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Isolation and Innovation – Two Contradictory Concepts? Explorative Findings from the German Laser Industry

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Isolation and Innovation – Two Contradictory Concepts? Explorative Findings from the German Laser Industry

Abstract

We apply a network perspective and study the emergence of core-periphery (CP) structures in innovation networks to shed some light on the relationship between isolation and innovation. It has been frequently argued that a firm's location in a densely interconnected network area improves its ability to access information and absorb technological knowledge. This, in turn, enables a firm to generate new products and services at a higher rate compared to less integrated competitors. However, the importance of peripheral positions for innovation processes is still a widely neglected issue in literature. Isolation may provide unique conditions that induce innovations which otherwise may never have been invented. Such innovations have the potential to lay the ground for a firm's pathway towards the network core.

The aim of our paper is twofold. Firstly, we analyze the emergence of CP patterns in the German laser industry. We employ publicly funded Research and Development (R&D) cooperation project data over a period of more than two decades. Secondly, we explore the paths on which firms move from isolated positions towards the core (and vice versa). Our results indicate the emergence and solidification of CP patterns at the overall network level over time. We also found that the paths on which firms traverse through the network are characterized by high level of heterogeneity and volatility.

Keywords: innovation networks, core-periphery, laser industry

JEL Classification: C45, D85, O31/O32

Isolation und Innovation – zwei gegensätzliche Konzepte? Explorative Ergebnisse aus der deutschen Laserindustrie

Zusammenfassung

Wir legen eine Netzwerkperspektive zugrunde und untersuchen die Entstehung von Kern-Peripherie- (CP-) Strukturen in Innovationsnetzwerken, um den Zusammenhang zwischen Isolation und Innovation vertiefend zu beleuchten. In bisherigen Studien wurde argumentiert, dass die Lage eines Unternehmens in dicht verknüpften Bereichen eines Netzwerks seine Fähigkeit verbessert, auf Informationen zuzugreifen und technologisches Wissen zu absorbieren. Dies erlaubt es solchen Unternehmen, neue Produkte und Dienstleistungen in einem höheren Maße zu generieren als weniger integrierte Konkurrenzunternehmen. Die Bedeutung peripherer Positionen für Innovationsprozesse ist jedoch bisher ein weitestgehend vernachlässigter Aspekt in der Literatur. Isolation kann ein einzigartiges Umfeld bereitstellen, das Innovationen induzieren kann, die anderenfalls niemals entstanden wären. Solche Innovationen können die Grundlage für den Pfad eines Unternehmens in Richtung des Netzwerk-Kerns bilden.

Unser Beitrag verfolgt zwei Ziele. Erstens untersuchen wir die Entstehung von CP-Strukturen in der deutschen Laserindustrie. Dazu verwenden wir Projektdaten zu öffentlich geförderten Kooperationen über einen Beobachtungszeitraum von mehr als zwei Jahrzehnten. Zweitens untersuchen wir die Pfade, auf denen sich Unternehmen aus isolierten Positionen in Richtung des Kerns bewegen (und umgekehrt). Unsere Ergebnisse eröffnen eine Reihe von Fragestellungen an der Schnittstelle zwischen Geographie, Wirtschaft und Netzwerkforschung.

Schlagwörter: Innovationsnetzwerke, Kern-Peripherie, Laserindustrie

JEL-Klassifikation: C45, D85, O31/O32

1 Why Study core periphery Patterns in Innovation Networks?

Nowadays it is well recognized that the structural characteristics of real-world networks differ in many respects from random networks. For instance, Barabasi and Albert (1999, p. 510) have shown that "[...] large networks self-organize into a scale-free state". In a similar vein, previous empirical studies have analyzed the structural emergence of small world networks (Baum et al. 2003). Several authors have demonstrated that large-scale network characteristics, in particular small-world properties, are likely to affect the exchange of information, ideas and knowledge and thus enhance creativity and innovativeness of embedded actors in various ways (Uzzi and Spiro 2005; Fleming et al. 2007; Schilling and Phelps 2007).

In this paper we focus on the detection and analysis of core-periphery (CP) patterns in innovation networks over time. The existence of a CP structure in an innovation network is accompanied by at least two theoretical implications. On the one hand, it has been argued that a firm's embeddedness in the core of the industry's innovation network goes along with a better access to critical information and knowledge (Rank et al. 2006). The underlying argument is that densely connected network areas provide access to external knowledge stocks via direct and indirect linkages. Cattani and Ferriani (2008, p. 826) argue that the core is composed of "[...] key members of the community, including many who act as network coordinators and have developed dense connections between themselves." The prominent positioning of a firm in the industry's network core is usually assumed to be positively related to its innovativeness and economic performance.

The other important implication is that we are obviously confronted with a separation or isolation problem. Peripheral network positions are closely related to the concept of isolation. Hall and Wylie (2014, p. 358) argue that isolation only rarely appears in the literature on economics and innovation as a stringent analytical concept but is usually used in a descriptive or metaphoric way being clearly defined. They make the point that isolation is a pervasive element of all kinds of social and economic system which can be exogenous but also self-imposed (Hall and Wylie 2014, p. 373). The consequences of isolation for technological innovation are not yet fully understood. However, it is important to note that isolation in a geographical, social or cognitive sense is not necessarily negatively related to innovativeness. Instead, isolation can provide a unique environment and induces innovation processes, that otherwise may never have happened (Hall and Wylie 2014, p. 374).

Inspired by the idea of Hall and Wylie (2014), according to whom isolation can provide a unique environmental setting that breeds the ground for innovation, we formulate our working hypothesis that collective innovation processes (R&D cooperation) often have their origins in isolated areas of the network. We believe that the network periphery can provide quite unique but fruitful conditions for the emergence of new ideas simply because isolated firms have not the same set of opportunities like well-embedded actors located in the core of the network. Firms located in peripheral network areas are forced to use unorthodox techniques to solve technical problems and they often need to take higher risks throughout the research and development process. However, the generation of such an innovation is a necessary but not sufficient prerequisite for isolated firms to compete with competitors. Once isolated firms have entered an industry's innovation network through its periphery they need to get access to well-established technological knowledge that is likely to be found at the very core of the network. Hence, we are particularly interested in understanding the factors that determine the firms paths on which firms move from isolated positions towards the core and/or vice versa. In a nutshell, we argue that connectivity and isolation are not mutually exclusive concepts; instead they are linked by the temporal dimension and should be accordingly analyzed in a longitudinal setting.

To address the issues raised above, we explore a unique dataset encompassing the full population of German laser source manufacturers since the onset of this industry (cf. Buenstorf 2007). We collect data on publicly funded R&D cooperation projects from two complementary sources - Foerderkatalog database and CORDIS database - for the entire German laser source manufacturing industry between 1990 and 2010 (cf. Kudic 2015). We are not the first to use publicly funded R&D cooperation projects to construct knowledge-related innovation networks (see, e. g., Broekel and Graf 2011; Fornahl et al. 2011; Scherngell and Barber 2009; Scherngell and Barber 2011; Cassi et al. 2008).

The remained of the paper is structured as follows. In Section 2 we provide an interdisciplinary overview of methodological papers on the measurement of CP patterns. Section 3 focuses on applications of the CP concept in an innovation network context. In Section 4 we provide a brief overview of the German laser industry and we introduce our dataset. Empirical methods and results are presented in Section 5. These are finally discussed in Section 6, along with some remarks on possible limitations and fruitful avenues for future research.

2 Current Debate on Innovation Networks and Core Periphery Structures

In a most basic sense, any kind of network consists of two basic elements: nodes and ties between these nodes (Wasserman and Faust 1994). In accordance with this quite general notion of network, Brass et al. (2004, p. 795) define a network "[...] as a set of nodes and the set of ties representing some relationship, or lack of relationship, between the nodes." These two definitions have several important implications (cf. Kudic 2015). Firstly, the network perspective emphasizes the interconnectedness of a well-defined population of actors. Secondly, not only realized but also missing linkages or potentially realizable linkages are important for an in-depth understanding of the network's structural configuration. Thirdly, the network actors can be linked by many types of usually non-hierarchical connections and flows, such as information, materials, financial resources, services, and social support (Provan and Kenis 2007, p. 482). For each of these dimensions of interconnectedness, all ties put together form a particular network structure (Borgatti and Halgin 2011, p. 1169) which affects the embedded network actors in multiple ways.

In this paper we focus on innovation networks. In accordance to Cantner and Graf (2011) as well as Brenner et al. (2011), we define an innovation network as follows (cf. Kudic 2015, p. 47): an innovation network (I) consists of a well-defined set of independent economic actors, (II) the actors are directly or indirectly interconnected and these linkages allow for unilateral, bilateral or multilateral exchange of ideas, information knowledge and expertise, (III) it is embedded in a broader socio-economic environment, and (IV) has a strategic dimension in a sense that the actors involved cooperate to recombine and generate new knowledge enclosed in goods or services to meet market demands and customer needs.

2.1 On the Measurement of CP Structures

Having in mind the importance of overall network topologies for a comprehensive understanding of collective innovation processes, the lack of research on the detection of core-periphery structures in innovation networks in economics and management science is astonishing. Only very few path-breaking studies in related research areas have explicitly addresses the measurement of CP patterns.

We start the debate on CP structures with some intuitive considerations. According to Doreian and Woodard (1994, p. 269) a core of a network is a more cohesive and richly connected area of the network, relative to the overall structure of the entire network. Technically spoken, from a graph theoretical perspective the specification of a network core is nothing else but the specification of a cohesive subgraph by using concepts such as n-cliques, k-plexes, k-cores and related concepts (ibid). This notion is also reflected in currently used definitions. In its most basic sense, the CP concept is based on the notion of "[...] a dense, cohesive core and a sparse, loosely connected periphery" (Borgatti and Everett 1999, p. 375). The core of the network occupies a dominant position in contrast to the subordinated network periphery (Muniz et al. 2010, p. 113). The core is composed of "[...] key members of the community, including many who act as network coordinators and have developed dense connections between themselves." (Cattani and Ferriani 2008, p. 826). In contrast, the periphery is populated with actors that are loosely connected to the core and scarcely interconnected among one another (ibid).

In their seminal article, Borgatti and Everett (1999) introduce two formalizations of the CP concept. The basis of these two models lies in the intuitive concept of a "dense, cohesive core and a sparse, unconnected periphery" (Borgatti and Everett 1999, p. 375). The characteristic feature of the core in these (idealized forms of the) models is that all nodes of the core are fully interconnected to each other and the nodes of the periphery are separated from each other and only "loosely connected" to the core (Borgatti and Everett 1999, p. 377). First, they propose a discrete model in which the core-periphery pattern is dichotomous. Second, they relax the dichotomous restriction and outline a continuous model in with each node a measure of "coreness" is assigned (Borgatti and Everett 1999, p. 387). The underlying idea of the continuous CP model is to compare a real-world network with a theoretically optimal, or idealized, CP structure. Borgatti and Everett (1999 p. 379) argue that "a network exhibits a core-periphery structure to the extent that the correlation between the ideal structure and the data is large". The proposed algorithm by Borgatti and Everett (1999) generates quite good results compared to other CP detection methods (Rombach et al. 2013). Nonetheless, we still face several difficulties when it comes to the measurement of CP patterns in real-world networks. For instance, Borgatti and Everett (1999) provide no statistical test for the significance of the core-periphery structures found by their algorithms.

Another CP-detection method applies the so called k-core concept (Seidman 1983; Doreian and Woodard 1994).[1] The basic idea behind the k-core concept is straightforward: "A k-core is a subgraph in which each node is adjacent to at least a minimum number, k, of the other nodes in the subgraph" (Wasserman and Faust 1994, p. 266). The k-core concept is not a component-based concept. It allows us to identify cohesive subgraphs in a network based on the actors' nodal degree. This, however, implies that high degree nodes can be found in both peripheral components as well as in the main component. In other words, nodes with the same k-core value can be spread over the whole network regardless of whether they belong to the main component or a peripheral component. The repeated calculation of k-core values in well-specified time intervals enables network actors to be categorized and grouped according to their nodal degree. Holme (2005) and Alvarez-Hamelin et al. (2006) have used this cohesive sub-graph concept to operationalize and identify CP structures in real world networks.

Since then, several improvements of the two initially proposed CP detection methods have been discussed in the literature (Rombach et al. 2013). However, Csermely et al. (2013, p. 114) come in a recent methodological review article to the conclusion that there is still no clear discrimination between a network's core and its periphery. We agree with them and add the argument that the use of single indicators runs the risk of providing a somewhat biased picture of the actual network structure. We will address this issue more in detail later in Section 4.3.

2.2 Applications of CP models in an Innovation Context

Even though methodological papers in innovation research are rare, we found several interesting applications of the CP concept. By now we know that industry networks,

[1] Since then several refinements (Holme 2005; Alvarez-Hamelin et al. 2006; Tomasello et al. 2013) and applications of the k-core based CP-detection method were proposed and discussed in the literature.

like many other networks, show a core-periphery structure and a high nestedness (Csermely et al. 2013, p. 112). We start our review of contemporary CP concept application by taking a brief look at the study of Cattani and Ferriani (2008). They study the relationship between core-periphery structures in social networks and creative performance by analyzing data from the Hollywood motion picture industry between 1992 and 2003. Their results show that individuals who occupy an intermediate position between the core and the periphery of their social system are in a favorable position to achieve creative results.

Others have focused on the firm level and analyzed CP characteristics by exploring sectoral and/or spatially defined innovation networks. The structural configuration of an innovation network is important from an economic standpoint as it affects knowledge transfer processes among the actors involved. Rank et al. (2006, p. 75ff.) explicitly address this issue in their investigation of a regional biotechnology network in southern Germany by arguing that core firms are supposed to have better access to critical information and knowledge compared to peripheral firms. In addition they put forward the argument that firms located in the core of a network have a favorable position for negotiating with peripheral actors. Rank et al. (2006) employ cross-sectional quantitative survey data. Their results indeed reveal the existence of a core-periphery structure. Both studies provide empirical evidence for the existence CP patterns by applying the continuous core-periphery model, originally proposed by Borgatti and Everett (1999).

In a comprehensive study on the evolution of multiplex organizational networks in U.S. biotech industry, Amburgey et al. (2008) conducted a k-core decomposition at the overall network level over two decades and analyze the emergence of a core-periphery structure in the industry's Research and Development (R&D) and Marketing and Distribution (M&D) network. They conclude that both networks are fragmented throughout the observation period and that we can observe in both cases the emergence of a core periphery structure over time (Amburgey et al. 2008, p. 182). Most recently, Tomasello et al. (2013) have analyzed R&D networks between 1986 and 2009. The employed a slightly modified version of the k-core based CP measure, originally proposed by Holme (2005). They report for all analyzed sectors, with some minor exceptions, a rise and fall dynamics for the core periphery coefficient in 1990-1993 and 1994-1997.

3 The interrelatedness between core and peripheral network positions and technological progress

According to Levinthal (1998, p. 217) literature on technological change can be broadly separated into two streams. Some have argued that technological change processes are incremental in nature and innovation occurs rather gradually as a step-wise improvement process whereas others have put forward the argument innovations appear as spontaneous and rather discontinuous events (ibid).

Levinthal (1998) provides a framework that brings together these two perspectives by drawing upon biological speciation theory (Eldredge and Cracraft 1980). He argues that spontaneous innovation occurs in niches characterized by quite unique selection and resource constellations. The application of an existing technology to a new domain of application - an environment with other resource and selection mechanisms - leads to the emergence of new technological forms. Accordingly, his notion of creative recombination emphasizes a shift from one application domain to another. Levinthal's theoretical framework implicitly entails a dynamic perspective: "The pace of development becomes much more rapid if the technology is able to satisfy the needs of not only the possibly peripheral niche to which it may have first entered but, as the technology develops in functionality or cost is reduced, the technology may subsequently penetrate larger, more mainstream niches" (Levinthal 1998, p. 221).

The framework provides a solid theoretical basis for studying the occurrence and the interplay between incremental and spontaneous innovation. This is because he explicitly addresses the importance of isolated surroundings for the emergence of novel goods or services. Even though Levinthal (1998, p. 222) draws in his line of argument on what he calls "isolated niches", he did not define isolation in his framework more in detail (Hall and Wylie 2014).

We draw upon Levinthal's (1998) framework and respond to the issue raised by Hall and Wylie (2014) by adding a structural innovation system perspective. More precisely, in the following we address innovation processes that are assumed to occur in peripheral regions of an industry innovation network and (at least theoretically) shift over time to broader application domains located at the very core of the network.

Neo-Schumpeterian scholars (Freeman C. 1988; Lundvall 1988, 1992; Nelson 1992) have addressed the collective nature of innovation processes by introducing the concept of “national innovation systems”. Since then, several refinements of the originally proposed concept have been discussed in the literature (cf. Kudic 2015). According to Carlsson et al. (2002) the common ground of all systemic concepts is that they: (I) involve creation, diffusion and use of knowledge, (II) feed-back mechanisms are inherently built in, (III) they can be fully described by a set of components and relationships among these components, and (IV) the configuration of components, attributes, and relationships is constantly changing. Consequently, innovation networks can be seen at an integral part of an innovation system (Kudic 2015). The above discussed literature on CP structures in networks allows us to substantiate, identify and measure isolated and non-isolated areas in a complex and continuously evolving system of mutually interconnected innovating actors.

The implications of being located in the periphery of an innovation network are obvious. A peripheral network area can be interpreted as an environment that provides a unique selection and resource constellations. These very specific conditions may breed innovation that otherwise would not have happened. In contrast, the core of the network where the majority of technological knowledge is concentrated provides a quite different - more application oriented - surrounding. The shift from peripheral areas to the core is accompanies by two important considerations. Firstly, according to Levinthal (1998, p. 221) an initially new and radical innovation becomes sooner or later adapted to the need of a greater mass. Given a firm’s entry to the industry’s innovation network in a peripheral area with a radical innovation, it is plausible to assume that this idea will be exploited by the firm to commercial ends; this, in turn, will lead to several applications throughout the following periods. In other words, one dazzling idea may pave a firm’s way toward the core of the industry’s innovation network where the majority of industry specific technological and commercial knowledge is likely to be found. The natural question that arises in this context is: How do these firms progress through the network? This brings us to the second issue addressed be Levinthal (1998, p. 221). He argues that the mode of development is influenced by the particular features of the new surrounding, while the pace of development is driven by the resources that this new surrounding is able to provide (ibid).

Obviously an in-depth understanding of both (I) structural configuration of the network’s core periphery structure and (II) the firm-specific network paths towards the core are needed to gain a comprehensive picture of how path-breaking novelties are interrelated to application-oriented incremental innovations in subsequent time periods.

4 Industry, data and analytical approach

To shed some light on the questions raised above we draw upon the German laser industry. In Section 4.1 we briefly introduce the characteristics of the empirical setting followed in Section 4.2 by a presentation of raw data source applied for the purpose of this study. Last but not least, in Section 4.3 we outline the analytical steps on which the subsequent analysis is based. In doing so, we address some methodological issues related to the employed CP indicators.

4.1 Introducing the German Laser Industry

The natural question that arises in this context is what qualifies the German laser industry for the purpose of this investigation. Firstly, laser technology requires knowledge from various academic disciplines, such as physics, optics and electrical engineering (Fritsch and Medrano 2010). It can clearly be characterized as a science-driven industry in which a firm's ability to innovate is a key factor in its performance and success (Grupp 2000). The interdisciplinary and science-based character of the industry is reflected in the high level of collaboration activities between German laser source manufacturers (LSMs) among themselves and with laser-related public research organizations (PROs) (Kudic 2015).

Secondly, the economic potential of the industry is meanwhile well recognized by national and supra-national political authorities. The laser industry is a small but interesting part of the German optical technology industry, which is regarded as one of the key technologies for the innovativeness and prosperity of the German economy as a whole (BMBF 2010). Over the past few decades, Germany has developed into a world market leader in many fields of laser technology (Mayer 2004). In 2006, the revenue of German laser sources and optical component producers amounted to 8.0 billion Euro, and about 45,000 workers were employed in the industry (Giesekus 2007, p. 11).

Thirdly, our data reveal a pronounced tendency towards geographical clustering of LSMs and PROs. Hence, the industry provides an ideal setting to analyze as to what extent geographic factors affect the cooperation activities of firms. Our focus is on LSMs, which are at the heart of the value chain in the laser industry since they develop and produce the laser beam unit, the key component of every laser-based machine or system. Last but not least, we explicitly consider R&D linkages to all PROs actively operating in the field of laser research.

4.2 Raw Data Sources

For the purpose of this study we employ a unique longitudinal database[2] for the German laser industry that covers the entire population of laser source manufacturing firms for the observation period between 1990 and 2010. The following raw data sources were tapped to conduct this study: industry data and network data.

Industry data came from a proprietary dataset containing the entire population of German LSMs between 1969 and 2005 (Buenstorf 2007). Based on this initial data set we used additional data sources to gather information about firm entries and exits after 2005.[3] We chose the business unit or firm level. That is, we broke down the internal organizational structure of all LSMs in the dataset to identify firm level units with laser-related activities. Furthermore, we included 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 like, for instance, new company formations or spin-offs from existing firms or PROs were treated separately.[4] Data from Germany's official company register (i. e. *"Bundesanzeiger"*) and two additional data sources i. e. *MARKUS* database[5], provided by Bureau van Dijk Publishing and the *Creditreform* archival database, provided by the Creditreform Company[6] were tapped to supplement information on firm characteristics our extended database.

[2] For an in-depth description of raw data sources and variable specification, see Kudic (2015).

[3] Three additional data sources were employed: In the first instance, we were given access to updated German laser industry data, again provided by Guido Buenstorf. Secondly, we used annually published laser industry business directories (i. e. *"Europäischer Laser Markt"*) provided by the *B-Quadrat* Publishing Company. Finally, we employed data provided by the official German trade register.

[4] All changes in firm names and legal status over time were adequately considered.

[5] The *MARKUS* database contains information on 1.4 million officially registered companies in Germany, Austria and Luxembourg. Data on insolvent companies are usually excluded from this database. Data access was provided by the IWH department "Formal Methods and Databases".

[6] The Creditreform Company stores firm data on insolvent companies in an historical archive database.

Moreover, we identified all PROs (including universities) with laser-related activities by using two complementary methods. We started with the "expanding selection method" due to Doreian and Woodard (1992). Taking the initial list of all LSMs we screened our collaboration database and marked all laser-related research entities as long as these organizations established a link to at least one firm of our initial list. For each of these cases we checked whether the identified research entity was active in the field of laser research or not. We created an extended membership list that contains all LSMs and a full set of all identified PROs. This method, however, is limited insofar as it completely ignores non-cooperating laser-related PROs.

Based on a bibliometric analysis we identified all PROs which published laser papers, conference proceedings or articles in academic journals over the past two decades. These data provided by the LASSSIE project consortium (Albrecht et al. 2011) originate from the INSPEC database.[7] They were augmented by a search for laser-related publications in the ISI Web of Science database.[8] This allowed us to generate a comprehensive list of all PROs which have published at least one paper in the field of laser research. By comparing and consolidating the results of the expanding selection method and the bibliometric analysis we ended up with a final list of all laser-related PROs for the observation period. Then, entry and exit dates were retrieved for all PROs in the dataset.

R&D cooperation data used for this study came from two electronically available archival sources: the *Foerderkatalog* database provided by the German Federal Ministry of Education and Research (BMBF) and 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. The two data sources allow 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. Based on these data sources we compiled a dataset that cover the R&D cooperation activities among LSMs and PROs beginning in the 1990s for more than two decades.

[7] The INSPEC database contains over 11 million abstracts. The database includes journal articles, conference proceedings, technical reports and other literature in the fields of physics, electronics and computing. For further information see `http://www.ovid.com/site/catalog/DataBase/107.jsp`.

[8] The following ISI Web of Science archives were used: SCI 1995-2011, SSCI 1980-2011, AHCI 1995-2011. For detailed information on the database packages, their scope, and contents see `http://www.wokinfo.com`.

4.3 Setting the stage - analytical approach and CP identification

In the following we proceed in four analytical steps. Firstly, based on the data described above we construct an innovation network dataset that covers the network involvement for the entire population of German laser source manufacturers between 1990 and 2010. Both R&D cooperation data sources were used to construct 84 quarterly innovation network layers. In doing so, we exclude cases where the cooperation starts at the same time as the firm enters, i. e. R&D joint ventures are not considered. This dataset provided the basis for conducting next analytical step.

Secondly, we employ the two most frequently cited CP indicators, i. e. continuous CP model (Borgatti and Everett 1999) and a k-core based CP indicator (Seidman 1983; Alvarez-Hamelin et al. 2006) to gain a first intuition as to what extend firms belong to the core or rather to the periphery of the network.[9] The core-periphery analysis is conducted according to the approach proposed by Borgatti and Everett (1999). The continuous CP calculation procedure based on the MINRES algorithm implemented in UCI-Net 6.2 (Borgatti et al. 2002) was used to calculate firm-specific coreness values on a quarterly basis for a total of 21 years. The parameter ρ, which can be interpreted as a Pearson correlation coefficient between the optimal and the real network structure, is the outcome of the model and indicates the overall network coreness. The coreness measure ranges from 0 to 1 whereas large values indicate a high fit between the optimal core-periphery structure and the empirically observed network. Similarly, we used the algorithms implemented in UCINet 6.2 (Borgatti et al. 2002) to calculate k-cores at the firm level. We normalized the k-core outcome to make the indicator comparable to other CP indicators. The normalized k-core measure ranges from 0 to 1 whereas large values indicate core position.

Thirdly, in response to the commonly formulated limitations of established indicators we introduce a combined CP indicator and propose some methodological refinements to ensure statistical significance of our results. Our indicator is based on a quite simple but effective idea. We utilize the information value enclosed in two distinct CP indicators introduced above which are based on different conceptual ideas but characterized by comparably high correlation coefficients. Figure 1 (left) illustrates the resulting two-dimensional space - first dimension: k-core based CP measure; second dimension: continuous CP model based measure. Firms located in the

[9] The standard software packages UCINet 6.2 (Borgatti et al. 2002) was used for analytical purposes.

quadrant Q2 clearly can be declared as core members, firms positioned in Q4 are considered to be peripheral actors and firms in Q1 and Q3 are bundled into a third intermediate group of network actors. The major problem that arises with this concept is a reliable definition that allows us to separate the two-dimensional space into four distinct quadrants. One solution to this problem is to divide the range of k-core values into terciles (cf. Figure 1, right).

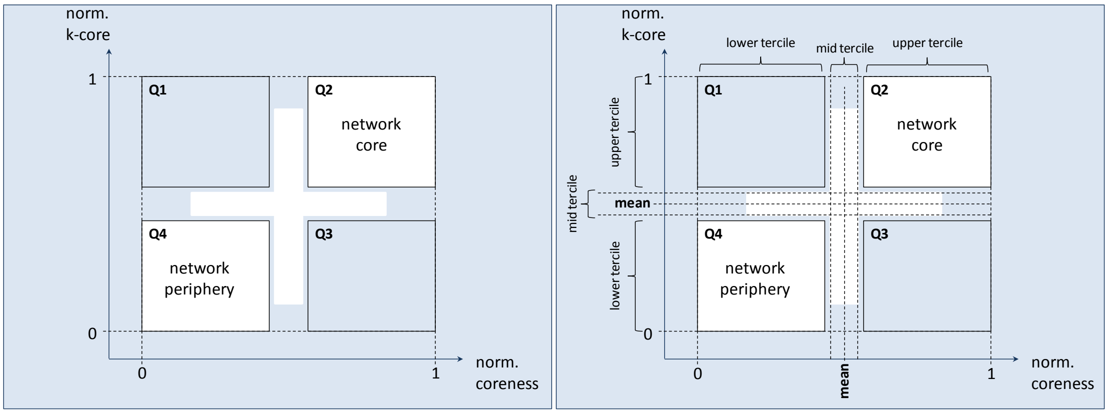

Figure 1: Concept of the two-dimensional CP indicator.
Source: Own illustration.

Finally, in our fourth and last step we employ the method described above to explore the data at the firm level and identify typical network paths. As we will refer to more in detail later, we repeatedly observed four characteristic patterns that seem to be characteristic for the actors involved in the German laser industry innovation network.

5 Results on the Emergence of Core-Periphery Patterns in the German Laser Industry

In this section, we check for the existence and emergence of core-periphery structure in the German laser industry by using the continuous CP model (Borgatti and Everett 1999) and a k-core based CP measure (Seidman 1983; Alvarez-Hamelin et al. 2006).

We start our descriptive analysis by calculating coreness values and k-cores for each organization over all 84 observation periods. Next, we employ a simple concentration measure at the industry-level - the Gini coefficient - to provide an overall picture of how similar the actors are in terms of their embeddedness in cohesive subgraphs.

Figure 2a: Emergence of CP patterns over time: 1990q1 – 2010q4.

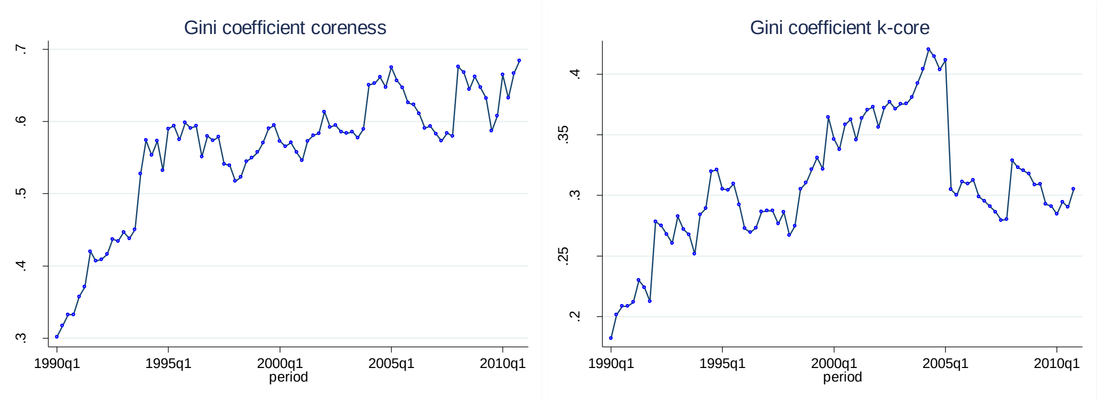

Figure 2b: German laser industry innovation network layers: 1990q1 and 2005q1.

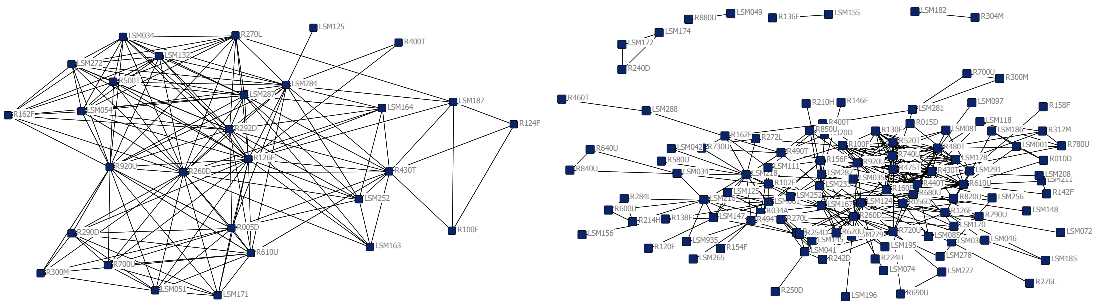

Figure 2c: 'Erdös-Renyi' Random-Graph networks, comparable in terms of size and density.

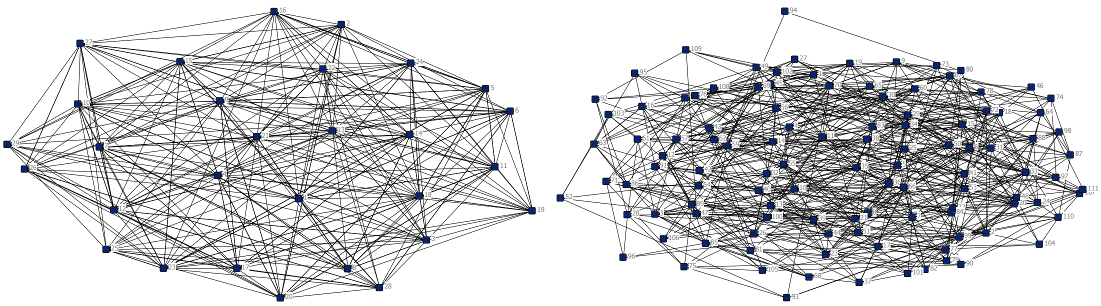

Figure 2: Emergence of CP patterns in the German laser industry.
Source: Own calculations and illustration.

Figure 2a illustrates the calculation results based on the two initially introduced core-periphery indicators (left side: coreness, right side: k-core) for the German laser industry innovation network between 1990 and 2010. Besides some minor fluctuation, we clearly see the emergence and solidification of a CP structure at the overall network level over time. In addition, we have visualized two exemplary network layers (1990q1 and 2005q1) by using a spring-embedded layout algorithm, originally proposed by Eades (1984) and Fruchterman and Reingold (1991).[10] The algorithm plots closely connected actors in the center of a network plot while loosely connected actors can be typically found in the outer areas of the network plots. Finally, we constructed random benchmarks which are comparable to the real-world network layers in terms of size and density (cf. Figure 2c). The comparison of the real-world network snapshots (cf. Figure 2b) with these random benchmarks (Figure 2c) indicates that the CP structure of the German laser industry innovation network seems to solidify over time. Even though these initial explorations provide some interesting insights, they call at the same time for a more detailed exploration at the micro-level.

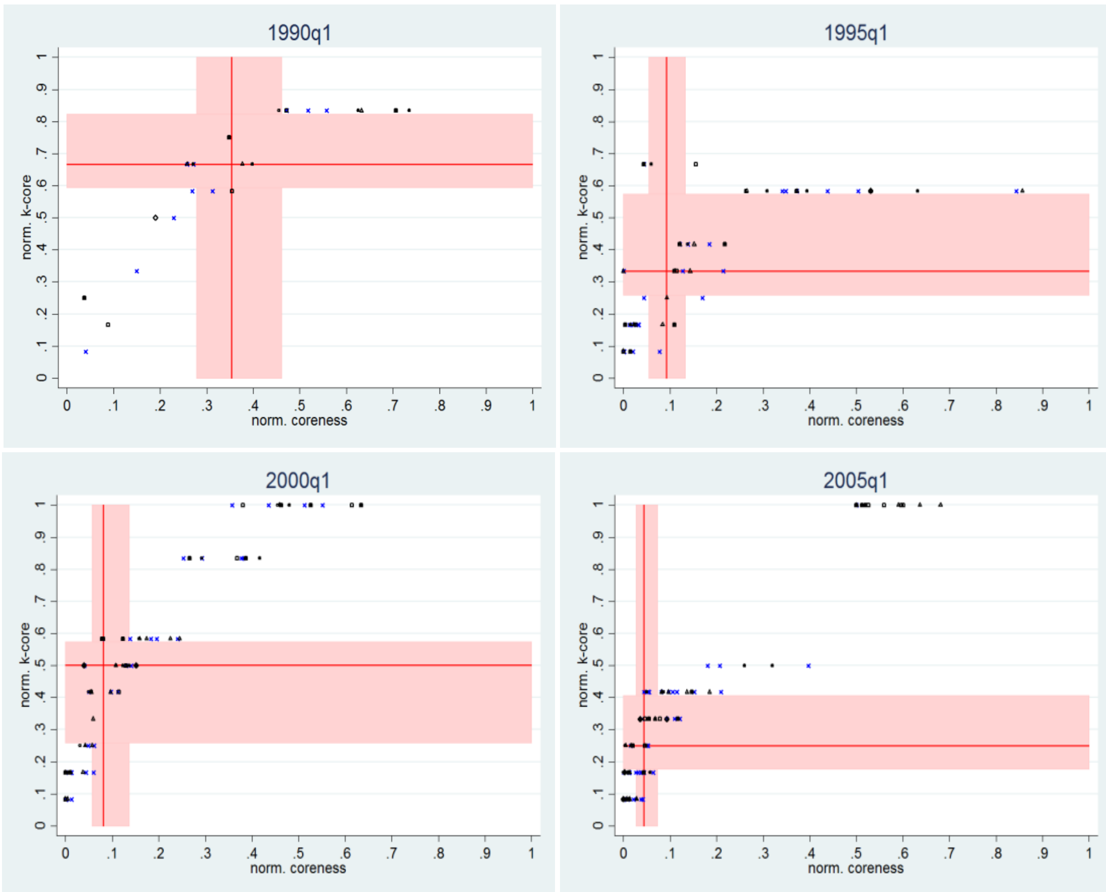

Figure 3: Empirical results for the two-dimensional CP indicator, tercile-based.
Source: Own calculations and illustration.

Figure 3 shows the separation of firms into core, intermediate and peripheral nodes based on two-dimensional CP indicator introduced above. The horizontal (vertical)

[10] We have employed the NetDraw 2.0 software package to visualize the network layers.

red lines represent the median of the normalized k-core (normalized coreness) indicator. The shaded background indicates the middle tercile around the population mean. Several peculiarities catch the eye. Firstly, the crosshair (i. e. intersection of the two median lines) shifts over time from the upper right to the lower left. Secondly, the interval around the population means get increasingly narrower from one observation window to the other. Finally, the dispersion of the point cloud significantly changes over time. In 1990, we have a comparably high dispersion in terms of k-core and coreness values. In 2005, we can observe a strong concentration in the lower left corner accompanied by a small number of organization with much above-average k-core and coreness values. In summary, these findings substantiate our initially presumption of an emergence and solidification of a CP structure over time.

Now we turn our attention on the analysis of firm-specific network paths (cf. Figure 4). Our analysis reveals four typical paths on which firms progress through the network. The firm-specific explorations reveal a significant proportion of organizations that enter the network in the periphery and remains in peripheral position over the entire observation period. Figure 4a illustrates a typical flat curve progression for one exemplary organization. Another group of network actors shows a comparable network entry behavior; these organizations, however, seem to find their way towards the network core over time. Again, the illustration demonstrates for one particular firm an increasing curve progression over time (cf. Figure 4b). The positioning sequence of a third group of network actors follows an inverted u-shape pattern (cf. Figure 4c). It is remarkable that all these actors enter the network in peripheral positions. The only exception is the fourth group of organization (cf. Figure 4d). Actors in this group enter the network in by linking themselves to the core of the industry's innovation network. Obviously, this favorable initial position seams to diminish over time.

Figure 4a: Flat curve progression.

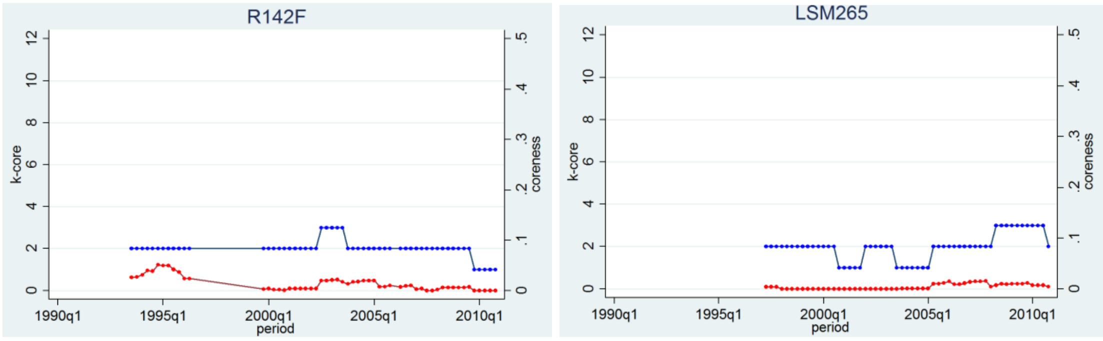

Figure 4b: Increasing curve progression.

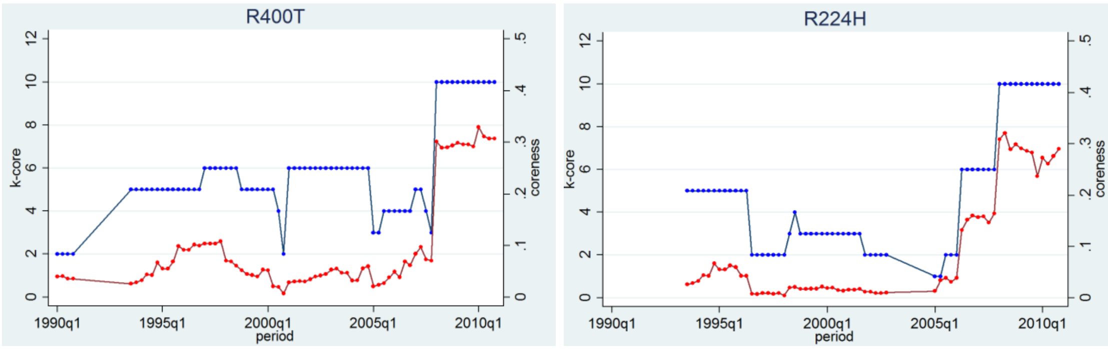

Figure 4c: Inverted U-Shape.

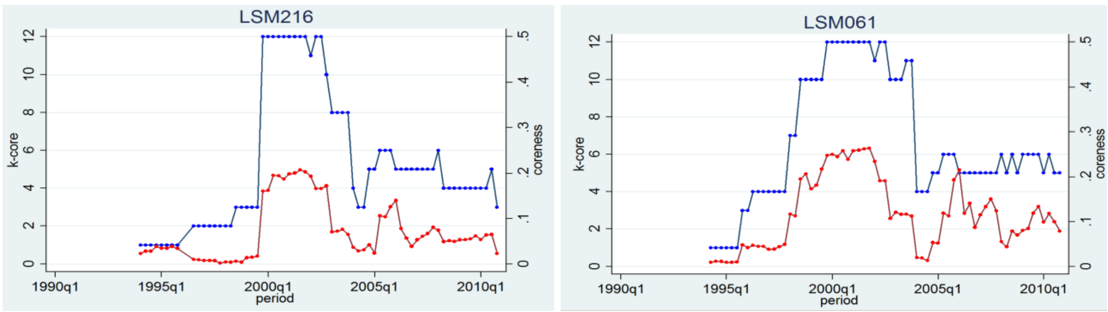

Figure 4d: Decreasing curve progression.

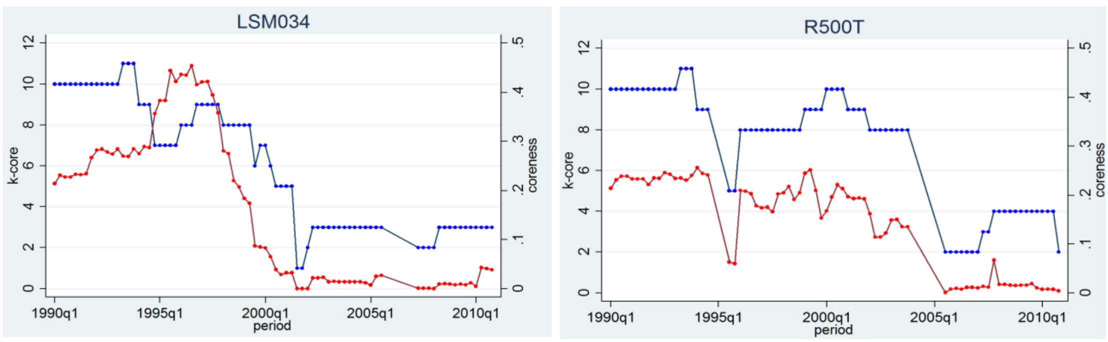

Figure 4: Typical network paths.
Source: Own calculations and illustration.

6 Concluding remarks and further research

The interrelation between innovation and isolation (in all its facets) is an interesting phenomenon that is certainly worthwhile giving further consideration. Inspired by the arguments of Hall and Wylie (2014) according to which isolation of economic actors is not necessarily negative for their innovativeness we adopted and transferred this idea in a network context. Researchers from various scientific fields have studied typical structural characteristics of real-world networks and observed, in almost all cases, the emergence of core-periphery structures over time. We have argued that the periphery of an innovation network provides an environment which is closely related to the concept of social (or network) isolation. Up to now the importance of peripheral positions for innovation processes has been widely neglected in the literature. Our main theoretical argument was that isolation (i. e. peripheral positions) and connectivity (i. e. core positions) are not necessarily exclusive. Instead, firms may start with a radical new idea in the periphery of the network, which is, at least to some extent, triggered by the environment in which the firm is embedded in. Over time, this initial idea needs to be further developed to generate marketable products and services. Hence, it is plausible to assume that firms start their innovative efforts in the periphery and proceed later on towards the network core, where the industry's established technological knowledge is concentrated.

We were curious to see where firms enter the industry's innovation network (core vs. periphery) and how these entry positions change over time. To do so, we gathered data on bi- and multilateral R&D cooperation activities for the full population of German laser source manufacturers and constructed 84 quarterly network layers between 1990 and 2010. We employed two frequently used CP indicators, i. e. the continuous CP model (Borgatti and Everett 1999) and a k-core based CP indicator (Seidman 1983; Alvarez-Hamelin et al. 2006), constructed a combined CP indicator and employed this indicator in our empirical setting.

Our explorations at the overall network level indicate the emergence and solidification of core-periphery patterns over time. This result is not very surprising and in line with our initial expectations. While dynamics of CP structures in our data can be seen already in gross concentration measures (such as the Gini coefficient), our CP classification enables us to look into driving forces of such dynamics in more detail at the micro-level. We find that the majority of firms typically enter the network via the periphery (three out of four groups of firms). The paths on which firms traverse through the network are quite heterogeneous and volatile. Based on both CP indicators, we found a (I) flat curve progression, an (II) increasing curve progression and an (III) inverted u-shape progression. Apparently, innovation in isolation is more the rule than the exception. There is also one group of firms (IV) that enters the industry's innovation network through the core. Surprisingly, the same firms move in later time periods towards the network periphery. Our initial expectation was that core positions are highly stable over time and typically occupied by very few technologically leading firms. The reasons for the instability of the core positions offers opportunities for further research.

To conclude with, this study is a very first step towards a better understanding of how the two concepts of innovation and isolation are interrelated. At this initial stage, we decided to remain on an exploratory level. In a next step, we plan to use an event history approach to analyze the firm-specific factors affecting the timing and propensity to enter the network periphery (or the network core). Finally, the improvement of our combined CP indicator is an important next step on our research agenda. The separation into core actors and peripheral actors is quite arbitrary and at this stage not statistically validated. The next logical step is to set the boundaries based on a statistically backed optimization procedure. Recently, we have started to apply Monte Carlo (MC) simulation methods to test the identified real-world network patterns against repeatedly generated random benchmarks.

References

Albrecht, H.; Buenstorf, G.; Fritsch, M. (2011): System? What system? The (co-) evolution of laser research and laser innovation in Germany since 1960. Working paper.

Alvarez-Hamelin, J. I.; Dall'Asta, L.; Barrat, A.; Vespignani, A. (2006): Large scale networks fingerprinting and visualization using the k-core decomposition. In: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.68.2609&rep=rep1&type=pdf.

Amburgey, T. L.; Al-Laham, A.; Tzabbar, D.; Aharonson, B. S. (2008): The structural evolution of multiplex organizational networks: research and commerce in biotechnology. In: J. A. Baum & T. J. Rowley, Advances in

Strategic Management - Network Strategy (Vol. 25, pp. 171-212). Bingley UK: Emerald Publishing.

Baum, J. A.; Shipilov, A. W.; Rowley, T. J. (2003): Where do small worlds come from? Industrial and Corporate Change 12 (4), pp. 697-725.

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

BMBF (2010): Ideas, innovation, prosperity - high-tech strategy 2020 for Germany. Bonn: Federal Ministry of Education and Research.

Borgatti, S. P.; Everett, M. G. (1999): Models of core/periphery structures. Social Networks 21 (4), pp. 375–395.

Borgatti, S. P.; Everett, M. G.; Freeman, L. C. (2002): Ucinet for windows: software for social network analysis. Harvard, MA: Analytic Technologies.

Borgatti, S. P.; Halgin, D. S. (2011): On network theory. Organization Science 22 (5), pp. 1168-1182.

Brass, D. J.; Galaskiewicz, J.; Greve, H. R.; Tsai, W. (2004): Taking stock of networks and organizations: a multilevel perspective. Academy of Management Journal 47 (6), pp. 795-817.

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

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.

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.

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.

Cattani, G.; Ferriani, S. (2008): A Core/Periphery Perspective on Individual Creative Performance: Social Networks and Cinematic Achievements in the Hollywood Film Industry. Organization Science 19 (6), pp. 824–844.

Csermely, P.; London, A.; Wu, L.-Y; Uzzi, B. (2013): Structure and dynamics of core/periphery networks. Journal of Complex Networks 1 (2), pp. 93–123.

Doreian, P.; Woodard, K. L. (1992): Fixed list versus snowball selection of social networks. Social networks 21 (2), pp. 216-233.

Doreian, P.; Woodard, K. L. (1994): Defining and locating cores and boundaries of social networks. Social Networks 16 (4), pp. 267–293.

Eades, P. (1984): A heuristics for graph drawing. Congressus numerantium 42, pp. 146-160.

Eldredge, N.; Cracraft, J. (1980): Phylogenetic patterns and the evolutionary process. New York: Columbia University Press.

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, 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.

Fritsch, M.; Medrano, L. F. (2010): The Spatial Diffusion of a Knowledge Base – Laser Technology Research in West Germany, 1960 – 2005. In: Jena Economic Research Papers 4.

Fruchterman, T. M. J.; Reingold, E. M. (1991): Graph Drawing by Force-Directed Placement. Software - Practice & Experience 21 (11), pp. 1129–1164.

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

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

Hall, P.; Wylie, R. (2014): Isolation and technological innovation. Journal of Evolutionary Economics 24 (2), pp. 357-376.

Holme, P. (2005): Core-periphery organization of complex networks. Physical Review E 72 (4).

Kudic, M. (2015): Innovation Networks in the German Laser Industry – Evolutionary Change, Strategic Positioning, and Firm Innovativeness. Heidelberg: Springer.

Levinthal, D. A. (1998): The Slow Pace of Rapit Technological Change: Gradualism and Punctuation in Technological Change. Industrial and Corporate Change 7 (2), pp. 217-247.

Lundvall, B.-A. (1988): Innovation as an interactive process: from user-producer interaction to the national system of innovation. In: G. Dosi, C. Freeman, R. R. Nelson, G. Silverberg, & L. Soete, Technical Change and Economic Theory (pp. 349-369). London: Pinter.

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

Mayer, A. (2004): Laser in der Materialbearbeitung - Eine Marktübersicht. Laser Technik Journal 1 (1), pp. 9-12.

Muniz, A. S.; Raya, A. M.; Carvajal, C. R. (2010): Core periphery valued models in input-output field: A scope from network theory. Papers in Regional Science 90 (1), pp. 111-121.

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

Provan, K. G.; Kenis, P. (2007): Modes of network governance: structure, management, and effectiveness. Economics of Innovation and New Technology 18 (2), pp. 229-252.

Rank, C.; Rank, O.; Wald, A. (2006): Integrated Versus Core-Periphery Structures in Regional Biotechnology Networks. European Management Journal 24 (1), pp. 73–85.

Rombach, M. P.; Porter, M. A.; Fowler, J. H.; Mucha, P. J. (2012): Core-Periphery Structure in Networks. In: http://arxiv.org/pdf/1202.2684v2.pdf.

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.

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.

Seidman S. (1983): Network structure and minimum degree. Social Networks 5, pp. 269-287.

Tomasello, M. V.; Napoletano, M.; Garas, A.; Schweitzer, F. (2013): The Rise and Fall of R&D Networks. In: http://arxiv.org/pdf/1304.3623v4.pdf.

Uzzi, B.; Spiro, J. (2005): Collaboration and Creativity: The Small World Problem. American Journal of Sociology 111 (2), pp. 447–504.

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