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Small-world network characteristics and firm innovativeness - Empirical evidence from the German laser industry

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Abstract

In the late 1960s Stanley Milgram conducted an experiment that is still highly topical, especially in the field of network research. The specific concern of his research project was to understand how communication processes work in social systems (Uzzi & Spiro, 2005, p. 450). He sent letters to a randomly chosen set of participants who were scattered throughout the United States. Written instructions were included asking the recipients to pass the letter forward to a specified target individual (Newman, 2010, p. 55). It turned out that almost one third of the letters sent reached even far targets after roughly six distinct steps on average. Milgram?s (1967) groundbreaking experiment showed that people in the US are separated by more or less six degrees of separation.

Milgram?s findings are highly relevant for innovation researchers. An in-depth understanding of the overall innovation network structure is important for at least three reasons. Firstly, there are good reasons to assume that network topologies affect the exchange of information, ideas and knowledge in multiple ways. Second, systemic level studies are still scant but highly relevant for understanding the collective nature of innovation processes. Finally, systemic level studies have some straightforward implications, not only for firms but also for policy makers, by providing an informative basis for the evaluation of cooperation-related innovation policies at the national and supra-national level.

Against the backdrop of these arguments, it is all the more astonishing that small-world network properties have been widely neglected in the field of interorganizational alliance and network research over the past decades (for a review see, Uzzi et al. (2007). The overall goal of this study is to contribute to a deeper understanding of the small-world phenomenon in an innovation network context. Inspired by previous research (cf. Uzzi & Spiro 2005, Fleming et al. 2007; Schilling & Phelps 2007) we put the ?small-world hypothesis? to the test according to which small worlds are assumed to enhance creativity and the ability to create novelty in terms on innovations. We draw upon Zahra & George?s (2002) potential and realized absorptive capacity concept to provide the missing theoretical link between small-world network properties and firm innovativeness.

We employ a unique longitudinal dataset that encompasses industry data, innovation data and network data for the entire population of 233 German laser source manufactures between 1990 and 2010 to analyze the relationship between small-world network properties at the macro level and the firm specific patenting activities at the micro level over time. In line with Fornahl et al.(2010) we used data on 570 publicly funded R&D cooperation projects to construct annual networks. Estimation results from a Negative Binomial panel data model with fixed and random effects indicate a positive relatedness between a network?s average path lengths and firm level innovative performance (measured by patent applications) at later points. Our findings for network clustering do not confirm our initial theoretical expectations. Finally, in line with previous findings by Schilling & Phelps (2007) we found sound empirical evidence for a positive relatedness between a network?s small-world nature and a firm?s subsequent innovativeness.

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Small world network characteristics and firm innovativeness – empirical evidence from the German laser industry

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Abstract:

Previous research demonstrates that large-scale network properties are likely to affect the exchange of information, ideas and knowledge in various ways. In this paper we put the "small-world hypothesis" to the test according to which innovation networks with comparably short path lengths and a high level of clustering are assumed to enhance creativity and the ability to create novelty at the micro level. More precisely, we employ a unique longitudinal dataset that encompasses industry data, innovation data and network data for the entire population of 233 German laser source manufactures between 1990 and 2010 to analyze the relationship between small-world network properties at the macro level and the firm specific patenting activities at the micro level over time. Estimation results from a Negative Binomial panel data model indicate a positive relatedness between a network's average path lengths and firm level innovative performance at later points. Our findings for network clustering do not confirm our initial theoretical expectations. Finally, in line with previous findings by Schilling & Phelps (2007) we found sound empirical evidence for a positive relatedness between a network's small-world nature and a firm's subsequent innovativeness.

Key words: Laser industry, small world, innovation network, firm innovativeness

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1 Introduction

In the late 1960s Stanley Milgram conducted an experiment that is still highly topical, particularly in the field of network research. The specific concern of his research project was to understand how communication processes work in social systems (Uzzi & Spiro, 2005, p. 450). The constellation of his so-called "letter-passing" experiment was quite simple. He sent letters to a randomly chosen set of participants who were scattered throughout the United States. Written instructions were included asking the recipients to pass the letter on to a pre-specified target individual (Newman, 2010, p. 55). It turned out that almost one third of the letters sent even reach far away targets after an average of around six distinct steps. Milgram's (1967) groundbreaking experiment demonstrated that people in the United States are separated by more or less six degrees of separation.

Milgram's findings have some far-reaching implications for innovation networks. Innovation networks allow organizations to exchange existing information, knowledge and expertise (Cantner & Graf, 2011, p. 373). At the same time, innovation networks provide the basis to commonly generate new knowledge which can be embodied in new products, services or processes (ibid.). The experiment implies that not only a firm's strategic network positioning (Powell et al. 1996) but also the overall network topology itself is likely to affect the exchange of knowledge among economic actors in innovation networks. This, however, substantiates the assumption that large-scale network properties at the macro level affect the innovative performance of network actors at the micro level.

A closer look at large-scale network patterns is important for several reasons. Firstly, there are good reasons to assume that network topologies affect the exchange of information, ideas and knowledge in multiple ways. Second, systemic level studies are still scant but highly relevant for understanding the collective nature of innovation processes. Finally, systemic level studies have some straightforward implications, not only for firms but also for policy makers, by providing an informative basis for the evaluation of cooperation-related innovation policies at the national and supra-national level.

In a nutshell, the overall goal of this study is to contribute to a deeper understanding of the small-world phenomenon in an innovation network context. Inspired by previous research (Uzzi & Spiro 2005, Fleming et al. 2007; Schilling & Phelps 2007) we put the "small-world hypothesis" to the test according to which small worlds are assumed to enhance creativity and the ability to create novelty in terms on innovations. To accomplish this task we employ a unique panel dataset for the entire population of 233 German laser source manufactures between 1990 and 2010. All network measures were calculated annually on the basis of 570 knowledge-related publicly funded R&D cooperation projects. Our data allows for an exact time tracking of all firm entries and exits on the one hand, and all tie formations and tie terminations on the other. We draw upon exploratory network analysis methods and employ panel data estimation techniques. Patent grant and patent applications with a one and two year time-lag were used as proxies for firm innovativeness.

The paper is organized as follows: in Section **2** we briefly discuss some selected studies and specify our research question. We continue in Section **3** by providing the graph theoretical underpinnings of small-world network properties. Then, we introduce our conceptual framework and derive a set of testable hypotheses. In Section **4** we provide a short overview of industry, data and methods that were used for the purpose of analysis. In Section 5 we continue with a description of the empirical model and present our estimation results. Finally, after a brief discussion of our main findings we conclude with some critical remarks.

2. State of the art and research question

It is all the more astonishing that large-scale network properties have been widely neglected in the field of interorganizational alliance and network research over the past decades.[1] Only recently have economists, sociologists and management scholars started to address the "small-world" phenomenon.[2] One possible explanation is that it took scholars about thirty years to quantify Milgram's initial idea. Watts & Strogatz (1998) have shown that the "small-world" phenomenon can be empirically analyzed by using relatively simple network measures. This analytical approach was originally designed for the analysis of unipartite networks. Only a few years later, a reconceptionalization for bipartite networks has been proposed by Newman and his colleagues (2001). Since then a few excellent empirical studies were conducted which explicitly analyzed the relationship between "small-world" properties and the creation of novelty and innovation (Uzzi & Spiro, 2005; Fleming, et al. 2007; Schilling & Phelps, 2007).

[1] Most notable exceptions are the studies by Baum et al. (2003), Corrado & Zollo (2006), Uzzi & Spiro (2005), Fleming et al. (2007), Schilling & Phelps (2007) and Cassi & Zirulia (2008).
[2] For a comprehensive overview of previous research in this area see Uzzi et al. (2007).

One of the first empirical studies on collaboration, creativity and small-worlds was conducted by Uzzi & Spiro (2005). The authors analyzed the relationship between small-world properties in the Broadway musical industry and creativity in terms of the financial and artistic performance of musicals produced from 1945 to 1989. This setting is remarkable for two reasons. Firstly, the network measures were constructed based on bipartite network data. In other words, groups of artists were treated as fully connected cliques. To handle the data properly, novel statistical techniques (Newman et al. 2001) were applied for the detection and interpretation of small-world properties which were explicitly designed for the analysis of bipartite networks. Finally, it is interesting to note that Uzzi & Spiro (2005) measured performance outcomes at the team level and not the actor level. They reported a parabolic small-world network effect in a sense that performance initially increased and then decreased after a certain point.

In a similar vein, Fleming and colleagues (2007) raised the question of why some regions outperform others in terms of innovativeness. Like Uzzi & Spiro (2005) they focused explicitly on small-world networks. However, both "small-world" properties and innovative performance were measured at the regional level. Based on patent co-authorship data they showed that comparably short path lengths and larger connected components are positive correlated to increased innovation. Nonetheless, they failed to find empirical evidence that the small-world properties of the regional innovation network enhanced firm innovativeness.

The most comprehensive study on small-worlds and firm innovativeness was provided by Schilling & Phelps (2007). They analyzed the patent performance of 1,106 firms in 11 industry level alliance networks based on a comprehensive panel dataset. The findings of the study provide support for the small-world hypothesis by showing that networks with comparably short path lengths and high clustering have a significant impact on the innovativeness of the firms involved. The authors came to the conclusion that local density and global efficiency can exist simultaneously, and in particular, the combination of these two network characteristics enhances innovation (Schilling & Phelps, 2007, p. 1124). Despite these interesting findings the study has some limitations. The most notable is that the authors had to make assumptions about alliance duration due to a lack of information on alliance termination dates. They assumed that alliance relationships last for three years on average. In the worst case, this could result either in a systematic underestimation or overestimation of small-world network properties.

All of these studies provide us with valuable insights into the small-world phenomenon. However, this discussion also reveals that recent empirical findings have so far been rather mixed and inconclusive. In addition, we still lack an in-depth understanding of how large-scale network properties affect firm innovativeness. In other words, we have to open up the black box in order to understand through which mechanisms or transmission channels firm innovativeness is affected by systemic level network properties.

Consequently, the aim of this examination is twofold. From a theoretical point of view, we draw upon a reconceptualization of the absorptive capacity concept proposed by Zahra & George (2002) to provide the missing link between overall network characteristics and a firm's innovative performance. From an empirical point of view, we put the "small-world" hypothesis to the test according to which small-world networks are assumed to enhance an embedded firm's creativity and its ability to create novelty in term of innovation. More precisely, we analyze the relationship between distinct large-scale patterns (i.e. "weighted clustering coefficient" ***or*** "avg. path-length") and firm innovativeness on the one hand, and small-world properties (i.e. "weighted clustering coefficient" ***and*** "avg. path-length") and firm innovativeness on the other.

3 Large-scale network properties, absorptive capacity and the "small-world hypothesis"

3.1 Graph theoretical foundation of the "small-world" phenomenon

Small-world networks are characterized by two structural particularities: a high level of clustering and short average path lengths. The theoretical conceptualization and quantification of the small-world phenomenon can be traced back to the pioneering work of Watts & Strogatz (1998). The authors argued that a compression of real-world networks and randomly generated networks should reveal some systematic differences with regard to network clustering and actor reachability. They proposed using two simple graph theoretical concepts – "cluster coefficient" and "average distance" – and calculating two ratios – "clustering coefficient ratio" (CC ratio) and "path length ratio" (PL ratio) – in order to check for the existence of small-world properties in real world network. Quantitative network analysis methods provide a rich toolbox for quantifying the concepts (cf. Wasserman & Faust, 1994).

We start with the clustering coefficient (cf. Watts 1999; Watts & Strogatz, 1998). The clustering coefficient is a graph theoretical concept that allows the connectedness and crowding in a network to be quantified. This more indirect tie-related concept captures the density of an actor's surrounding and measures how many of its direct partners are interconnected. A network is said to be highly clustered or cliquish when many of the actor's contacts are connected to each other (Uzzi, et al. 2007). The overall network clustering coefficient is the average of all individual clustering coefficients for the entire network. In contrast, the weighted overall clustering coefficient is defined as the weighted mean of the clustering coefficient of all the actors, each one weighted by its degree (Borgatti, et al. 2002). The calculation of the clustering coefficient is straightforward. The indicator simply measures the density of triangles in a given network (Newman, 2010, p. 264). Firstly, it is important to consider that the percentage of closed triads is three times the total number of closed triads (Uzzi, et al. 2007, p. 79). Secondly, we have to quantify the number of triangles (numerator) and the number of connected triples (denominator). This lead to the following definition of the clustering coefficient (Uzzi, et al. 2007, p. 79):

$$(1) \qquad \mathrm{CC} = \frac{3\,x\ number\ of\ triangles}{number\ of\ triples}.$$

The coefficient varies from 0 to 1 where a value of zero represents no clustering and a value of one represents full clustering (Uzzi, et al. 2007, p. 79).

Now we take a closer look at the shortest paths (or distances) between network actors. In order to quantify the average reachablility among actors in a connected graph, we have to quantify the geodesics[3] between all pairs of actors. In this context it is important to note that paths between two actors can have different lengths in directed networks (Newman, 2010, p. 242). In unconnected networks (i.e. networks with at least two components) the distance for at least one pair of actors can reach infinity (Wasserman & Faust, 1994, p. 110). As most real world networks are not fully connected (Newman, 2010, p. 237) this issue is usually tackled by focusing on the main component.[4] The average path length captures the reachability among all network actors in a connected graph or sub-graph. The measure can be defined as "[…] the average number of

[3] The shortest path between a pair of network actors is referred to as the geodesic distance (Wasserman & Faust, 1994, p. 110).

[4] Newman (2010, p. 235) reports that the main component usually fills more than 90% of the entire network in the majority of real world networks such as social networks, biological networks, information networks or technological networks. For the German laser industry network we found that the main component fills 94.51% of the network on average.

intermediaries, that is, the degrees of separation, between any two actors in the network along their shortest path of intermediaries" (Uzzi et al. 2007, p. 78). Calculating the shortest path distance between pairs of nodes in a network is much harder than calculating the clustering coefficient and no exact expression for the mean distance has been found yet (Newman, 2010, p. 560). As a consequence, we refer to the so-called average distance weighted reach concept (Borgatti, et al. 2002; Schilling & Phelps, 2007) to capture the reach of the network:

$$(2) \qquad AR = \left[\sum_n \sum_j \frac{1}{d_{ij}}\right] / \text{ n .}$$

The number of network nodes is given by n, and d_{ij} is defined as the number of smallest geodesic distances from actor i to a partner j; with i≠j (cf. (Schilling & Phelps, 2007, p. 1118). The measure provides an important macro level indicator by quantifying how far the distances between all pairs of network actors are on average.

Watts & Strogatz (1998) demonstrated that real-world networks with a CC ratio much higher than 1.0 and a PL ratio of about 1.0 have a small-world character. A related indicator is the so-called "small-world Q" (defined as: the CC ratio divided by the PL ratio), where Q values that are much greater than 1.0 indicate the small-world nature of a real-world network (Uzzi, et al. 2007, p. 79). In addition, Newman et al. (2001) have shown that the "path length ratio" in bipartite networks has basically the same interpretation as in unipartite networks (Uzzi & Spiro 2005, p. 454). In contrast, the "clustering coefficient ratio" has to be interpreted differently in the sense that a coefficient ratio of about 1.0 indicates within-team clustering whereas an exceeding clustering coefficient ratio indicates an increase in between-team clustering (Uzzi & Spiro 2005, p. 454-455).

What do these graph theoretical considerations tell us with regard to firm innovativeness? Or to put it another way, what is the theoretical explanation that substantiates the assumption that small-world properties at the systemic level enhance a firm's ability to innovate? Earlier researchers have argued as follows (Schilling & Phelps, 2007, pp. 1114-1115): On the one hand, a high level of clustering increases the network's information transmission rate, enhances a firm's willingness and ability to exchange knowledge and enables richer and greater amounts of information and knowledge to be integrated. On the other hand, networks with short average path lengths enhance reachability among actors and generally improve information accessibility at the systemic level. There is no doubt that these arguments provide an intuitive reasoning behind the consequences of potential firm level innovation outcomes caused by increased information permeability in a small-world network. However, these arguments do not directly address what is happening at the firm level during the firm's efforts to innovate.

3.2 Potential and realized absorptive capacity – the missing link

We argue that Zahra & George's (2002) reconceptualization of Cohen & Levinthal's (1990) initially proposed "absorptive capacity" concept provides the missing link in understanding the interrelationship between systemic network level properties and firm level innovation outcomes.

The originally proposed "absorptive capacity" concept by Cohen & Levinthal (1989; 1990) has significantly enhanced our understanding of a firm's ability to identify, exploit and assimilate external knowledge and apply it for commercial ends. Cohen & Levinthal (1989) focused initially on the costs of acquiring new technological knowledge and on the incentives for learning that determine the firm's willingness to invest in creating and establishing absorptive capacity. Later the authors enriched the construct by emphasizing the relevance of individual learning processes and incorporating the notion that learning is a cumulative process (Cohen & Levinthal, 1990). Furthermore, they adapted insights from research on individual cognitive structures and individual learning processes. They applied these findings to the organizational level and emphasized that an organization's absorptive capacity is path-dependent, builds on prior investments in individual absorptive capacity and depends on an organization's internal communication processes and its ability to share knowledge (Lane, et al., 2006, p. 838). In addition, they pointed to the fact that prior accumulated knowledge enables the firm to predict and appraise new technological trends and developments in a timely way. Since then the concept has attracted a great deal of attention.[5] Several scholars have proposed insightful reconceptualizations and refinements of Cohen & Levinthal's original concept (Lane & Lubatkin, 1998; Van Den Bosch, et al. 1999; Zahra & George, 2002).

For the purpose of this analysis we draw upon the concept proposed by Zahra & George (2002). This reconceptualization builds upon the distinction between "capabilities" and

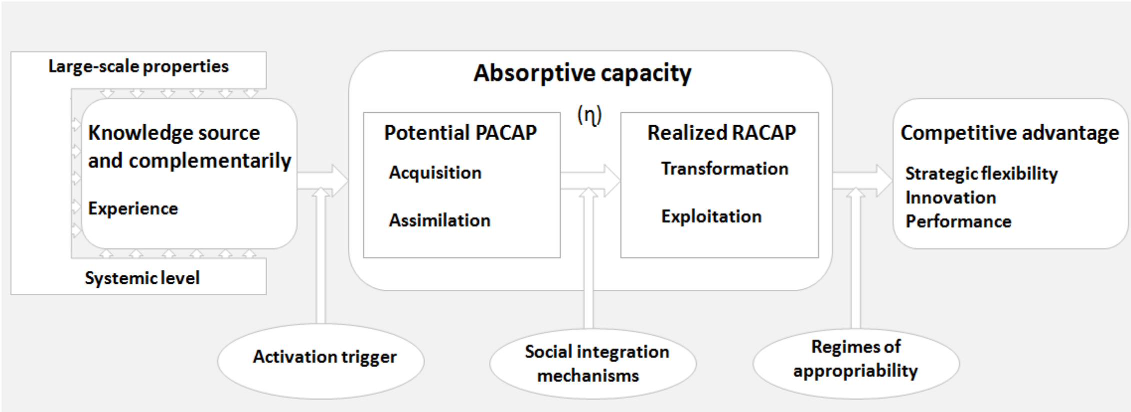
[5] Lane et al. (2006) identified a total of 289 papers in 14 academic journals between July 1991 and June 2002 that cite Cohen & Levinthal's (1990) initially proposed "absorptive capacity" concept.

“dynamic capabilities”. By starting from the dynamic capability perspective (Teece, et al. 1997; Teece 2007; Katkalo, et al. 2010) they suggest a separation of the original absorptive capacity concept into potential absorptive capacity and realized absorptive capacity and introduce an efficiency factor η that captures the interrelationship between these two constructs (Zahra & George, 2002, p. 194). They argue that four capabilities[6]– i.e. knowledge acquisition, assimilation, transformation, and exploitation – are combinative in nature and build upon each other. These four capabilities make up a firm’s absorptive capacity that has to be regarded as a dynamic capability pertaining to knowledge creation and utilization that enhances a firm's innovative performance and ability to gain and sustain a knowledge-based competitive advantage (Zahra & George, 2002, p. 185). They define absorptive capacity as “[…] a set of organizational routines and processes by which firms acquire, assimilate, transform, and exploit knowledge to produce a dynamic organizational capability” (Zahra & George, 2002, p. 186).

Figure 1 illustrates Zahra & George’s (2002) model. The refined absorptive capacity construct, at the core of the model (cf. Figure 1, center), is divided into potential absorptive capacity (PACAP), which includes knowledge acquisition and assimilation, and realized absorptive capacity (RACAP), that consists of knowledge transformation and exploitation capabilities. This absorptive capacity construct connects the antecedents, i.e. external knowledge sources, knowledge complementarities and experiences (cf. Figure 1, left) with firm level outcomes, i.e. firm innovativeness and sustainable competitive advantages (cf. Figure 1, right). In addition, the model accounts for several moderating effects: “activation triggers”, “social integration mechanisms”, and “regimes of appropriability”. Moreover, an efficiency factor η is integrated into the model that captures a firm’s ability to transform and exploit external knowledge sources in order to gain a sustainable competitive advantage. This factor reflects the extent to which a firm can make commercial use of potentially available knowledge. In other words, RACAP approaches PACAP in firms with a high efficiency factor (Zahra & George, 2002, p. 191). This model paves the way for a dynamic conceptualization of absorptive capacity and provides several interesting implications for systemic level network studies. Below we argue that a simple extension of the model provides the missing link for understanding how large-scale properties at the overall network level affect innovation outcomes at the firm level.

6 Zahra & George (2002) draw upon Winter (2003, p. 983) who defines as capabilities “[...] a high-level routine that, together with its implementing input flows, confers upon an organization's management a set of decision options for producing significant outputs of a particular type".

Figure 1: **Conceptual framework – an adapted model of potential and realized absorptive capacity**



Source: **Zahra & George (2002, p. 192), modified.**

In doing so, we have to take a closer look at the first element of the framework (cf. Figure 1, left). According to the model originally proposed by Zahra & George (2002, p. 191) there is a direct link between external knowledge sources and complementarities and a firm's PACAP. These external knowledge sources encompass, among other things, various structural forms of interorganizational relationships such as R&D consortia, alliances, or joint ventures.[7] Thus cooperative relationships to external partners can serve as a vehicle for accessing new information and knowledge. However, it is important to note that not only direct but also indirect interorganizational linkages have to be considered in this context (Gulati, 1998). As a consequence, we apply here not a relational but rather a structural network embeddedness perspective. One particular feature of a network is that a particular firm can even reach far distant organizations that are spread throughout the entire network space by second or third tier ties. This means that a firm that is a part of the industry's innovation network has potential access to an extensive pool of external technological knowledge sources spread throughout the entire network. Thus, in line with previous systemic-level studies (Uzzi & Spiro, 2005; Fleming, et al. 2007; Schilling & Phelps, 2007), we argue that actual access to information and other firms' knowledge stocks is likely to be affected by the structure of the network in question. The network topology itself plays a key role in the permeability of the network.

In contrast to previous research, we believe that an extension of the absorptive capacity concept outlined above and an in-depth exploration of structural network characteristics adds extra value in our understanding of how large-scale properties at the systemic level

[7] Due to the purpose of this study we focus explicitly on the innovation network as one particular type of external knowledge source that can be tapped by the firms.

affect a firm's efforts to innovate (cf. Figure 1, left). Or to put it differently, given that network topologies can facilitate but also hamper the flow of information and knowledge among actors in an innovation network, the question arises as to what these structural network patterns look like.

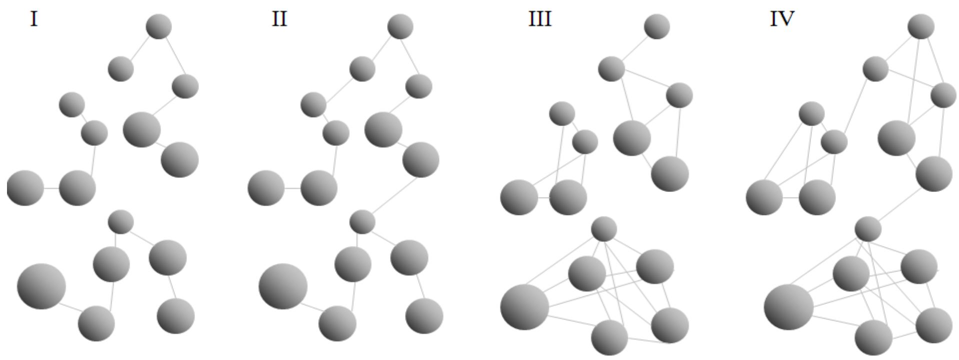
3.3 Large-scale network properties – opening up the black box

Networks can exhibit quite heterogeneous structural patterns. Figure 2 illustrates four fairly different network topologies. To start with, we look at a typically random network. It is important to note that the emergence of these networks is not very likely under realistic conditions. Nonetheless, we explicitly consider and discuss all four cases to develop our theoretical arguments.

The first network example is characterized by a rather fragmented network structure that consists of five components (cf. Figure 2, I). The structural configuration of the network shows no significant peaks in term of the actors' nodal degrees. The minimum degree is one and the maximum degree is two. Network actors within a component are not directly but rather are indirectly connected to other actors in the same component. The benefits of a firm in participating in such a fragmented, randomly distributed network are rather limited. The reasons for this are straightforward. Firstly, the pool of potentially accessible knowledge sources is limited by the size of the component in which the firm is embedded. Secondly, the geodesic distances to most other actors are infinite due to the high degree of fragmentation. Thus, knowledge transfer processes are likely to be hampered by the component's size or even entirely prevented by the overall network structure.

These issues lead to our second network example. Figure (2, II) illustrates a fully connected but randomly distributed network structure. Like before there are no systematic biases in the degree distribution at the overall network level. The main difference is that the network consists of only one large component. This, however, has some important implications with regard to knowledge diffusion processes. Theoretically, we would expect that a firm's participation in such a network broadens the scope and variety of potentially accessible information and knowledge sources. One could argue that the firm's chance of identifying and actually accessing external knowledge sources that fit with its own set of capabilities increases with the number of potentially accessible knowledge sources. The crucial point is that such an increased set of opportunities would allow a firm to make better use of its knowledge exploitation capabilities. According to Zahra & George (2002) this would be reflected in a higher efficiency factor η and lead to a higher firm level innovation outcome at subsequent points in time. In fact the actual situation looks somewhat different. The likelihood of successfully exchanging knowledge between two indirectly connected network actors decreases with the number of other actors that lie on the geodesic between them. A closer look at our network example illustrates this point (Figure 2, II). In this case we have up to eleven intermediates between the most distant actors in the network.

Figure 2: **Illustration of network topologies**



Source: **Author's own illustration.**

Next, we turn our attention to a somewhat more realistic network structure. By now, it is well-recognized that some nodes attract ties at a higher rate than others. This is reflected in real world networks by the emergence of a strongly biased degree distribution at the overall network level. These types of networks are also known as power law distributed or scale free networks (Barabasi & Albert, 1999; Barabasi & Bonabeau 2003). Real-world network topologies can differ significantly in terms of their structural features.

Our third network example consists of three components (two peripheral & one main component) and the nodal degrees range from one to five (cf. Figure 2, III). The network is disconnected and clustered. The nodes within these components are well-connected among one another but they have no linkages to actors in other areas of the network. We start our line of argument by focusing on the network's main component (cf. Figure 2, III, bottom). A firm's involvement in a highly interconnected main component of a disconnected network has some considerable advantages. Firstly, all main component firms are connected to one another. A main component firm can reach most other actors in the same component in only a few steps. Short paths are likely to facilitate potential knowledge transfer and learning processes. Most innovation researchers would agree that a decreasing path length is positively related to firm innovativeness (Fleming, et al. 2007, p. 941). Secondly, a high degree of interconnectedness allows a focal firm to achieve cooperation-related synergy effects. These effects can result from direct but also from indirect linkages among a focal actor's directly connected partners (White, 2005; Hoffmann, 2005). Redundant knowledge transfer channels allow firms to circumvent potentially emerging knowledge transfer barriers. It has been argued that clustering promotes collaboration, resource pooling and risk sharing (Fleming, et al. 2007, p. 940).[8]

In summary, the previously outlined arguments substantiate the assumption that a firm's embeddedness in the main component of a highly clustered but disconnected innovation network enhances a firm's scope and variety of accessible knowledge sources. Two structural characteristics, i.e. short path lengths and a high level of clustering are considered to be important in this context. With the extension of Zahra & George's (2002) absorptive capacity model in mind, it is plausible to assume that these structural features enhance a firm's efficiency factors η. This, in turn, is likely to be positively related to firm-level innovation outcomes at later points in time. The arguments above form our first two hypotheses:

H1 **Short average path lengths** in the overall network enhances a firm's efficiency factor η; this, in turn, is positively related to its innovative performance at later points in time.

H2 A **high degree of clustering** at the overall network level enhances a firm's efficiency factor η; this, in turn, is positively related to its innovative performance at later points in time.

Last but not least, we address small-world properties of innovation networks. It becomes apparent that the previously discussed real-world network in itself encounters barriers in information and knowledge transfer. As already stated above, the network consists of several densely interconnected components which are not connected to one another. This leads us to take a look at the last network example. Figure (2, IV) illustrates a highly clustered but fully connected real-world network. The simultaneous occurrence of cohesive subgroups and short paths in a network has some interesting implications.

[8] It is important to note that these considerations only hold true as long as the number of disconnected network components is comparably small. The benefits diminish with an increasing number of disconnected subgroups in the network. Or to put it another way, increasing fragmentation disestablish the benefits described above.

Firstly, such a network is rich in structural holes and the cohesive subgroups are interconnected through network brokers (Burt, 1992). They bridge structural gaps in a network and establish important connections between otherwise unconnected or at least loosely connected network subgroups (ibid.). This, however, significantly decreases the average path lengths at the overall network level and increases, at the same time, information permeability. Secondly, the benefits of cohesive subgroups in a firm's close network surrounding are be maintained. The simultaneous occurrence of clustering and short average path lengths indicate the small-world nature of a network (Watts & Strogatz 1998).

In line with previous research (Schilling & Phelps, 2007) we argue that small-world network properties are accompanied by some extra additive effects which are assumed to enhance a firm's efficiency factor η. The simultaneous occurrence of both high clustering and short average path lengths is likely to catalyze and foster local cooperation effectiveness and enhance global information transmission efficiency (Schilling & Phelps, 2007, p. 1116). These considerations substantiate our last hypothesis:

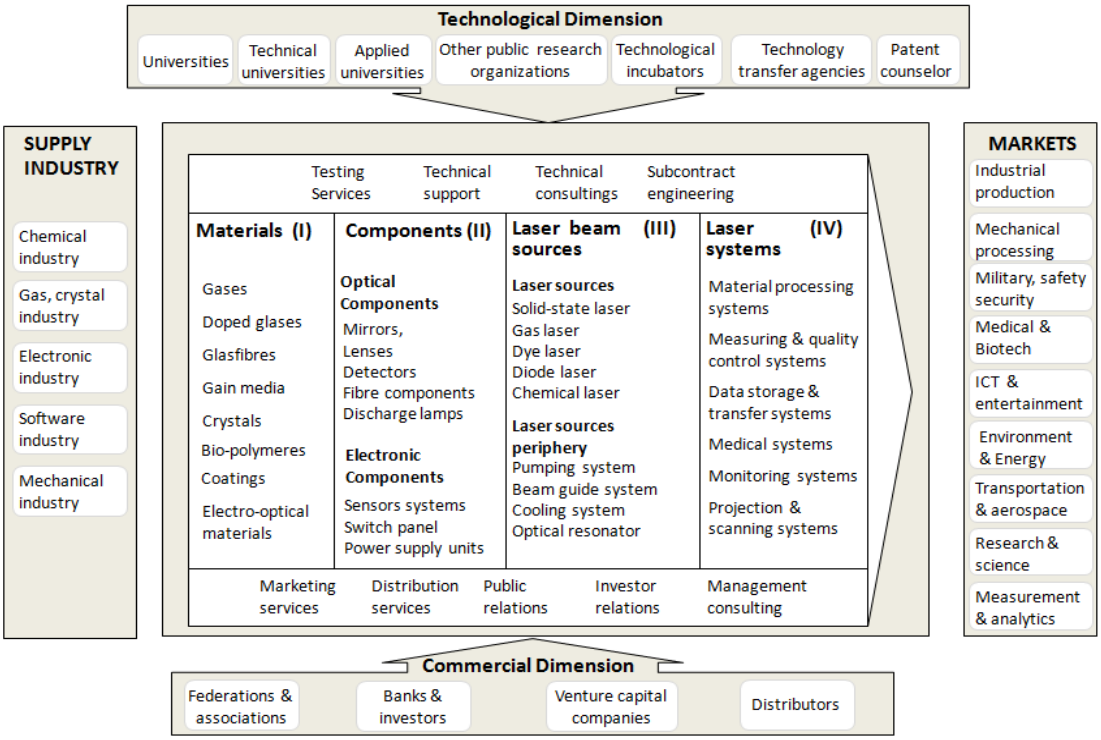
> **H3** A firm's participation in a **small-world network** (characterized by short average path lengths and a high level of clustering) enhances its efficiency factor η; this, in turn, is positively related to its innovative performance at later points in time.

4 Industry, data and methods

4.1 Introducing the German laser industry

To start with, we take a brief look at the industry's value chain (cf. Figure 3). The laser industry value chain itself consists of the four main elements: "materials", "components", "laser beam sources & periphery" and "laser systems" accompanied by cross-sectional services that provide these four elements with certain technical and commercial advice. In addition, Figure 3 illustrates the linkages to the supply and market side as well as the contact points to technology and commercial partners. Laser source manufacturers (LSMs) are considered to be the heart of the industry's value chain because they develop and produce the key component of every laser-based machine or system. As a consequence, this study focuses primarily on laser source manufacturers (LSMs) and their cooperation activities. However, not only LSMs but also universities or other public research organizations (PROs) are an important source of new technological knowledge (Agrawal, 2001, p. 285). To account for this fact we explicitly considered all linkages and interactions between LSMs and all other kinds of laser related public research organizations (PROs) in this study.

Figure 3: **Laser industry value chain**



Source: **Author's own illustration, based on: (TSB, 2010, p. 18)[9]**

The German laser industry provides an ideal setting for studying small-world properties of interorganizational innovation networks for several reasons. Firstly, the development of laser technologies requires knowledge from various academic disciplines, such as physics, optics and electrical engineering (Fritsch & Medrano, 2010). Moreover, the industry can clearly be characterized as a science-driven industry (Grupp, 2000) in which a firm's ability to innovate is a key factor in its performance and success. The interdisciplinary and science-based character of the industry is reflected in the high level of cooperation activities between German laser source manufacturers among themselves and with laser-related public research organizations (Kudic, et al. 2011). Secondly, the economic potential of the industry is meanwhile well recognized by national and supra-national political authorities. Over the past few decades Germany has developed into a world market leader in many fields of laser technology. For instance, Mayer (2004) reports that 40% of all laser beam sources purchased worldwide in 2003 were produced by German laser source manufacturers. The world market share for laser sources used in

[9] TSB Innovationsagentur Berlin GmbH, www.tsb-optik.de (accessed: November 2011).

laser processing systems was even higher and amounted to 50% in the same year. Finally, there are only very few empirical studies that have explicitly analyzed the relatedness between network characteristics and innovative performance in the optical industry (Ouiment et al. 2007; Lerch 2009; Sydow et al. 2010) and even less research has been conducted on networks in the laser industry (Noyon et al. 1994; Shimizu & Hirao 2009). To the best of our knowledge, there is up to now no longitudinal empirical study that has analyzed the relationship between large-scale network properties and firm-level innovation processes in the German laser industry

4.2 Data, variables and methods

Basically four main data sources were used to construct a longitudinal panel dataset: patent data, industry data, geographical data and network data.

Patent data was used to measure innovative performance at the firm level. We are not the first to use patent data as an innovation proxy (Jaffe, 1989; Jaffe, et al. 1993). There is a longstanding discussion in the literature on the conceptual background of innovation measurement (cf. Smith, 2005). Previous studies provide us with important insights into the pros and cons of using patents to measure innovation performance.[10] In accordance with contemporary research (Schilling & Phelps, 2007) we decide in favor of annual patent application counts as a proxy for innovation output to specify our endogenous variable [*pacnt*]. Three patent data sources were tapped to gather the patent data needed. In order to generate a complete overview of the firms' patent activities[11] we used the European Patent Office's database (PatStat, Version 2010)[12] as the primary data source. DEPATISnet (the German Patent and Trade Mark Office's online database) and *ESPACEnet* (European Patent Office database) were employed for data completion and for cross checking the results from our initial data gathering procedure.

Industry data came from a proprietary dataset containing the entire population of German laser source manufacturers between 1969 and 2005 (Buenstorf, 2007). Based on this initial dataset we used additional data sources to gather information about firm

10 For a detailed discussion on the measurement of innovation see for instance Smith (2005), Fritsch & Slavtschev, (2007) and Brenner & Broekel (2011).

11 By drawing upon the initially complied list of 233 LSMs, we conducted a firm-specific search in order to identify and extract all patents which were assigned to the firms. A list of various ways to spell each firm's name was used to deal with spelling issues. In the case of micro firms (i.e. firms with less than 10 employees) we also searched for the founder's name.

12 Data access was provided by the IWH department "Formal Methods and Databases". For an overview and detailed description of the raw data source used see EPO (2010).

entries and exits after 2005.[13] We chose the business unit or firm level for the purpose of this analysis. In addition, we identified 145 universities and public research organizations with laser-related activities by using two complementary methods – the expanding selection method and the bibliometric approach.[14]

Network data was gathered from two official databases on publicly funded R&D collaboration projects – the *Foerderkatalog* database and *CODRIS* database.[15] In other words, we focus on a particular type of formal knowledge-related linkages i.e. publicly funded R&D cooperation projects. These partnerships are very well documented by official funding authorities. Other researchers have provided solid theoretical as well as methodological arguments for the use of nationally funded R&D cooperation project data (cf. Broekel & Graf, 2011, p. 6; Fornahl, et al. 2011) and supra-nationally funded R&D cooperation project data (cf. Scherngell & Barber, 2009; Scherngell & Barber, 2011) for the construction of knowledge-related innovation networks. The *Foerderkatalog* database contains information on more than 110,000 ongoing or completed subsidized research projects. The second raw data source was an extract from the *CORDIS* project database which includes a complete collection of R&D projects for all German companies which were funded by the European Commission. This database extract encompasses a project dataset with over 31,000 project files and an organization dataset with over 57,100 German organizations and roughly 194,000 international project partners. In total, we were able to identify, for the entire population of 233 German laser source manufacturers, 570 R&D projects with up to 33 project partners from various industry sectors, non-profit research organizations and universities.

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[13] The following data sources were tapped: (I) we were given access to updated German laser industry data, again provided by Guido Buenstorf; (II) annually published laser industry business directories (i.e. *"Europäischer Laser Markt"*) provided by the *B-Quadrat* Publishing Company; (III) firm data from Germany's official company register (i.e. *"Bundesanzeiger"*); (IV) and two additional data sources i.e. *MARKUS* database, provided by Bureau van Dijk Publishing and the *Creditreform* archival database, provided by the Creditreform Company.

[14] At first, we applied the expanding selection procedure originally proposed by Doreian & Woodard (1992) to identify laser-related public research organizations (PROs). The identification procedure starts with a "fixed list" (in our case the annually complied LSM lists) and adds all PROs that are linked to LSMs to create an "extended list". However, this procedure ignores all PROs that were actively operating in the field of laser research but had no cooperation linkages to any LSM between 1990 and 2010. Consequently we applied a complementary method based on bibliometric data to complete the PRO lists. Data for this analysis was provided by the LASSSIE consortium (Albrecht et al. 2011).

[15] Data on publicly funded R&D cooperation projects can be accessed by tapping the following online interface: Foerderkatalog data: http://foerderportal.bund.de/foekat/jsp/StartAction.do (accessed: May - September 2011); CORDIS data: http://cordis.europa.eu/search/index.cfm?fuseaction=search.advanced (accessed: May 2012).

The data sources described above were used to construct interorganizational innovation networks and calculate network indicators on a yearly basis. We calculated weighted clustering coefficients *[nw_wclust]* and average path length *[nw_areach]* on an annual basis (cf. Equations 1 & 2). An interaction term was calculated to capture the small-world properties of the network *[inter_sw]*. Several additional control variables were calculated. We measured firm-specific cooperation activities with two cooperation count measures based on the *Foerderkatalog* data *[coopcnt_fk]* and *CORDIS* data *[coopcnt_c]*, respectively, as well as a combined cooperation count indicator *[coopcnt_fkc]* consisting of the sum of both. Moreover, we accounted for cooperation funding by including a variable that measures the firm's amount of cooperation funding received annually *[coopfund_fkc]* in thousand euros. We also included a linear firm age measure *[firmage]* as well as a squared term *[firmage_sq]* to account for firm maturity. In addition, two network level variables were included to control for the structural network characteristics at the overall network level. The first variable captured the size of the overall network *[nw_size]* defined as the proportion of firms with at least one dyadic partnership in a given year. The second variable measured the connectedness of the overall network *[nw_density]*. Standard algorithms implemented in UCI-Net 6.2 were used to calculate the network measures (Borgatti et al. 2002).

Next, we take a brief look at the variable description and basic summary statistics (cf. Table 1). In total, we have 2645 firm-year observations in the time span between 1990 and 2010. The average number of observations per firm amounts to 11.35. Table 2 reports the correlation coefficients for all variables in our empirical models.

Table 1: Descriptive statistics – clustering, reach and small-world properties

Variable	Variable definition	Summary statistics				
		Obs.	Mean	Std. Dev.	Min	Max
Endogenous variables						
papcount	Patent applications (annual count)	2645	2.662004	17.43323	0	366
pgrcount	Patent grants (annual count)	2645	0.339130	1.635554	0	28
Control variables						
firmage	Age of the firm	2645	8.055955	6.800477	0	43
firmage_sq	Age of the firm, squared	2645	111.1274	177.8146	0	1849
coopcount	Count of cooperation events (annual)	2645	0.275992	0.774138	0	8
coopfund	Annual cooperation funding received (in k€)	2645	132.2991	851.8748	0	31863
nw_size	Network size (overall network level)	2645	0.381853	0.060200	0.240506	0.472393
nw_density	Network density (overall network level)	2645	0.088119	0.069955	0.037300	0.440500
Network level properties						
nw_wclust	Weighted clustering coefficient	2645	0.5815221	0.1610685	0.345	0.906
nw_areach	Average distance based reach measure	2645	3.094311	0.5041826	2.075	3.786
inter_sw	"Small world" indicator (nw_wclust x nw_areach	2645	1.732396	0.2989206	1.14021	2.18748

<u>Source:</u> Author's own calculation.

Table 2: Correlation matrix – clustering, reach and small-world properties

	pgr count	pap count	firm age	firm age_sq	coopcount	coopfund	nw _size	nw _density	nw_wclust	nw_areach	inter_sw
papcount	1.0000										
pgrcount	0.6506	1.0000									
firmage	-0.0566	0.0105	1.0000								
firmage_sq	-0.0455	-0.0047	0.9276	1.0000							
coopcount	0.2535	0.2726	0.0101	0.0272	1.0000						
coopfund	0.3923	0.3114	-0.0279	-0.0100	0.5112	1.0000					
nw_size	0.0448	0.0670	0.2131	0.1603	0.0442	0.0147	1.0000				
nw_density	-0.0529	-0.0832	-0.2006	-0.1450	-0.0182	-0.0145	-0.6576	1.0000			
nw_wclust	-0.0529	-0.0835	-0.2530	-0.1901	-0.0074	-0.0153	-0.4684	0.6934	1.0000		
nw_areach	0.0637	0.0965	0.2761	0.2062	0.0164	0.0100	0.7154	-0.7499	-0.8255	1.0000	
inter_sw	-0.0219	-0.0414	-0.1639	-0.1275	0.0026	-0.0141	-0.0656	0.3186	0.8357	-0.4020	1.0000

Source: Author's own calculation.

Based on the data sources described above we conducted an initial exploratory analysis to get an idea of what the overall network topology looks like. Figure 4 (top) displays the weighted overall clustering coefficients and the average overall path length for both the German laser industry innovation network and a randomly generated Erdös-Renyi network.[16] Network measures are calculated on an annual basis and the period under observation is from 1990 to 2010. All measures are calculated using UCI-Net 6.2 (Borgatti et al. 2002). The corresponding CC ratios, the PL ratios and the small-world Q values are reported in the table below (cf. Figure 4, bottom). The following structural patterns are noteworthy.[17]

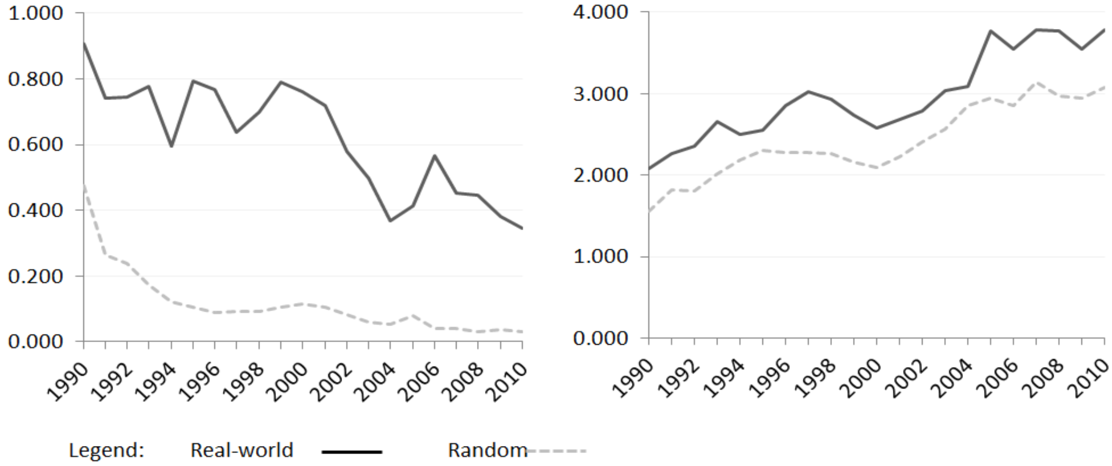
Firstly, the German laser industry innovation network shows a relatively high level of clustering and rather short average path lengths overall. Secondly, over time we can observe decreasing weighted clustering coefficients and increasing average path lengths. This is primarily due to the fact that the German laser industry network has demonstrated a pronounced growth tendency over time. In other words, the number of laser-related organizations that actively participate in the industry's innovation network increases over time. Thirdly, small-world measures indicate the emergence and consolidation of the network's small-world nature. More precisely, a comparison of the real-world network with a randomly generated reference network reveals that the German laser industry innovation network exhibits both higher overall clustering coefficients and longer average path lengths for each year throughout the entire

[16] To ensure comparability between the real world and the random networks we proceeded as follows: firstly, we generated a total number of 21 Erdös-Renyi random networks for the period under observation, one network for each year. Secondly, both the size and the density parameters were adapted to the actual proportions of the real networks. Standard procedures implemented in UCI Net 6.2 were used to generate the random networks (Borgatti et al. 2002).

[17] Note that the calculations are based on bipartite network data. This is in line with the study by Uzzi & Spiro (2005). However, the use of bipartite network data generates relatively high clustering coefficients. This should be kept in mind when interpreting the results.

observation period. The annually calculated CC ratios are clearly above 1.0 and increase over time. PC ratios do not exceed the value range between 1.0 and 1.35 and the small-world Q ratio lies significantly above 1.0 and demonstrates, like the CC ratio, a pronounced tendency towards increasing values over time.

Figure 4: Weighted overall clustering coefficient and avg. overall path length



year	weighted overall clustering coefficient			avg. overall path-length (among reachable pairs)			small-world properties
	Real-world	Random	CC	Real-world	Random	PC	(Q)
1990	0.906	0.477	1.899	2.075	1.560	1.330	1.4279609
1991	0.743	0.263	2.825	2.268	1.820	1.246	2.26705159
1992	0.746	0.240	3.108	2.351	1.810	1.299	2.39305969
1993	0.777	0.175	4.440	2.658	2.020	1.316	3.37426637
1994	0.595	0.120	4.958	2.501	2.180	1.147	4.32193789
1995	0.793	0.105	7.552	2.553	2.300	1.110	6.8039468
1996	0.767	0.088	8.716	2.852	2.280	1.251	6.96783756
1997	0.638	0.093	6.860	3.027	2.280	1.328	5.16725812
1998	0.701	0.093	7.538	2.929	2.270	1.290	5.841731
1999	0.791	0.104	7.606	2.735	2.160	1.266	6.00675011
2000	0.761	0.115	6.617	2.579	2.090	1.234	5.36267849
2001	0.720	0.105	6.857	2.685	2.220	1.209	5.66959298
2002	0.579	0.082	7.061	2.789	2.410	1.157	6.10145257
2003	0.499	0.059	8.458	3.040	2.560	1.188	7.12221231
2004	0.369	0.053	6.962	3.090	2.860	1.080	6.44403737
2005	0.413	0.078	5.295	3.768	2.950	1.277	4.14540122
2006	0.567	0.042	13.500	3.548	2.850	1.245	10.8441375
2007	0.452	0.039	11.590	3.786	3.140	1.206	9.6122015
2008	0.446	0.032	13.938	3.768	2.970	1.269	10.9857683
2009	0.380	0.036	10.556	3.548	2.950	1.203	8.77646248
2010	0.345	0.031	11.129	3.786	3.080	1.229	9.05372936
mean	0.6185	0.1157		2.9684	2.4171		
sd.	0.1692	0.1037		0.5386	0.4582		

Source: Author's own calculation and illustration.

Concerns were expressed that, unlike unipartite networks, bipartite[18] networks significantly exaggerate the network's true level of clustering and understate the true path length (Uzzi & Spiro, 2005, p. 453). To check for this issue we put our data to the test. Based on the pioneering work of Watts & Strogatz (1998) a new interpretation of small-world indicators for bipartite networks was proposed by Newman et al.

[18] Bipartite networks are based on the assumption that all members of a team form a fully connected clique (Uzzi & Spiro, 2005, p. 453). We explicitly checked for this issue, as our network data is compiled on the basis of multi-partner R&D cooperation projects.

(2001).They showed that the "path length ratio" in bipartite networks has the same interpretation as in the case of unipartite networks (Uzzi & Spiro 2005, p. 454). In contrast, according to Newman et al. (2001) and Uzzi & Spiro (2005), the "clustering coefficient ratio" has to be interpreted in a different way. A clustering coefficient ratio of about 1.0 indicates within-team clustering whereas an exceeding clustering coefficient ratio indicates an increase in between-team clustering (Uzzi & Spiro 2005, p. 454-455). In our case, both the comparably low path length ratio throughout the observation period, ranging from 1.05 to 1.3, and the high and increasing tendency towards comparably high clustering coefficient ratios over time, confirms our initial suggestions.

In summary, the results of the exploratory analysis of large-scale network properties for the German laser industry are suggestive of an increasing emergence and solidification of small-world properties over time.

5 Estimation results and empirical findings

5.1 Model specification and estimation strategy

As our endogenous variable – annual patent application counts – only accepts nonnegative integer values we choose a count data model specification for the purpose of this analysis. Following Ahuja (2000), Stuart (2000) and Schilling & Phelps (2007) we estimated panel data count models (Hausman et al. 1984).[19] Basically, two estimation techniques can be differentiated: the fixed effects and random effects methods. In general, the use of fixed effects models provides some important advantages. The fixed effects estimator is unbiased as it includes dummy variables for the different intercepts and is more robust against selection bias problems than the random effects estimator (Kennedy, 2003, p. 304). The problem that occurs with fixed effects models is that all time-invariant explanatory variables are thrown out because the estimation procedure fails to estimate a slope coefficient for variables that do not vary within an individual unit (Kennedy, 2003, p. 304). In addition, using only within-variation leads to less efficient estimates and the model loses its explanatory power (Cameron & Trivedi, 2009, p. 259). In contrast, random effects estimators make better use of the information values of patent data and generate efficient estimates with higher explanatory power. In addition, random effects estimators can generate coefficient

[19] We used STATA 10.1 (Stata, 2007), a standard software package for statistical data analysis.

estimates of both time-variant as well as time-invariant explanatory variables (Kennedy, 2003, p. 307). The major drawback of the random effects model is that correlations between the error term and the explanatory variables generate biased estimates and thus inconsistent estimation results (Kennedy, 2003, p. 306).

We adopted the following estimation strategy to test our hypotheses. First, we implemented a two-year time lag structure in our empirical setting. Then, we estimated panel Poisson models in order to obtain an initial idea of the relationship between cooperation counts, network positioning measures and firm-specific patenting activity. As our endogenous variables exhibited strong overdispersion, we then turned to a negative binomial model specification with random effects (Cameron & Trivedi 1990). This generalization of the Poisson model allows for overdispersion by including an individual, unobserved effect into the conditional mean (Schilling & Phelps, 2007, p. 1119). In the next step, we estimated both fixed effects and random effects models. Usually, the Standard Hausman Test (Hausman 1978) is used to decide which results to interpret. In this analysis, most fixed effects and random effects estimates are consistent. In a final step, we ran consistency checks to ensure the robustness of our results by using a one-year time lag structure.

5.3. Estimation results

The presentation and discussion of our empirical findings is centered on the Negative Binomial model for panel count data reported in Table 3. Robustness of our findings is ensured by additional estimation results reported in Table 4. Results from both estimation techniques (fixed effects and random effects) are reported in the tables below (cf. Table 3 & Table 4).

Table 3 includes information on the total of five models. In addition to a baseline model (i.e. BL Model), there is one model that entails the network clustering coefficient (i.e. Model I), one model that compromises the overall average path length indicator (i.e. Model II), and one model that accounts for small-world properties of networks (i.e. Model III). The last of the five models is the fully-specified model that incorporates indicators of a network’s clustering, reach and small world nature at the same time (i.e. Model IV).

The baseline model (cf. Table 3, BL Model) provides results for firm level controls (i.e. firm age & firm age squared), cooperation-related controls (i.e. cooperation counts & cooperation funding) and overall network level control variables (i.e. network size &

network density). Results from a random effects specification (cf. Table 3, Model IV) reveal a positive and significant coefficient for cooperation counts. This should be viewed with great caution because the fixed effects specification fails to show a positive and significant relationship between cooperation counts and firm innovativeness. The same is true for both the fixed effects and the random effects model with a time lag t+1 (cf. Table 4, Model IV). The situation looks fairly different for overall network control variables, especially for network size. Estimation results (cf. Table 3, Model IV, FE & RE; Table 4, Model IV, FE & RE) provide strong empirical evidence for a negative relatedness between network size and firm innovativeness.

Now we address clustering, reach and small-world effects. In general, interaction effects in panel data models have to be interpreted cautiously. In contrast to Fleming et al. (2007) the study by Schilling & Phelps (2007) explicitly addresses this issue. According to the latter study, three aspects in particular have to be considered (Schilling & Phelps, 2007, pp. 1121-1122). Firstly, the individual effects of clustering and reach have to be interpreted as "simple" and not as "main" effects. Secondly, in a strict sense, each individual effect (reach or clustering) on a firm's patent counts (in the full model) is conditioned on the other variable taking on the value of zero. When controlling for this issue in different model specifications signs can change. At the same time, this implies that, for instance, negative signs for reach or clustering must not necessarily be interpreted as a negative main effect.[20] Finally, multiplicative interaction terms are best interpreted as mutually reinforcing effects. Keeping these issues in mind, we now move towards the interpretation of individual and combined effects.

Hypothesis H1 suggests that a short average path length at the overall network level is positively related to a firm's innovative performance. Hypothesis H2 assumes a positive relationship between clustering at the overall network level and a firm's innovative performance. Our last Hypothesis H3 suggests a positive relatedness between a network's small-world nature and a firm's innovative performance.

[20] For an in-depth discussion of interdependent effects in panel count data models see Winkelman (2003) and Jaccard & Turrisi (2003).

Table 3: Estimation results – clustering, reach and small-world properties; patent applications, time lag (t+2)

Variables	Estimation results									
	Baseline Model		Model (I)		Model (II)		Model (III)		Model (IV)	
	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects
firmage	.01022012	.01024719	.02827257	.02714577	.02608898	.02586384	.02002634	.01947403	.03510981	.03408033
firmage_sq	-.00073156	-.00052259	-.00118264	-.00095319	-.00111437	-.00091046	-.00098806	-.00076586	-.00139787	-.00117428
coopcnt	.05714882	.09544829 **	.05419512	.09080471 **	.05701504	.09396949 **	.05424240	.09156302 **	.05772866	.09451238 **
coopfund	.00000789	.00001272	.00000904	.00001399	.00000728	.00001199	.00000962	.00001464	.00000755	.00001235
nw_size	-3.8560791 ***	-4.0591897 ***	-4.2459032 ***	-4.4569542 ***	-3.0717744 ***	-3.1756426 ***	-4.8507463 ***	-5.0871176 ***	-3.964878 ***	-4.1247011 ***
nw_density	-3.9025440 ***	-3.7342787 ***	-5.4885633 ***	-5.4673971 ***	-4.5450498 ***	-4.522689 ***	-4.8823746 ***	-4.7819077 ***	-2.104296	-2.034096
nw_wclust			1.1088603 ***	1.1611018 ***					-10.647051 ***	-10.926502 ***
nw_areach					-.28236740 *	-.31326415 *			-1.9565952 ***	-2.0235219 ***
inter_sw							.44901422 ***	.46640724 ***	3.9582876 ***	4.059178 ***
_cons	1.4738306 ***	1.4692506 ***	1.0165371 **	1.0050505 **	2.0200482 ***	2.0895598 ***	1.100405 **	1.0870732 **	6.5866316 ***	6.7742169 ***
ln_r_cons		-.13420195		-.13538645		-0.136454		-0.132991		-0.130151
ln_s_cons		-.97386831 ***		-.97281046 ***		-.96994511 ***		-.97476673 ***		-.97493714 ***
chi^2	24.34534	30.054709	29.330156	35.970943	26.690456	33.130402	30.034183	36.51918	38.983625	46.106422
ll	-1470.542	-2093.197	-1467.086	-2089.242	-1469.06	-2091.269	-1466.963	-2089.259	-1461.758	-2083.538
aic	2955.0837	4204.3934	2950.1725	4198.4833	2954.1204	4202.5388	2949.9263	4198.5174	2943.5166	4191.0759
bic	2991.3389	4255.573	2991.607	4255.3495	2995.5549	4259.405	2991.3608	4255.3836	2995.3097	4259.3153
N	1312	2179	1312	2179	1312	2179	1312	2179	1312	2179

Legend: *p<.1; **p<.05; ***p<.01

Source: **Author's own calculation.**

Table 4: Robustness check – clustering, reach and small-world properties; patent applications, time lag (t+1)

Variables	Estimation results									
	Baseline Model		Model (I)		Model (II)		Model (III)		Model (IV)	
	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects
firmage	.00994378	.00829882	.03733312 *	.03220746	.00423757	.00460507	.03259915	.02808188	.02264873	.01932762
firmage_sq	-.00053489	-.00034804	-.00105358	-.00081466	-.00041663	-.00026863	-.00089849	-.0006686	-.00064746	-.00043355
coopcnt	-.01811569	.01934418	-.01818331	.01694328	-.01846864	.01938771	-.01811078	.01728223	-.01511595	.02101314
coopfund	.000009877	.00001396	.00001412	.00001792	.00001004	.0000141	.000017	.00002073	.00001719	.00002084
nw_size	-2.9475613 ***	-3.1684482 ***	-3.3421082 ***	-3.5298766 ***	-3.2089678 ***	-3.3685447 ***	-4.2628185 ***	-4.468513 ***	-4.3673734 ***	-4.6031774 ***
nw_density	-2.8696261 ***	-2.88051 ***	-4.8546 ***	-5.0429677 ***	-2.6009588 ***	-2.6603955 ***	-4.1461309 ***	-4.3348133 ***	-1.166331	-1.366484
nw_wclust			1.5707897 ***	1.5695806 ***					-7.5314347 **	-7.3631523 **
nw_areach					.11411269	.08427262			-1.0156439 *	-.98847287 *
inter_sw							.81154585 ***	.81613743 ***	3.2792295 ***	3.2349863 ***
_cons	1.0926888 ***	1.1293445 ***	.35436373	.4183161	.85300282 *	.94940078 *	.18453871	.2419253	3.2542514 *	3.218743 *
ln_r_cons		-.09498949		-.09417647		-0.093793		-.08599318		-.08131833
ln_s_cons		-.91609186 ***		-.91730297 ***		-.91830232 ***		-.92419009 ***		-.92832271 ***
chi^2	15.736744	17.259548	30.991406	33.142983	16.399322	17.688214	44.277213	46.67405	53.675483	55.881409
ll	-1674.14	-2339.276	-1665.82	-2330.532	-1673.883	-2339.127	-1659.293	-2323.877	-1655.568	-2320.24
aic	3362.2801	4696.5511	3347.6395	4681.064	3363.7664	4698.2529	3334.5855	4667.7534	3331.1359	4664.48
bic	3399.6523	4748.645	3390.3506	4738.9461	3406.4775	4756.135	3377.2966	4725.6355	3384.5248	4733.9386
N	1539	2412	1539	2412	1539	2412	1539	2412	1539	2412

Legend: *p<.1; **p<.05; ***p<.01

Source: **Author's own calculation.**

To start with, the estimation results are robust for both time lags (Table 3, time lag t+2; Table 4, time lag t+1) and for both estimation techniques (i.e. random effects & fixed effects models). Coefficient estimates for network clustering are negative and highly significant at the 0.01 level (cf. Table 3, Model IV) and the 0.05 level (cf. Table 4, Model IV), respectively. Similarly, estimation results for average path length are negative and show a strong significance at the 0.01 level (cf. Table 3, Model IV) and the 0.1 level (cf. Table 4, Model IV), respectively. Finally, coefficient estimates for the small-world indicator are positive, consistent over all specifications and highly significant at the 0.01 level. In summary, our estimation results provide empirical support for Hypotheses H1 & H3 whereas Hypothesis H2 has to be rejected.

6 Discussion, limitations and further research

Our results for the overall average path lengths (Hypothesis H1) are as expected and in line with previous empirical findings (Schilling & Phelps, 2007; Fleming, et al. 2007). Both studies report a negative[21] and, in most cases, highly significant correlation between the average path length at the overall network level and firm innovativeness. Schilling & Phelps (2007) pay little attention to these individual effects. Fleming et al. (2007, p. 949) conclude: "Shorter path length […] correlate with an increase in subsequent patenting".

It is interesting to note that our findings for the individual clustering are not in line as initially expected with our theoretical considerations (Hypothesis H2) but in line with previous empirical findings. Schilling & Phelps (2007, p. 1122) report in four out of six empirical settings a negative but not significant. Similarly, the results of Fleming and colleagues (2007, p. 948) reveal negative and significant coefficient estimates. This is an issue that clearly calls for clarification and further research.

Last but not least, we take a look at a network's small-world properties. Firstly, the descriptive analysis shows that the German laser industry network clearly fulfills the small-world criteria according to Watts & Strogatz (1998). Moreover, results are suggestive of an increasing solidification of small-world properties over time. Secondly, in our estimation results clearly support Hypothesis H3 and provide empirical evidence for a positive relatedness between a network's small-world nature and a firm's subsequent innovativeness. This is in sharp contrast to the findings of Fleming et al (2007, p. 949); the authors conclude: "The small world effect is not observed in our data". However, our results are in line with previous findings by Schilling & Phelps (2007) who summarize their findings as follows: "[…] networks that have both the high information transmission capacity enabled by clustering, and the high quantity and diversity of information provided by reach, should facilitate greater innovation by firms that are members of the network" (Schilling & Phelps 2007, 1124).

[21] Note that Fleming and colleagues (2007) use an inverse path length measure. Thus, the coefficient estimates are positive.

This empirical analysis has several important implications for both managers and policy makers. Most noteworthy is the recognition that the network topology itself seems to affect the innovative performance of firms at the micro level in multiple ways. In other words, analyzing firm-specific cooperation patterns is necessary but not sufficient for a comprehensive understanding of a firm's innovative performance. Another important implication is that regional innovation networks can significantly gain in effectiveness when they concurrently show high clustering and short average path lengths. Moreover, regional networks should have a certain degree of openness in a sense that trans-regional linkages should be established and maintained.

Like any empirical study this paper also has some appreciable limitations. Firstly, the database has to be extended in all three areas: industry data, network data and innovation data. This encompasses not only data gathering but also the inclusion of more sophisticated indicators. Work has already begun on two areas. On the one hand, we have started to gather data on non-funded strategic alliances and we are currently including the new information in our database. On the other hand, we started systematically exploring data on product launches based on several archival raw data sources in order to gain a more appropriate indicator for firm innovativeness. Secondly, more sophisticated empirical methods are needed to address some of the empirical limitations of our study. For instance, the conditional fixed effects estimation approach which is usually implemented in standard statistic software packages (e.g. STATA) has been criticized (Schilling & Phelps 2007). The implementation and use on an unconditional estimation procedure according to Allison & Waterman (2002) is currently work in progress. Thirdly, some more specific issues need to be addressed. On the one hand, we a curious to understand why our empirical findings for network clustering do not confirm our initial theoretical expectations. On the other hand, we have to address the bipartite nature of the networks more explicitly. Both issues clearly call for clarification in future research. Finally, not only a network's small world nature but also an in-depth analysis of other types of large scale network characteristic are still widely unexplored. Particularly, core-periphery patterns (Borgatti & Evert 1999; Rank, et al. 2006) of large-scale innovation networks provide promising opportunities for further research. These challenges constitute the next steps on our research agenda.

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