction and interactive learning (Saxanian, 1990, Maskell & Malmberg, 1999) and one focusing on spatially mediated knowledge spillovers (Feldman, 1993; Audretsch & Feldman, 1996). Proponents of the first strand would agree upon the argument that geographical proximity is likely to breed trust among actors located in the region. This, however, is likely to affect their willingness to initially form a R&D cooperation. On the one hand, the knowledge spillovers perspective acknowledges the partially non-rival, dynamic and cumulative character of knowledge (Oerlemans & Meeus 2005) and puts forward the argument that knowledge tends to spill over locally between firms of the same industry – so-called intra-industry or MAR externalities (Marschall, 1890; Arrow, 1962; Romer, 1986) – or between firms of different industries – so-called inter-industry or Jacobs externalities (Jacobs, 1969). In this study we especially focus on intra-industry knowledge spillovers, again contrasting science-driven and scale-intensive industries.

Firms in science-driven industries usually develop and produce highly specialized products and services. To do so, they depend on a range of diverse and, at the same time, highly specific stocks of applied and basic knowledge. Strategic cooperation in R&D provides an important channel to reach beyond the organizational boundaries and get access external knowledge stocks. Against this backdrop, it is plausible to assume that geographical co-location plays a subordinated role when knowledge is highly specific, scant and decisive for a firm's development process. In other words, firms in science-driven industries search for the R&D cooperation partners that provide them with expertise, information and knowledge they need, irrespective of whether they are co-located geographically or not. In scale-intensive industries the picture looks slightly different. Generally, the motives to cooperative in large and scale intensive industries often follow a quite different logic. For instance, in the automotive industry it is not unusual that strategic suppliers build subsidies in the direct neighborhood of automotive manufacturers to minimize transportation and other transaction costs. Similarly, when it comes to knowledge transfer and interorganizational learning processes the choice of partners is likely to follow a different logic. Products and services are much more standardized compared to science-driven industries. Accordingly, the knowledge stock of firms operating in scale-intensive industries is usually more homogenous and less specific. This substantiates the assumption that firms in scale-intensive industries can choose from a much wider range of potential R&D cooperation partners to complement their incomplete knowledge base. Hence, other determinants, such as geographical factors, become more relevant for cooperation decisions. Hence, we assume:

H3 ***Geographical proximity (measured by geographical co-location) affects a firm's propensity to build new R&D ties; the effect is expected to be more pronounced in a scale-intensive industry.***

Last but not least, cognitive proximity is an important explanatory factor for R&D cooperation processes. The notion of technological proximity refers to "shared technological experiences and knowledge-bases" (Knoben & Oerlemans, 2006). Thus, it does not express the similarity of technological equipment, processes etc., but rather reflects the similarity of the underlying knowledge-bases (Buchmann & Pyka, 2013). This understanding is very similar to the cognitive proximity as described by Boschma (2005).

Firms in science-driven industries are in many cases highly specialized as they draw upon very specific stocks of basic and applied knowledge to generate a narrow set of products and services. Previous literature shows that one of the main cooperation motives for these firms is to exchange knowledge and learn from each other throughout the cooperation process. It has been argued that firms need a certain level of absorptive capacity (Cohen & Levinthal, 1990) to identify and make use of external knowledge. The cognitive or technological dimension of proximity addresses the similarity or dissimilarity of knowledge stock of potential cooperation partner. The cooperation incentives for firm with very similar technological knowledge stock are quite low whereas firms operating in entirely different technological fields have no common denominator to cooperate in R&D. Thus, it is plausible to assume that firms operating in the same technological field choose R&D cooperation partners with a common technological understanding but which a rather dissimilar knowledge base. Against the backdrop of the previously outlined arguments, this effect is expected to be more pronounced in science-driven industries due to the higher specificity of the underlying knowledge base, and the higher heterogeneity of competences needed in the innovation process. In summary, this leads to our last hypothesis:

H4 ***Technological distance is positively related with a firm's propensity to build new R&D ties; the effect is expected to be more pronounced in a science-driven industry.***

5. Data sources and variable specification

5.1 Industry data

Industry data for the German laser industry came from a proprietary database originally compiled by Guido Buenstorf (2007) and provides exact information on entries and exits of German laser source manufactures between 1960 and 2005.[8] Based on this initial dataset we collected additional information on firm entries and exits after 2005. For the purpose of this study, we consider the business unit or firm as the relevant level of analysis: corporate level entities are decomposed and broken down into the business functions or market segments they serve. Furthermore, we include predecessors of currently existing firms in our sample. Firm exits as a result of mergers, acquisitions, or insolvencies, as well as different modes of population entries, such as new company formations or spin-offs from existing firms or PROs, are treated separately.[9] We end up with an industry dataset encompassing 233 LSMs over the full period under observation. To ensure comparability with our second dataset we restrict the observation period to the time span between 2002 and 2006. After excluding firms not showing any R&D cooperation or patenting activity during the observation period and five years prior to, our final dataset includes 73 firms.

Same as for the Laser industry dataset we build a sample of German automotive firms. Since our reasoning is led by the knowledge-based view, we select firms based on the characteristic of their patent portfolio instead of, for instance, applying a standard industry classification such as NACE. A scan of the patent portfolios of the German OEMs and the largest suppliers (OECD June 2010 Regpat database which is an extraction from Patstat) shows, that the 3-digit IPC class “B60” is strongest in the industry. Thus, we take all firms which filed at least one patent application in this class within the observation period 1998 to 2006 and pick out those which are or were exclusively operating in the market for commercial vehicles or car accessory kits. Hence, we exclude all firms which are not directly related to the production of passenger cars. We also exclude

8 We thank the LASSSI Project team, especially xxx, xxx and xxx for providing us access to data on the German laser industry.

9 Three additional data sources were used: 1) updated German laser industry data, again provided by xxx; 2) annual laser industry business directories ("Europäischer Laser Markt") provided by the B-Quadrat Publishing Company; 3) data from the German trade register and Creditreform.

firms which have not been involved in at least one of the examined research projects. This sampling resulted in 148 firms belonging to the studied network sample.

5.2 Network data

Network data based on joint cooperation in public funded R&D projects came from two electronically available archival sources: 1) the Förderkatalog database provided by the German Federal Ministry of Education and Research (BMBF) and 2) the CORDIS database provided by the European Community Research and Development Information Service (CORDIS). Both sources provide detailed information on the starting date, duration, funding, and characteristic features of the project partners involved.

Table 1: Network density indicators

Period	*1*	*2*	*3*	*4*	*5*
		Laser industry			
density (degree)	0.015	0.014	0.014	0.018	0.019
average degree	1.096	0.986	0.986	1.288	1.342
number of ties	40	36	36	47	49
number of actors	73	70	72	73	71
		Automotive industry			
density (degree)	2.243	1.851	1.514	1.595	2.676
average degree	166	137	112	118	198
number of ties	2.243	1.851	1.514	1.595	2.676
number of actors	138	137	139	139	139

Source: own calculation.

For both datasets we use information on publicly funded R&D cooperation projects. There are good arguments for the use of these archival data sources in analyses of the evolution of innovation networks and we are not the very first to do so.[10] With regard to publicly R&D cooperation projects subsidized by the German federal state there are good reasons to assume that participating organizations have strong incentives to innovate as they have to agree upon a number of regulations that explicitly facilitate mutual knowledge exchange and the generation of novelties (Broeckel & Graf, 2011).

10 For instance, Broekel & Graf, (2011), Scherngell & Barber, (2009; 2011), Cassi et al., (2008).

Basically the same argument holds true for European framework program. The EU has funded thousands of collaborative R&D projects in order to support transnational cooperation activities, increase mobility, strengthen the scientific and technological bases of industries, and foster international competitiveness (Scherngell & Barber, 2009). Similarly, the enabling of knowledge transfer across partners and the enhancement of leaning processes are key elements of EU framework programs.

Table 2: Network dynamics: Tie changes per period

Period/tie change	*0 → 0*	*0 → 1*	*1 → 0*	*1 → 1*	*Jaccard*
			Laser industry		
1 → 2	2,581	7	11	29	0.617
2 → 3	2,576	16	16	20	0.385
3 → 4	2,577	15	4	32	0.627
4 → 5	2,571	10	8	39	0.684
			Automotive industry		
1 → 2	10,698	14	43	123	0.683
2 → 3	10,727	14	39	98	0.649
3 → 4	10,703	63	57	55	0.314
4 → 5	10,655	105	25	93	0.417

Source: own calculation.

Furthermore, information about firms participating in joint subsidized projects documents research activities at an earlier stage compared to patent data. R&D subsidies have become a frequently used instrument of innovation policy to spur collaborative research for a number of reasons: First, due to the sheer scale of some projects, individual firms cannot afford to handle them alone. Second, knowledge transfer from public to private organizations is fostered by the participation of universities and other public research institutes such as the Max Planck and Fraunhofer Institutes. Third, it represents a powerful tool to directly influence rate and direction of research activities with the means of public funding (Pavitt, 1998). The projects listed in the "Förderkatalog" are considered to contribute to knowledge transfer (Broekel & Graf 2010). The participants have to sign agreements explicitly stipulating that gained knowledge within the project will be freely shared among the participants. They even have to grant free access to their know-how and IPRs within the scope of the projects. They commit to actively collaborate with the aim to find new solutions (BMBF, 2008). Table 1 provides some key indicators on the structural characteristics of the laser and automotive networks for the years of observation 2002 – 2006.

The dynamics of tie creation (0→1), dissolution (1→0) and maintenance (1→1) in both networks are provided in table 2. The application of stochastic actor-oriented models, as we do during the course of this paper, requires the networks under observation to show a certain dynamic. However, too drastic structural changes between observation periods might indicate a violation of the gradual change assumption. To ensure suitable structural properties of our networks, we consult the Jaccard index[11] provided in Table 2, which is a common measure of similarity between two networks. Snijders (2002) suggest this index to have a value between 0.3 and 0.8, which is given in all periods in both networks under study here. Overall, the first inspection suggests a data structure suitable for utilizing stochastic actor-based models.

5.3 Patent data

Three data sources were tapped to gather the patent data needed. The European Patent Office's database (PatStat version: October 2012) was used as the primary data source to generate a complete overview of the firms' patent activities.[12] Additionally, two patent data sources accessible online – DEPATISnet German Patent and Trade Mark Office database & ESPACEnet European Patent Office database – were tapped for data completion and to check results for integrity and consistency. For our automotive industry dataset, we make additionally use of the OECD Regpat database. We employe a search procedure (cf. Kudic, 2012) based on firm ID lists to extract patent information for the firms in quest. Various ways of spelling each firm's name were explicitly considered to deal with typing errors and misspellings. Patent applications are dated by using the application filing date. Information on patent families is used to avoid double counts of patents. Information on IPC classes is recorded for each patent.

5.4 Variable specification

11 The Jaccard index as a measure of similarity between two network waves is computed by $\frac{N_{11}}{N_{11}+N_{01}+N_{10}}$, where N_{11} represents the number of ties stable over both waves, N_{01} the newly created and N_{10} newly dissolved ties in the second wave.

12 Data access was provided by the IWH department "Formal Methods and Databases".

We specify four groups of independent variables: (I) organizational level, (II) geographical level, (III) network level, and (IV) technological level.

(I) Organizational variables: we use information of the number of employees to control for firms of small (10-49 employees, size small), medium (50-249 employees, size medium), and large (250+ employees, size large, omitted) size. Since a larger size of the firm also indicates a higher capacity to manage multiple collaborations, we expect a positive impact on collaboration activity in R&D projects.

Data from Germany's official company register ("Bundesanzeiger") is used to reconstruct firms' age in years. With increasing age, firms are able to accumulate reputation and creditability, which supposedly makes them a more attractive collaboration partner. However, after a firm has survived its first critical years and came over the "liability of newness (Freeman et. al., 1983), it also establishes a performance history and certain reputation. Thereafter, we expect the effect of age to diminish, what we operationalise with using the variable in its logarithmic transformation.

(II) Geographical variables: Again, Germany's official company register data is used to reconstruct firms' current addresses and address changes for the entire observation period. We employed the ESRI ArcMap 10.0 Software package and a freely accessible geo-coding application[13] to collect GPS coordinates (latitude and longitude) on an annual basis for each firm in the sample. We then calculate the dyadic distances between all organizations. Geographical distance represents the geodesic distance between ego and alter in kilometer and is expected to negatively affect tie-formation processes. However, since with increasing distance actors may substitute means of transportation (car, train, plain, etc.; cf. Sorenson & Stuart, 2001, 2008), we assume distance to have decreasing marginal effects, therefore again use this measure in its natural logarithm.

(III) Network variables: Bases on publicly funded R&D cooperation project data we specify several cooperation and network variables. We operationalise social proximity as the existence of a shared connection in form of a transitive triad between ego and alter. As argued during the course of this paper, we expect social proximity to have a positive impact on tie-formation processes.

9 http://www.netzwelt.de/software/google-maps.html (accessed: Nov. 2011)

A further very standard effect to be controlled for in actor-oriented models is given by the outdegree (degree), which is the number of currently existing ties of an actor and represents a measure of centrality in the current network. Since the amount of ties that can be managed by an actor at the same time is usually limited, this effect in most cases shows a negative coefficient.

The amount of former participations in public funded R&D projects (cooperation experience) serves as a measure of accumulated reputation as well as experience in managing this kind of projects. To avoid trends, we operationalize this variable as a five-year moving window of cumulated R&D project participation. As argued during the course of this paper, we expect cooperation experience to positively affect collaboration behavior.

(IV) Technological variables: Patent data is used to construct technological proximity indicators. Former patenting experience can be interpreted as a rough indicator for innovation capability and absorptive capacity. This variable is also constructed as an accumulation of activity in a five-year moving window.

To calculate the technological proximity between actors, we apply the following approach. First we disaggregate the firm's prior patenting activity in a five-year moving window by their assigned 3-digit IPC classes. Based on this patent count on the corresponding patent classes, we calculate a vector which places each firm in an N-dimensional space, where the number of dimensions is given by all patent classes firms in the corresponding industries showed activity during the observation periods.[14] To avoid the inclusion of "outlayer" patents completely unrelated to the industry, we remove those patent classes only appearing only once in all periods. Second, a dyadic measure of Euclidian distance over all dimensions between the vector of firm i and all other firms j-N is calculated, where N represents the number of firms in the corresponding industry network. Thus the technological proximity between two firms i and j is calculated as formula 1 suggests:

$$w_{i,j}^{techprox} = 1 - \sqrt{\sum_{c=1}^{N} (p_i^c - p_j^c)^2 / 2} \qquad (1)$$

14 To give an example, a firm i shows patenting activity in some five-year moving window of 4 patents in IPC class B60, 6 patents in IPC class 29, and 0 in all other classes. Its corresponding vector would be (p_1; p_{B29}; …; p_{B60};…; p_N) = (0; …; 0.6;…; 0.4; …, 0).

As already argued, we expect technological proximity to influence collaboration decisions differently in science-driven and scale intensive industries. Since there exist salient arguments for this effect to be of non-linear nature (e.g. Nooteboom et. al., 2007, Gilsing et al., 2007; Wuyts et. al., 2005), we also use the squared transformation to test for inversely U-shaped one.

Table 3: Descriptive statistics

Variable	Min.	Max.	Mean	Std. Dv.
Laser industry				
Firm level controls				
age	0.693	3.584	2.037	0.638
size small	0.000	1.000	0.717	0.451
size medium	0.000	1.000	0.200	0.401
Experience				
cooperation experience	0.000	9.000	1.277	2.002
patenting experience	0.000	6.935	1.807	1.503
Proximity				
geographical proximity	0.000	6.588	1.123	2.288
technological proximity	0.000	1.000	0.340	0.265
Automotive industry				
Firm level controls				
age	0.693	6.082	3.699	1.152
size small	0.000	1.000	0.764	0.425
size medium	0.000	1.000	0.142	0.349
Experience				
cooperation experience	0.000	125.000	5.216	15.324
patenting experience	0.000	8.646	2.819	1.946
Proximity				
geographical proximity	0.000	6.515	1.264	0.904
technological proximity	0.000	1.000	0.758	0.204

Source: own calculation.

Table 3 provides an overview of basic descriptive statistics on the variables utilized for both industries. All variables utilized for statistical analysis are dynamic of nature.

6. Modelling network evolution

The analysis of dynamic actor networks represents an empirical challenge which calls for distinct statistical models and methods (Steglich et al., 2010).

6.1 Principles of stochastic actor-based models of network dynamics

The class of stochastic actor-oriented models (SAOM) originally developed by Snijders (1996, 2001) represents an attractive solution, which scholars just recently started to deploy in the context of inter-organizational innovation networks (e.g. Balland, 2012; Giuliani, 2010; Hain & Jurowetzki, 2013; Ter Wal, 2011). In contrast to the quite restrictive log-linear approach for modeling network dynamics (e.g. Holland and Leinhardt, 1977; Wasserman, 1979), SAOM are able to jointly analyze multiple endogenous structural effects, such as tendencies toward transitivity or structural balance and also allows for continuous variable scales. In its core, SAOM combine a random utility model, continuous time Markov process, and Monte Carlo simulation. Given the context of the study, we consider SAOM as the most suitable class of dynamic network models and deploy it for the empirical analysis to follow.

Originally, SAOM was developed in a sociological context and designed to model group dynamics in interpersonal networks (e.g. Van De Bunt et al., 1999). However, actor oriented modeling is also particularly suitable to depict the interaction between macro outcomes and firms' micro choices (Macy & Willer, 2002) in inter-organizational alliance formation process. Here, the network structure is based on individual firms' choices, which are assumed to be driven by the expected amount of utility derived from the selection of collaboration partners with respect to individual, dyadic, structural and environmental determinants.

Snijders (1996) firstly proposed to address the problem of multiple endogeneity in the evolution of social network with transforming discrete datasets of panel waves into a continuous set of changes to be estimated as a Markov-chain. Unobserved changes between the waves are simulated as continuous actor choices at stochastically determined points of time. Formally, following a Poisson function of rate λ_i, the actors are allowed to create, maintain, or dissolve ties until the network is transformed to the new structure. The decision of actor i to change the state of one tie to another actor j leads to a new overall state of the network χ, where the probability P_i for choosing this structure is given by:

$$P_i(\chi^0, \chi, \beta^k) = \frac{\exp\{f_i(\chi^0, x, \beta_k)\}}{\sum_{\chi' \in C(\chi^0)} exp\{f_i(\chi^0, x', \beta_k)\}} \quad (2)$$

It technically resembles a multinomial logistic regression, modeling the probability that an actor chooses a specific (categorical) new network configuration P_i as proportional to the exponential transformation of the resulting networks objective function $f_i(.)$, with respect to all other possible configurations. The parameters coefficients are stepwise adjusted by Monte Carlo simulation techniques in order to obtain convergence between the estimated and observed model, and finally held fixed to allow their comparison and post-estimation analyses. The objective function contains actor i's perceived costs and benefits of a particular network reconfiguration leading to a network state χ, which are represented by the random utility model:

$$f_i(\chi^0, \chi, \beta^k) = \sum_k \beta_k \, s_i(\chi^0, \chi, v_i, v_j, c_{ij}, e, r) \quad (3)$$

It depends on the current state of the network χ^0, the potential new one χ, the ego i's and alter j's individual characteristics v_i and v_j, their dyadic covariates c_{ij}, exogeneous environmental effects e, and a random component r capturing omitted effects. Underlying assumption is that the actors observe current structure of the network χ^0 and the relevant characteristics of its actor set and make their collaboration decisions in order to optimize their perceived current utility (Jackson & Rogers, 2007).

6.2 Model specification

Based on joint participation in public funded R&D project, we construct yearly cooperation networks for both industries under observation. Formally, we transform the 2-mode network of actor and project affiliation in a 1-mode network in a way that all project participants are connected equally with undirected ties. Conceptualizing connections in these R&D networks as clique networks with undirected ties appears as most suitable since frequent interaction and a free flow of knowledge between all project participants can be expected. To depict the evolution of networks with undirected ties, we use a unilateral initiative and reciprocal confirmation model, as suggested to be most realistic in such settings by Van de Bunt and Groenewegen (2007). It operationalizes mutual tie formation decisions in two stages. First, by trying to optimize the utility of the individual objective function, actor i decides to form a tie with actor j. This collaboration, however, only takes place if in the second step confirmed by actor j according to the outcome of its objective function.

As outlined above, collaboration choices driving the evolution of the network are the outcome of the actors mutual attempts to optimize their expected utility with respect to their own and their potential alters' characteristics and the current and potential network structure as perceived by them (Jackson &Rogers, 2007). Thus, in our model, the dependent variable represents the probability of a tie between actor i and j to change its state from non-existing to existing.

Technically, we make use of the SAOM application of SIENA[15] (Ripley et al., 2001), a package for the statistical environment of R.

7. Results and discussion of main findings

Table 3 provides the coefficients of the estimated stochastic agent-based simulation models for the German laser industry and the German automotive industry, respectively. Positive (negative) coefficients indicate that an increase in the regressor variable is associated with a higher (lower) transition probability. All coefficients are reported in standardized version, divided by their mean.

Good convergence of parameter values estimated by the simulation and their corresponding observed real values is reached if the t-values are smaller than 0.1 (Snijders et. al., 2010) which we find for all variables of the objective function.

To test for time-variant exogenous effects, such as varying qualitative and quantitative preferences to fund research projects with certain characteristics, we conduct the score-test of time-heterogeneity proposed by Lospinoso et al. (2011). The results indeed indicate the heterogeneity of tie creation over time, most pronounced in firm level characteristics, for which we account with including time dummies interacted with the actor outdegree.

15 "Simulation Investigation for Empirical Network Analysis". The RSiena package is freely available on the CRAN website: http://cran.r-project.org/web/packages/RSiena/.

Table 3: Estimated results form a stochastic actor-oriented model

	Laser industry				Automotive industry			
	Model I		Model II		Model I		Model II	
Variable	*Coeff*	*SE*	*Coeff*	SE	*Coeff*	SE	*Coeff*	SE
				Network effects				
degree centrality	-2.339***	0.183	-2.361***	0.193	-2.186***	0.064	-2.190***	0.063
				Firm level controls				
age	-0.428***	0.189	-0.485*	0.200	-0.087	0.053	-0.091	0.053
size small	0.300	0.372	0.077	0.310	0.271	0.227	0.265	0.234
size medium	0.478	0.380	0.195	0.191	0.199	0.261	0.187	0.262
				Experience				
cooperation experience	0.160***	0.035	0.168***	0.037	0.014***	0.003	0.014***	0.003
patenting experience	0.189***	0.085	0.083	0.104	0.067*	0.035	0.056	0.049
				Proximity				
social proximity			0.986***	0.137			0.477***	0.032
geographical proximity			-0.473**	0.163			0.081*	0.036
technological proximity			-0.808*	0.410			0.236	0.233

Note: *, **, *** indicate p-values < 0.05, 0.01, 0.001

Source: own calculation.

The estimated experience parameters provide evidence for the suggestion that experience in cooperation is a factor which influences the propensity to cooperate. In particular, firms having more experience in cooperation are more open to participate in collaboration projects (select partners and be selected as a partner). The estimation results confirm Hypothesis H1 which proposes that the effect is stronger in a science-driven (laser) compared to a scale-intensive (automotive) industry. We assume that the differences are related to three factors: First, reputation is a particular important asset in scientific communities and experience is a strong indicator for reputation since only actors having a high level of reputation are attractive for cooperation. Second, experienced actors signal that they are trustworthy partners. This is a highly valued asset in a young industry in which the level of uncertainty is high and transferred knowledge is predominantly of tacit nature. Third, liability of newness (Freeman et. al., 1983) describes the tendency for younger firms to have a higher risk of failing compared to more experienced firms. In young industries which consist of many inexperienced firms, experienced firms which already know "the rules of the game" are particularly attractive as cooperation partners

Hypothesis 2, which suggests a high cliquishness among network partners, is also confirmed for both industries, where it is more pronounced in the science-driven (laser) one. This indicates a significant endogenous network effect leading to the formation of cohesive triadic subgroups caused by trusted partnerships. Information scarcity about the reliability of partners gets mitigated by the use of existing partnerships as information sources. The finding is in line with studies performed for other industries. Accordingly, it can be considered a general effect which always plays a role for innovation network evolution. However, it appears to be more pronounced in our science-driven industry, indicating the higher importance of trust based determinants of collaboration decisions in more explorative settings.

Hypothesis 3 indicates an inverse relationship between the propensity to cooperate and geographical proximity. We assume that this effect is stronger in the scale-intensive industry due to the relative strength of local or regional firms in knowledge generation. Interestingly, the effect of geographical proximity turned out to be positive only in the automotive, while negative in the laser industry. We believe that the sources of relevant knowledge are more dispersed in the laser industry, i.e., interesting cooperation partners are not necessarily located in close geographical distance but might have their seat in another region or even another country. Consequently, ties are not formed to the same extent as in the automotive industry with firms from within a geographic cluster. Thus, one might speculate the role of geographical proximity to be moderated by the heterogeneity of the local/regional knowledge base.

Hypothesis 4 addresses the role of technological proximity in the structural evolution of innovation networks. For the science-driven laser industry, we are indeed able to provide first evidence of its effect, even though only statistically significant at the ten percent level. The coefficient for technological proximity, operationalized as the Euclidian distance between the vectors of both firms cumulated patenting activity in relevant

IPC classes, shows with twice the value of geographical proximity a relatively high negative value. This means firms of the laser industry show a preference to team up for research projects with partners that provide them with complementary and diverse knowledge rather than with firms of similar competence. This reflects the interdisciplinary and explorative nature of the industry, where the access to knowledge and competences from a variety of distinct research fields is vital to secure a firm's long-run competitive advantage. For the automotive industry on the contrary, we do not find any significant effect of technological proximity on the firms' cooperation decisions.

8. Conclusion and avenues for further research

During the course of this paper, we have explored the evolutionary nature of alliance formation pattern in innovation and research networks. In particular, with drawing from and firstly combining, two very rich datasets on the German laser and automotive industry we contrast these processes in a young science-driven industry as well as a matured scale-intensive one.

Combining Neo-Schumpeterian thoughts with industry life-cycle theories, Pavitt's taxonomy of industries and Boschma's proximity concepts, we develop hypotheses derived from different strands of theory, and test them taking advantages of recent advances in dynamic network analysis. Deploying a stochastic actor-oriented model, we are able to reveal forces of network change which appear to substantially differ between younger science-driven and fully matured scale intensive industries.

We indeed find the effects of experience and reputation, as well as the social, geographical and technological dimensions of proximity to affect network formation processes significantly but yet differently pronounced in the two industries under study. Cooperation experience matters in both industries. Same holds true for social (network) proximity. These findings shed light on the importance of the social dimension of network development, which appears, as hypnotized, to be stronger in more explorative and science-driven settings. Geographical proximity has a significant impact in both industries, surprisingly in different directions. While R&D projects tend to cluster geographically in the automotive industry, firms in the laser industry seem to search out for partners in distance. This might reflect the strong dependence on access to diverse external knowledge, which cannot be found in homogenous local clusters. First results on the effect of technological distance support this argument. Firms in the laser industry indeed seem to search partners with very different knowledge-bases.

Our results are still preliminary in a sense that the underlying database has to validated and several consistency and robustness check are still work in progress. So far, the results of our analysis highly convince us of the fruitfulness of this avenue and call for further research. Indeed, there are still a lot of open questions to be addressed in order to provide a more comprehensive understanding of evolutionary processes in the formation of research and innovation networks. We still believe in the importance of technological proximity as a main driver of alliance decisions. In our analysis, we operationalise firms' knowledge bases with utilizing patent data, which appears reasonable due to the high importance of them in both industries. However, using patent data tends to over-pronounce knowledge related to product innovations compared to process and organizational innovation. In practice, very well a combination of technical product features and process/organizational knowledge might offer particularly beneficial synergies, which we are not able to capture with our measure. Thus, utilizing more fine-grained measures for firm competences is likely to reveal further insights on that issue.

References:

Amburgey, T., Aharonson, B.S. & Tzabbar, D. (2009). Heterophily in inter-organizational network ties. Conference paper: 25th EGOS Colloquium, Barcelona, pp. 1-40.

Amin, A. & Wilkinson, F. (1999). Learning, proximity and industrial performance: an introduction. Cambridge Journal of Economics, 23 (2), pp. 121-125.

Arino, A. & De La Torre, J. (1998). Learning from failure: towards an evolutionary model of collaborative ventures. Organization Science, 9 (3), pp. 306-325.

Arrow, K.J. (1962). The economic implications of learning by doing. The Review of Economic Studies, 29 (3), pp. 155-173.

Audretsch, D.B. & Feldman, M.P. (1996). R&D spillovers and the geography of innovation and production. American Economic Review, 86 (3), pp. 630-640.

Balland, P.A. (2012). Proximity and the evolution of collaboration networks: Evidence from research and development projects within the Global Navigation Satellite System (GNSS) industry. Regional Studies, 46 (6), pp. 741-756.

Balland, P.A., De Vaan, M. & Boschma, R. (2012). The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987–2007, Journal of Economic Geography, vol. 13(5), pp. 1-25.

Barabasi, A.-L. & Albert, R. (1999). Emergence of scaling in random networks. Science, 286 (15), pp. 509-512.

Baum, J.A., Calabrese, T. & Silverman, B.S. (2000). Don't go it alone: alliance network composition and startup's performance in Canadian biotechnology. Strategic Management Journal, 21 (3), pp. 267-294.

Borgatti, S.P. (2002). NetDraw: graph visualization software. Harvard MA: Analytic Technologies.

Boschma, R. (2005). Proximity and innovation: a critical assessment. Regional Studies, 39 (1), pp. 61-74.

Boschma, R. & Frenken, K. (2010). The spatial evolution of innovation networks: a proximity perspective. In R. Boschma & R. Martin, The Handbook of Evolutionary Economic Geography (pp. 120-135). Cheltenham UK: Edward Elgar Publishing.

Brenner, T., Cantner, U. & Graf, H. (2011). Innovation networks: measurement, performance and regional dimensions. Industry & Innovation , 18 (1), pp. 1-5.

Broekel, T. & Graf, H. (2010). Structural properties of cooperation networks in Germany: From basic to applied research, Jena Economic Research Papers, No. 2010, 78.

Broekel, T. & Graf, H. (2011). Public research intensity and the structure of German R&D networks: A comparison of ten technologies. Economics of Innovation and New Technology, 21 (4), pp. 345-372.

Buchmann, T. & Pyka, A. (2013). The evolution of innovation networks: The case of a German automotive network. FZID Discussion Papers 70-2013.

Buenstorf, G. (2007). Evolution on the shoulders of giants: entrepreneurship and firm survival in the German laser industry. Review of Industrial Organization, 30 (3), pp. 179-202.

Buskens, V. & Raub, W. (2002). Embedded trust: Control and learning in Group cohesion, trust and solidarity, eds. E. Lawler and S. Thye, Bingley: Emerald Group Publishing Limited, pp. 167-202.

Cantner, U. & Graf, H. (2011). Innovation networks: formation, performance and dynamics. In C. Antonelli, Handbook on the Economic Complexity of Technological Change (pp. 366-394). Celtenham UK: Edward Elgar Publishing.

Carlsson, B., Jacobsson, S., Holmen, M. & Rickne, A. (2002). Innovation systems: analytical and methodological issues. Research Policy, 31 (2), pp. 233-245.

Cassi, L., Corrocher, N., Malerba, F. & Vonortas, N. (2008). Research networks as infrastructure for knowledge diffusion in European regions. Economics of Innovation and New Technology, 17 (7), pp. 665-678.

Coff, R. W. (2003). The emergent knowledge-based theory of competitive advantage: an evolutionary approach to integrating economics and management. Managerial and Decision Economics, 24 (4), pp. 245-251.

Cohen, W.M. & Levinthal, D.A. (1990). Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly, 35 (3), pp. 128-152.

Cooke, P. (2001). Regional innovation systems, clusters, and the knowledge economy. Industrial and Corporate Change, 10 (4), pp. 945-974.

Deloitte Consulting (2009). Konvergenz in der Automobil-industrie. Mit neuen Ideen Vorsprung sichern.

Dierickx, I. & Cool, K. (1989). Asset stock accumulation and sustainability of competitive advantage. Management Science, 35 (12), pp. 1504-1511.

Doreian, P. & Stokman, F.N. (2005). The dynamics and evolution of social networks. In P. Doreia & F. N. Stokman, Evolution of Social Networks (2nd ed., pp. 1-17). New York: Gordon and Breach.

Doz, Y. L. (1996). The evolution of cooperation in strategic alliances: initial conditions or learning processes? Strategic Management Journal, 17 (1), pp. 55-83.

Dwyer, R.F., Schurr, P.H. & Oh, S. (1987). Developing buyer-seller relationships. Journal of Marketing, 51 (2), pp. 11-27.

Feldman, M.P. (1993). An examination of the geography of innovation. Industrial and Corporate Change, 2 (3), pp. 451-470.

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

Fornahl, D., Broeckel, T. & Boschma, R. (2011). What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location. Papers in Regional Science, 90 (2), pp. 395-418.

Freeman, J.; Carroll, G. & Hannan, M. (1983). The liability of newness: Age dependence in organizational death rates. American Sociological Review, pp. 692-710.

Freeman, C. (1988). Japan: a new national system of innovation. In G. Dosi, R. R. Nelson, G. Silverberg & L. Soete, Technical Change and Economic Theory (pp. 330-348). London: Pinter.

Freeman, J.; Carroll, G. & Hannan, M. (1983). The liability of newness: Age dependence in organizational death rates, American Sociological Review, 1983, 692-710

Fritsch, M. & Medrano, L. (2010). The spatial diffusion of a knowledge base - laser technology research in West Germany, 1960-2005. Jena Economic Research Papers.

Friedkin, N. (1998). A Structural Theory of Social Influence. Cambridge: Cambridge University Press.

Giesekus, J. (2007). Die Industrie für Strahlquellen und optische Komponenten - Eine aktuelle Marktübersicht von SPECTARIS. Laser Technik Journal, 4 (5), pp. 11-13.

Gilbert, N., Pyka, A. & Ahrweiler, P. (2001). Innovation networks - a simulation approach. Journal of Artificial Societies and Social Simulation, 4 (3), pp. 1-13.

Giuliani, E. (2010). "Network dynamics in regional clusters: The perspective of an emerging economy", Papers in Evolutionary Economic Geography (PEEG), [Online], vol. 10, no. 14.

Goerzen, A. (2005). Managing alliance networks: emerging practices of multinational corporations. Academy of Management Executive, 19 (2), pp. 94-107.

Graf, H. (2006). Networks in the innovation process. Cheltenham: Edward Elgar Publishing.

Granovetter, M.S. (1973). The strength of weak ties. American Journal of Sociology, 78 (6), pp. 1360-1380.

Granovetter, M.S. (1985). Economic action and social structure: the problem of embeddedness. American Journal of Sociology, 91 (3), pp. 481-510.

Grant, R.M. (1996). Towards a knowledge based theory of the firm. Strategic Management Journal, 17 (2), pp. 109-122.

Grant, R.M. & Baden-Fuller, C. (2004). A knowledge accessing theory of strategic alliances. Journal of Management Studies, 41 (1), pp. 61-84.

Grupp, H. (2000). Learning in a science driven market: the case of lasers. Industrial and Corporate Change, 9 (1), pp. 143-172.

Gulati, R. (1995). Social structure and alliance formation pattern: a longitudinal analysis. Administrative Science Quarterly, 40 (4), pp. 619-652.

Gulati, R. & Gargiulo, M. (1999). Where do interorganizational networks come from? American Journal of Sociology, 104 (5), pp. 1439-1493.

Hagedoorn, J. (2006). Understanding the cross-level embeddedness of interfirm partnership formation. Academy of Management Review, 31 (3), pp. 670-680.

Hain, D.S. & Jurowetzki R. (2013): Incremental by design? On the role and influence of incumbents in research networks – an evolutionary network analysis. Conference proceeding: 6th Annual Conference of the Academy of Innovation and Entrepreneurship, Oxford, August 2013.

Halinen, A., Salmi, A. & Havila, V. (1999). From dyadic change to changing business networks: an analytical framework. Journal of Management Studies, 36(6), pp. 779-794.

Hanusch, H. & Pyka, A. (2007). Principles of Neo-Schumpeterian economics. Cambridge Journal of Economics, 31 (2), pp. 275-289.

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), pp. 275-286.

Holland, P.W. & Leinhardt, S. (1977). A dynamic model for social networks. Journal of Mathematical Sociology, (5), pp. 5-20.

Jackson, M.O. & Rogers, B. W. (2007). Meeting strangers and friends of friends: How random are social networks? The American economic review, pp. 890-915.

Jacobs, J. (1969). The Economy of Cities. New York: Random House.

Kale, P., Singh, H. & Perlmutter, H. (2000). Learning and protection of proprietary assets in strategic alliances: building relational capital. Strategic Management Journal, 21 (3), pp. 217-237.

Kirman, A. (1993). Ants, rationality, and recruitment. The Quarterly Journal of Economics, 108 (1), pp. 137-156.

Knoben, J. & Oerlemans, L.A. (2006). Proximity and inter-organizational collaboration: A literature review. International Journal of Management Reviews, 8 (2), pp. 71-89.

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

Koka, B.R., Madhavan, R. & Prescott, J.E. (2006). The evolution of interfirm networks: environmental effects on patterns of network change. Academy of Management Review, 31 (3), pp. 721-737.

Kudic, M. (2012). Innovation networks in the German laser industry – evolutionary change, strategic positioning and firm innovativeness. Ph.D. thesis. University of Hohenheim, forthcoming.

Kumar, R. & Nti, K.O. (1998). Differential learning and interaction in alliance dynamics: a process and outcome discrepancy model. Organization Science, 9 (3), pp. 356-367.

Laursen K., Masciarelli, F. & Prencipe, A. (2012). Regions Matter: How Localized Social Capital Affects Innovation and External Knowledge Acquisition. Organization Science, 23 (1), pp. 177–193.

Lospinoso, J.A.; Schweinberger, M.; Snijders, T.A. & Ripley, R.M. (2011). Assessing and accounting for time heterogeneity in stochastic actor oriented models Advances in data analysis and classification. Springer, pp. 147-176.

Lundvall, B.-A. (1992). National systems of innovation - towards a theory of innovation and interactive learning. London: Pinter.

Macy, M.W. & Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. Annual review of sociology, pp. 143-166.

Maiman, T. H. (1960). Stimulated optical radiation in ruby. Nature, 187 (4736), pp. 493-494.

Malerba, F. (2002). Sectoral systems of innovation and production. Research Policy, 31 (2), pp. 247-264.

Marschall, A. (1890). Principles of economics - an introductory (1920, 8th ed.). London: Macmillan & Co.

Maskell, P. & Malmberg, A. (1999). Localized learning and industrial competitiveness. Cambridge Journal of Economics, 23 (2), pp. 167-185.

McPherson, M., Smith-Lovin, L. & Cook, J.M. (2001). Birds of a feather: homophily in social networks. Annual Review of Sociology, 27 (1), pp. 415-444.

Mowery, D.C., Oxley, J.E. & Silverman, B.S. (1996). Strategic alliances and interfirm knowledge transfer. Strategic Management Journal, 17 (2), pp. 77-92.

Mueller, M., Buchmann, T. & Kudic, M. (2013). Micros strategies and macro patterns in the evolution of Innovation networks. Conference paper, 2nd SKIN Community workshop, 31st May – 1st June, University of Koblenz-Landau, Koblenz, Germany.

Nelson, R. R. (1992). National innovation systems: a retrospective on a study. Industrial and Corporate Change, 1 (2), pp. 347-374.

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, G. & van den Oord, A. (2007). Optimal cognitive distance and absorptive capacity. Research Policy, 36, pp. 1016–1034.

Oerlemans, L.A. & Meeus, M.T. (2005). Do organizational and spatial proximity impact on firm performance? Regional Studies, 39 (1), pp. 89-104.

Oerlemans, L.A., Meeus, M.T. & Boekema, F.W. (2001). Firm clustering and innovation: determinants and effects. Papers in Regional Science, 80 (3), pp. 337-356.

Parkhe, A., Wasserman, S. & Ralston, D.A. (2006). New frontiers in network theory development. Academy of Management Review, 31 (3), pp. 560-568.

Pavitt, K. (1984). Sectoral patterns of technical change: Towards a taxonomy and a theory. Research Policy, 13 (6), pp. 343-373.

Pavitt, K. (1998). The inevitable limits of EU R&D funding. Research Policy, 27(6), pp. 559 – 568.

Podolny, J. M. (1993). A status-based model of market competition. American Journal of Sociology, 98 (4), pp. 829-272.

Podolny, J.M. (1994). Market uncertainty and the social character of economic exchange. Administrative Science Quarterly, 39 (3), pp. 458-483.

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), pp. 116-145.

Powell, W.W., White, D.R., Koput, K.W. & Owen-Smith, J. (2005). Network dynamics and field evolution: the growth of the interorganizational collaboration in the life sciences. American Journal of Sociology, 110 (4), pp. 1132-1205.

Pyka, A. (2000). Informal Networking and Industrial Life Cycles. Technovation, 20 , pp. 25-35.

Pyka, A. (2002). Innovation networks in economics: from the incentive-based to the knowledge based approaches. European Journal for Innovation Management, 5 (3), pp. 152-163.

Pyka, A. (2007). Innovation networks. In H. Hanusch, & A. Pyka, Elgar companion to Neo-Schumpeterian economics (pp. 360-377). Cheltenham : Edward Elgar Publishing .

Reagans, R. and McEvily, B. (2003). Network structure and knowledge transfer: The effects of cohesion and range, Administrative Science Quarterly, 48 (2), pp. 240-267.

Ring, P.S. & Van De Ven, A.H. (1994). Developmental processes of cooperative interorganizational relationships. Academy of Management Review, 19 (1), pp. 90-118.

Ripley, R.M.; Snijders, T.A. & Preciado, P. (2013).Manual for SIENA.

Romer, P. (1986). Increasing returns and long-run growth. The Journal of Political Economy, 94 (5), pp. 1002-1037.

Saxanian, A. (1990). Regional networks and the resurgence of Silicon Valley. California Management Review, 33 (1), pp. 89-112.

Scherngell, T. & Barber, M.J. (2009). Spatial interaction modeling of cross-region R&D collaborations: empirical evidence from the 5th EU framework programme. Papers in Regional Science, 88 (3), pp. 531–546.

Scherngell, T. & Barber, M.J. (2011). Distinct spatial characteristics of industrial and public research collaborations: evidence from the fifth EU framework programme. Annals of Regional Science, 46 (2), pp. 247-266.

Schilke, O. & Goerzen, A. (2010). Alliance management capability: an investigation of the construct and its measurement. Journal of Management, 36 (5), pp. 1192-1219.

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

Schwerk, A. (2000). Dynamik von Unternehmenskooperationen. Berlin: Duncker & Humblot.

Simonin, B.L. (1999). Ambiguity and the process of knowledge transfer in strategic alliances. Strategic Management Journal, 20 (1), pp. 595-623.

Sorenson, O. & Stuart, T. E (2001). Syndication Networks and the Spatial Distribution of Venture Capital Investments. American Journal of Sociology, 106 (6), pp. 1546-1588.

Sorenson, O. & Stuart, T.E. (2008). Bringing the Context Back. In: Settings and the Search for Syndicate Partners in Venture Capital Investment Networks. Administrative Science Quarterly, 53 , pp. 266-294.

Snijders, T.A.B. (1996). Stochastic actor-oriented models for network change. Journal of Mathematical Sociology, 21 (1-2), pp. 149-172.

Snijders, T.A.B. (2001). The statistical evaluation of social network dynamics. Sociological methodology, 31 (1), pp. 361-395.

Snijders, T. (2002). The statistical evaluation of social network dynamics Sociological methodology, 31, pp. 361-395

Snijders, T.A., Van De Bunt, G.G. & Steglich, C.E. (2010). Introduction to actor-based models for network dynamics. Social Networks, 32 (1), pp. 44-60.

Steglich, C., Snijders, T.A. & Pearson, M. (2010). Dynamic networks and behavior: Separating selection from influence. Sociological Methodology, 40, pp. 329-393.

Stuart, T.E. (2000). Interorganizational alliances and the performance of firms: a study of growth and innovational rates in a high-technology industry. Strategic Management Journal, 21 (8), pp. 791-811.

Sydow, J. (2003). Dynamik von Netzwerkorganisationen - Entwicklung, Evolution, Strukturation. In W. H. Hoffmann, Die Gestaltung der Organisationsdynamik - Konfiguration und Evolution (pp. 327-357). Stuttgart: Schäffer-Poeschel.

Ter Wal, A.L. (2013) The dynamics of the inventor network in German biotechnology: geographical proximity versus triadic closure, Journal of Economic Geography, 13(6).

Ter Wal, A.L., & Boschma, R. (2011). Co-evolution of firms, industries and networks in space. Regional Studies, 45 (7), pp. 919-933.

Tiberius, V. (2008). Prozesse und Dynamik des Netzwerk-wandels. Wiesbaden: Gaber.

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

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

Van Biesebroeck, J. (2003). Productivity Dynamics with Technology Choice: An Application to Automobile Assembly. Review of Economic Studies, 70 , pp. 167–198.

Van De Bunt, G.G., Van Duijn, M.A. & Snijders, T.A. (1999). Friendship networks through time: An actor-oriented dynamic statistical network model Computational & Mathematical Organization Theory, (5), pp. 167-192.

Van de Bunt, G.G. & Groenewegen, P. (2007). An Actor-Oriented Dynamic Network Approach. Organizational Research Methods, 10 (3), pp. 463-482.

Visser, E. J. (2009). The complementary dynamic effects of clusters and networks. Industry & Innovation, 16 (2), pp. 167-195.

Von Hippel, E. (1994). "Sticky Information" and the Locus of Problem Solving: Implications for Innovation. Management Science, 40 (40), pp. 429-439.

Wasserman, S. (1979). In Schuessler, K. (Ed.). A stochastic model for directed graphs with transition rates determined by reciprocity Sociological Methodology, Jossey-Bass, San Francisco, pp. 392-412.

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

Whittington, K.B., Owen-Smith, J. & Powell, W.W. (2009). Networks, propinquity, and innovation in knowledge-intensive industries. Administrative Science Quarterly, 54 (1), pp. 90-122.

Winter, S.G. (2006). Toward a Neo-Schumpeterian theory of the firm. Industrial and Corporate Change, 15 (1), pp. 125-141.

Wuyts, S., Colombob, M.G., Duttac, S. & Nooteboom, B. (2005). Empirical tests of optimal cognitive distance. Journal of Economic Behavior & Organization, 58 (2), pp. 277–302.