Chapter 8
Evolution of the Industry's Innovation Network

In the long history of humankind (and animal kind, too), those who learned to collaborate and improvise most effectively have prevailed.

(Charles Darwin)

Abstract At the very heart of this book is the analysis of R&D cooperation and networking activities of firms in science-driven industries. As outlined before, we have used two official databases to gather data on nationally and supra-nationally funded R&D cooperation projects (cf. Sect. 4.2.3). These two data sources provided the basis for the construction of the German laser industry innovation network. Network analysis methods (cf. Sect. 5.2) provide us with a broad range of instruments to explore and analyze structural characteristics of networks (Wasserman and Faust 1994; Degenne and Forse 1999; Carrington et al. 2005; Borgatti et al. 2013). These methods can be used to analyze both network snap-shots at a particular point in time, and evolving network patterns over time. This chapter is divided into three sections. Section 8.1 gives an overview of the organizations involved in publicly funded R&D cooperation projects from various angles. Based on these findings, we explore the proportion of LSMs and PROs participating in two types of publicly funded research projects – "CORDIS" and "Foerderkatalog". Then, we take an initial look at the large-scale topology of the German laser industry innovation network. Next we focus on the evolutionary change patterns of the German laser industry innovation network. In Sect. 8.2 we start our longitudinal exploration by analyzing a set of basic node-related and tie-related network measures over time. In Sect. 8.3 we provide an in-depth analysis of the network topology by testing for the existence of three distinct large-scale network properties. First, we analyze the overall degree distribution and check for the emergence of scale-free properties (Barabasi and Albert 1999). Then we test whether the German laser industry's innovation network exhibits small-world properties by applying the method proposed by Watts and Strogatz (1998). Finally, we use different but complementary methodological approaches to check for the existence of a core-periphery structure (Borgatti and Everett 1999). We finish off the descriptive analysis by visualizing the evolution of the German laser industry innovation network over time.

M. Kudic, *Innovation Networks in the German Laser Industry*,
Economic Complexity and Evolution, DOI 10.1007/978-3-319-07935-6_8

8.1 Laser-Related Publicly Funded R&D Cooperation Projects

The aim of this section is threefold. First we provide some basic descriptive statistics on publicly funded R&D cooperation projects broken down by cooperation type. Then we explore the involvement of LSMs and PROs in the cooperation projects over time. Finally, we take a look at all cooperation activities between German laser source manufacturers and laser-related public research organizations between 1990 and 2010. In other words, we illustrate the transition from a dyadic perspective to a network perspective by exploring the large-scale topology of the German laser industry innovation network over the entire observation period.[1]

8.1.1 Summary Statistics on Publicly Funded R&D Cooperation

Table 8.1 shows some descriptive statistics on publicly funded R&D cooperation projects based on both *Foerderkatalog* and *CORDIS* data for the period between 1990 and 2010.

The Foerderkatalog data encompasses, in total, information on approximately 110,000 completed or ongoing subsidized research projects. We were able to identify 416 laser-related R&D cooperation projects for the entire population of 233 German laser source manufacturers. A total of 2,656 organizations were involved in these projects. Data exploration revealed an overall involvement of 643 LSMs and 570 laser-related PROs. In other words, we found at the project level a significant degree of interconnectedness among organizations in our sample. Data on the remaining 1,443 organizations was fully recorded but due to the focus of this study and related network boundary specifications, they were not included. At the project level our data reveals a minimum of 2 and a maximum of 33 partners. An average of 6.39 organizations was involved in each project with a standard deviation of 3.96.

The overall number of project files in the *CORDIS* database is considerably smaller and consists of 31,000 files.[2] We identified a total of 154 R&D cooperation projects for the entire LSM population. We found that a total of 189 LSMs and 132 PROs were involved in these projects. As before, other types of organizations were fully registered but not included as they are not the subject of this analysis. *CORDIS* projects are considerably larger than *Foerderkatalog* projects. The

[1] We use the standard routines implemented in UCI-Net 6.2 (Borgatti et al. 2002) to calculate network measures and we employ the software package NetDraw (Borgatti 2002) for the visualization of the German laser industry innovation network.

[2] This figure refers to our database extract provided by the *CORDIS* Service Team, European Commission (latest update: end of 2010).

Table 8.1 Publicly funded R&D cooperation projects – broken down by cooperation type

Descriptives	Foerderkatalog projects	CORDIS projects
Overall number of project files	110,000	31,500
Total number of laser-related projects	416	154
Total number of organizations	2,656	1,607
Other types of organizations	1,443	1,286
Total number of LSMs	643	189
Total number of PROs	570	132
Max. no. of organizations at the project level	33	53
Min. no. of organizations at the project level	2	2
Avg. project size (no. of partners)	6.385	10.435
Std. dev. project size (no. of partners)	3.955	8.019

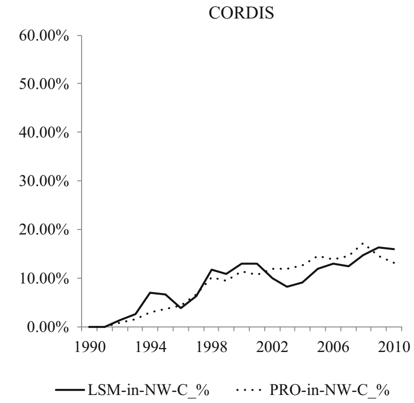
Source: Author's own calculations

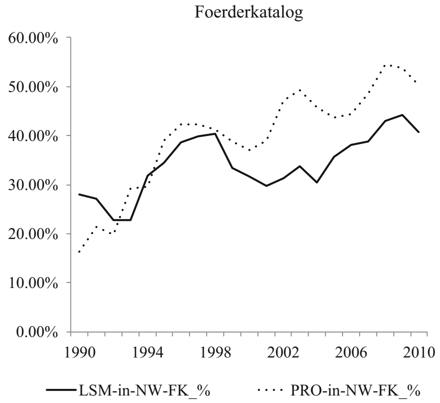
minimum and maximum number of project partners involved at the project level was two and 53 respectively. The average project size, based on the number of partners, came to 10.44 with a standard deviation of 8.02.

8.1.2 *R&D Cooperation Involvement of LSMs and PROs*

Figure 8.1 shows LSM (black line) and PRO (dotted line) participation in publicly-funded cooperation projects between 1990 and 2010 as expressed in terms of percentages at the national level. The line graph on the left shows the proportion of LSMs and PROs participating in *CORDIS* projects whereas the line graph on the right illustrates their involvement in *Foerderkatalog* projects. The line graph below these illustrates LSM and PRO participation in either *CORDIS* or *Foerderkatalog* projects. Basic descriptive statistics are reported below each of the three line charts.

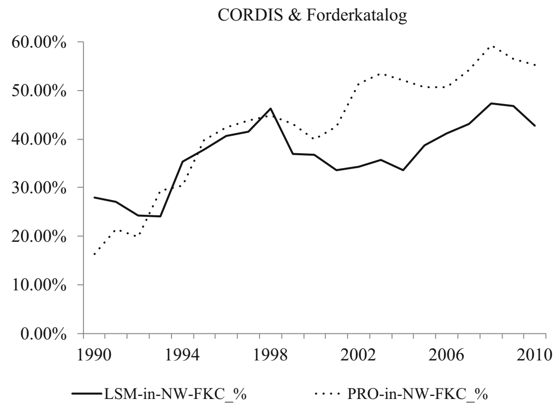
In general, we can observe an increasing percentage of organizations participating in publicly funded research projects. *CORDIS* project data indicates a maximum percentage of LSM and PRO involvement at 16.23 % and 17.24 % respectively. On average, cooperation project participation in *CORDIS* projects is slightly higher for LSMs (at 8.94 %) compared to PROs (at 8.85 %). In both types of organizations we see only minor deviations from the upwards-sloping long-term trend. In contrast, the involvement of LSMs and PROs in *Foerderkatalog* projects is significantly higher than in *CORDIS* projects. The exploration of our data reveals a maximum participation in *Foerderkatalog* projects of 44.16 % for LSMs and 54.48 % for PROs. The average participation of LSMs and PROs in *Foerderkatalog* projects is 34.11 % and 39.72 % respectively. In addition, we can observe higher fluctuations for PROs (standard deviation = 10.82 %) compared to LSMs (standard deviation = 6.12 %) for the period in question.





Descriptive stat.	max.	min.	avg.	std. dev.
LSM-in-NW-C	16.23%	0.00%	8.94%	5.09%
PRO-in-NW-C	17.24%	0.00%	8.85%	5.57%

Descriptive stat.	max.	min.	avg.	std. dev.
LSM-in-NW-FK	44.16%	22.78%	34.11%	6.12%
PRO-in-NW-FK	54.48%	16.36%	39.72%	10.82%



Descriptive stat.	max.	min.	avg.	std. dev.
LSM-in-NW-FKC	47.24%	24.05%	36.92%	6.90%
PRO-in-NW-FKC	59.31%	16.36%	42.74%	12.62%

Fig. 8.1 Participation OF LSMs and PROs in publicly funded cooperation projects (Source: Author's own calculations)

The overall participation in both types of publicly funded cooperation projects is displayed in the line graph below. Data on LSMs indicates a minimum participation of 24.05 % in 1990, a maximum participation of 47.24 % in 2008 and an average participation of 36.92 %. In contrast, PROs show a significantly lower rate of involvement in cooperation projects (16.36 %) at the onset. This initially low involvement in cooperation projects quickly changes direction after a rather short period of time. The overall participation of PROs in either *CORDIS* or *Foerderkatalog* projects increases about 2.5 times between 1990 and 1998. This trend continues with nearly the same intensity and some minor fluctuations until the end of the observation period. As a consequence, the average percentage of PROs participating in cooperation projects is 42.74 % and the maximum percentage of cooperation reaches nearly 60 % in 2008.

8.1.3 Large-Scale Network Topology of the Innovation Network

In general, the visualization of network is no trivial matter. It allows the researcher to obtain an initial and initiative understanding of the structural configuration of the system (Borgatti et al. 2013, p. 124). Figure 8.2 illustrates all cooperation activities between German laser source manufacturers and laser-related public research organizations between 1990 and 2010.

According to Borgatti et al. (2013, p. 101) there are three basic approaches to network layout: (a) an attribute-based scatter plot, (b) a multidimensional scaling (MDS) layout, and (c) graph theory-based layout algorithms.

We visualize the network by using a simple random layout (cf. Fig. 8.2a) and by applying a spring-embedded layout (Fig. 8.2b) which was originally proposed by Eades (1984) and Fruchterman and Reingold (1991) and it is still one of the most commonly used graph theoretical layout algorithms. The basic idea behind the algorithm is simple. "Its effect is to distribute nodes in a two-dimensional plane with some separation, while attempting to keep connected nodes reasonably close together" (Golbeck and Mutton 2005, p. 173). We employ the geodesic distance criterion, which is defined as the shortest path connecting any pair of nodes in the network (Wasserman and Faust 1994), to compute the layout. We used NetDraw 2.0 to visualize the network (Borgatti 2002).

These two simple initial explorations already contain some important information. For instance, the density of the network structure indicates a pronounced cooperation propensity among firms and other organizations in the industry. The size of the node is determined by the network actors' degree of connectedness (i.e. the number of direct linkages). Figure 8.2 indicates that some network actors seem to attract nodes at a higher rate than others. Both types of actors, LSMs[3] as well as PROs,[4] seem to be spread out over the entire network and occupy positions in densely as well as sparsely connected areas of the networks.

However, an in-depth exploration and analysis of the network properties requires a decomposition of the network. As a result, we apply a time-discrete

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[3] Each ID in Fig. 8.3 with the syntax: "LSMxxx" represents one of the 233 laser manufacturing firms. Note that the sequential ID number can be larger than the total number of firms in our sample.

[4] Public research organizations are symbolized by the following abbreviations: University = "RxxxU", University of Applied Sciences = "RxxxA", Technical University = "RxxxT", Fraunhofer Institute = "RxxxF", Max Planck Institute "RxxxM", Helmholtz Institute "RxxxH", Leibniz Institute "RxxxL" and other laser-related PROs = "RxxxD".

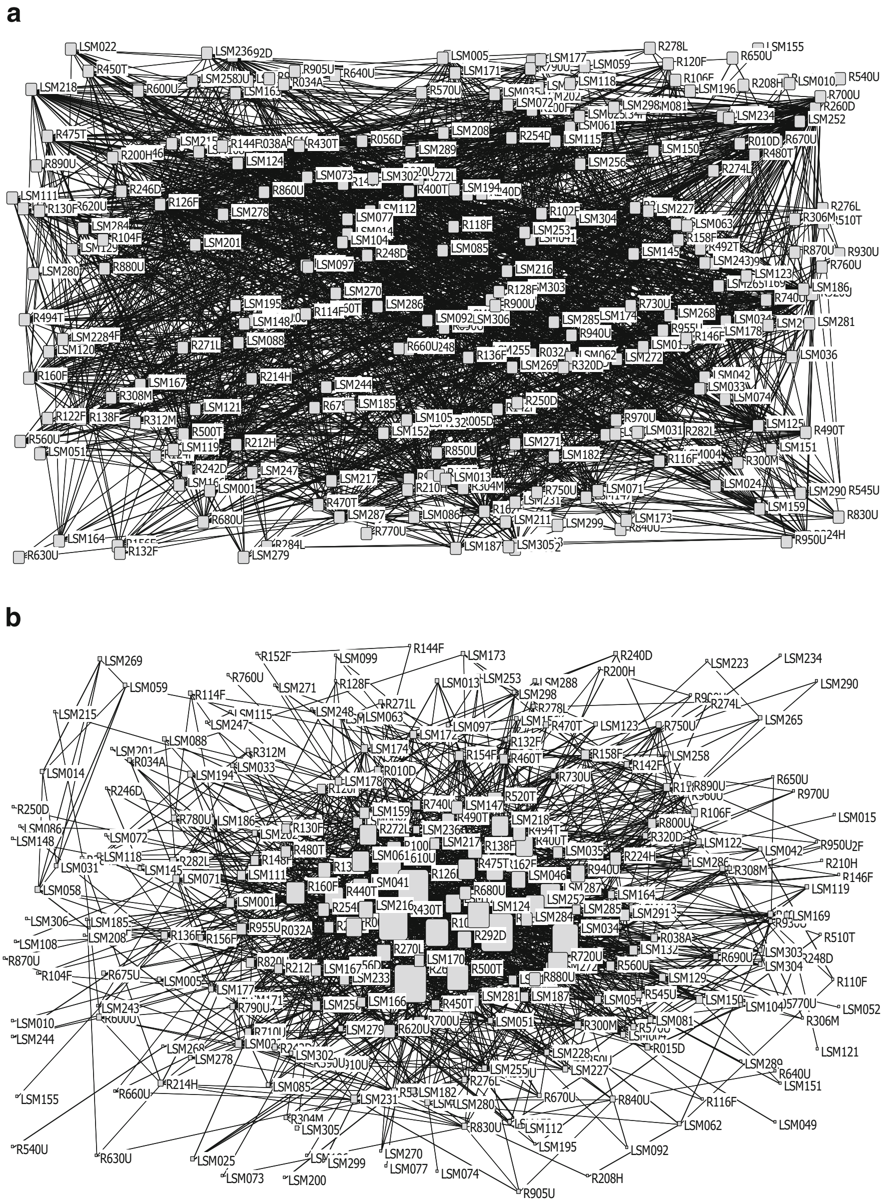


Fig. 8.2 The German laser industry innovation network. (**a**) Random layout. (**b**) Spring-embedded; degree-based node size (Source: Author's own calculations and illustration)

approach and analyze structural changes to both node-related and tie-related network characteristics broken down by year.

8.2 Longitudinal Exploration of Basic Network Characteristics

In this section we apply an exploratory social network analysis approach (De Nooy et al. 2005). The primary objective of this method is to reveal structural network particularities and make them measurable. Emphasis is not on refuting established structural hypotheses but rather on measuring, exploring and visualizing network properties. In other words, "[. . .] instead of testing pre-specified structural hypotheses, we explore social networks for meaningful patterns" (De Nooy et al. 2005, p. 5). Exploratory social network analysis is conducted in four steps: network definition, network manipulation, identifying network features and visualization (De Nooy et al. 2005, pp. 5–6).

8.2.1 Basic Network Change Patterns: Measures at the Node Level

In order to explore basic network measures at the node level over time, we chose a time-discrete approach and separated the network into annual slices of time. All network measures are calculated on a yearly basis by using both *Foerderkatalog* and *CORDIS* data. Note that this exploration differs significantly from the analysis reported before (cf. Sects. 8.1.1 and 8.1.2).

Now we are not focusing on the organizations' participation in different types of R&D multi-partner collaborations at the project level but on the involvement of both types of network actors in the overall German laser industry innovation network. Figure 8.3 illustrates the network boundaries and the size of the network.

The number of all actively operating LSMs and PROs determines the outer boundary of the innovation network. In other words, these are all organizations which are at risk of cooperating, irrespective of whether they are part of the network or not. All organizations with at least one dyadic R&D linkage to another LSM or PRO in the sample are considered to be an integral part of the innovation network. Thus, the outer circle (dotted line) in Fig. 8.3 illustrates the network's outer boundaries whereas the inner circle (solid line) reflects the actual size of the network over time. In 1990, only 20.1 % of all LSMs and PROs in the industry were actively involved in the innovation network. This comparably small participation rate nearly doubles over the course of just 5 years. In 1995, we register a network participation rate of 38.94 %. Despite some minor fluctuations, the participation rate continues to grow over the next 10 years. The percentage of LSMs and

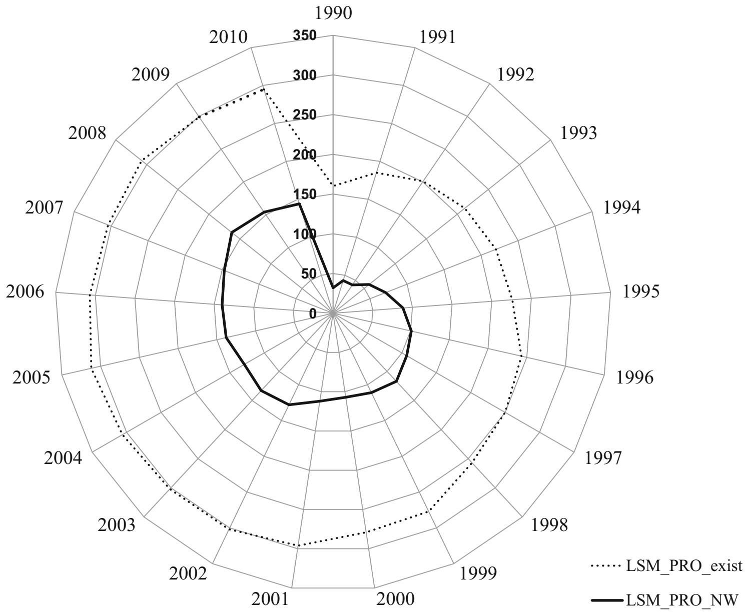
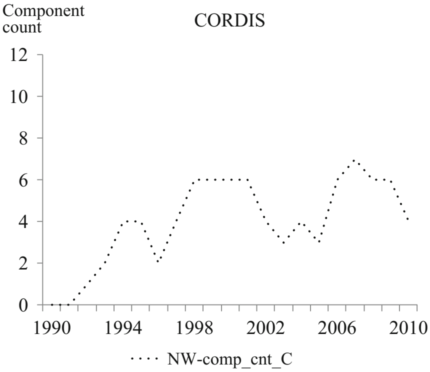


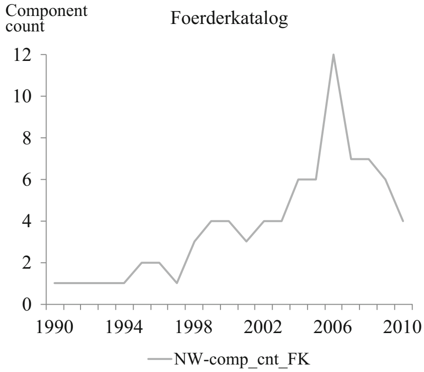
Fig. 8.3 Network boundaries and network size (Source: Author's own calculations and illustration)

PROs actively involved in the German laser industry innovation network ranges from 37.35 % in 2001 to 45.53 % in 1998. After 2005 we again record a noticeable increase in network entries with a maximum network participation rate of 52.92 % in 2008. Thereafter both trend lines begin to decrease.

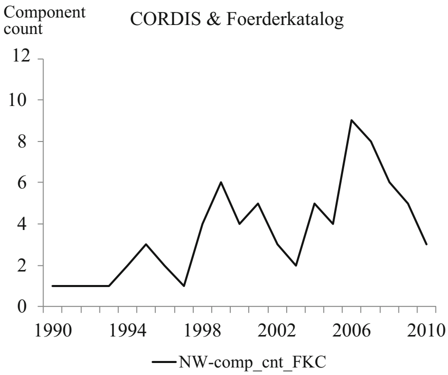
In addition to network size, the connectedness of a network is arguably one of the most salient network features if one wants to get an in-depth understanding of the structural network configuration itself (Wasserman and Faust 1994, p. 109) and to understand the evolutionary network change processes over time (Amburgey et al. 2008, p. 178). A network is called "connected" as long as there is at least one path that connects all pairs of actors in a network (Newman 2010, p. 142). In contrast, a "disconnected" network consists of at least two components where a component is defined as a subgroup of network actors that are connected with one another but have no connection to other connected network subgroups (Newman 2010, p. 142). Figure 8.4 illustrates the fragmentation of the German laser industry innovation network broken down by cooperation type. The ordinate records the number of network components and the abscissa captures the time dimension. On the left we see the *CORDIS* network (dotted line), on the right is the *Foerderkatalog* network (gray line), and at the bottom is the overall network consisting of both cooperation types (black line). On average, the *CORDIS* network is characterized by a higher fragmentation (average component count = 4) and exhibits less pronounced fluctuation tendencies (standard deviation = 2.1) compared to the



Descriptive stat.	max.	min.	mean	std. dev.
NW-comp_cnt_C	7	0	4	2.1



Descriptive stat.	max.	min.	mean	std. dev.
NW-comp_cnt_FK	12	1	3.81	2.8



Descriptive stat.	max.	min.	mean	std. dev.
NW-comp_cnt_FKC	9	1	3.62	2.33

Fig. 8.4 Network fragmentation – annual component counts (Source: Author's own calculations and illustrations)

Foerderkatalog network (average component count = 3.81; standard deviation = 2.8).

Comparing the two networks at two separate time intervals gives us a more detailed picture. Between 1990 and 2000 the connectedness of the *Foerderkatalog* network is clearly more pronounced than that of the *CORDIS* network. This tendency, however, changes after 2000. The fragmentation of the *Foerderkatalog* increases considerably and reaches a maximum of 12 unconnected network components in 2006. The component structure of the overall network reveals a slightly different picture. Just like with the two separate networks we can see an increasing tendency towards fragmentation for the overall network over time. This trend, however, is accompanied by some pronounced fluctuations. The overall network consists of 3.62 components on average with a standard deviation of 2.33. Between

1990 and 1993 and in the year 1997 the network is fully connected and consists of one single giant component. Only 2 years later, in 1999, we can observe a total of six components in the overall network. The fragmentation reaches a maximum of nine unconnected components in 2006 and decreases considerably in subsequent time periods.

In summary, we gain some interesting insights by exploring the size and component structure of the innovation network. Nonetheless, several questions remain unanswered. For instance, the node structure and tie structure within and between the network components remains entirely unconsidered. These issues will be addressed later. First, however, we focus on the exploration of some basic tie-related network characteristics.

8.2.2 Basic Network Change Patterns: Measures at the Tie Level

The overall network density measure provides an initial indication of a network's structural configuration. It simply indicates to what extent the network actors are connected to each other. Figure 8.5 shows the density measure for the German laser industry innovation network over time.

The overall density of an unvalued network is defined as the total number of ties divided by the total number of possible ties. If all nodes of a graph are adjacent, then it is equal to 1 and the graph is said to be complete (Wasserman and Faust 1994, p. 102).

The German laser industry innovation network had a maximum overall network density of 0.441 in 1990. The density decreased continuously until 1998. After a

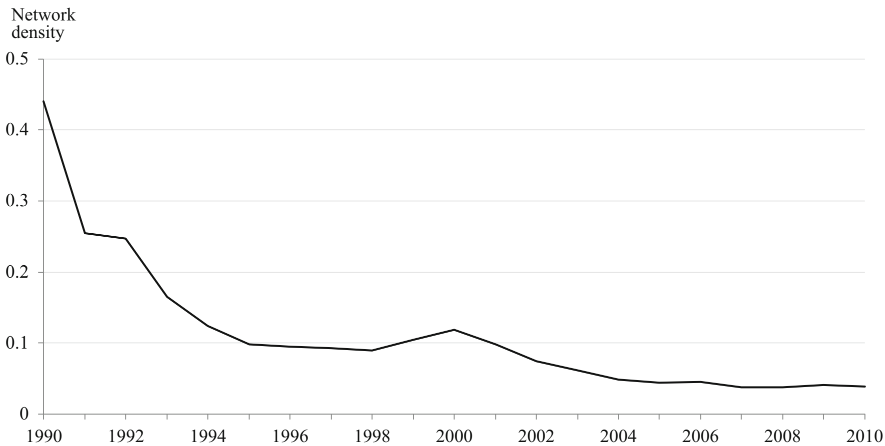


Fig. 8.5 Network density – overall network density (Source: Author's own calculations and illustration)

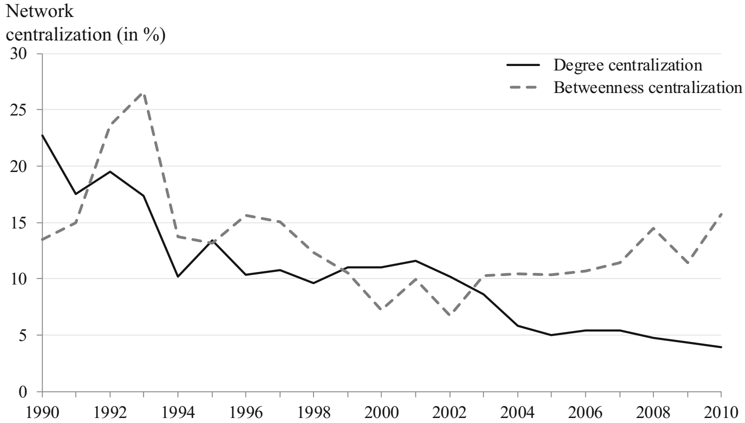


Fig. 8.6 Network centralization – degree and betweenness centralization indices (Source: Author's own calculations and illustration)

short-lived density peak in 2000 ($NW_d = 0.118$), the overall network density began decreasing again, reaching a minimum network density of 0.038 in 2010.

Now we turn our attention to global centrality measures originally proposed by Freeman (1979). Figure 8.6 displays two network centralization indices – degree and betweenness centralization – for the German laser industry network between 1990 and 2010.

The degree centralization index indicates an alignment of the network actors' degree centralities over time. The index has a maximum value of 22.74 % in 1990 and decreases with some marginal fluctuations. In 2010, the index reaches a minimum value of 3.96 % indicating that network actors show only minor disparities in terms of their degree centralities. Nonetheless, it should be noted that the degree centralities are by no means equally distributed.

The betweenness centralization index provides quite a different picture. Most remarkably, the index shows a much higher volatility compared to the degree centralization index. During the initial years we can observe a pronounced increase in the index from 13.52 % in 1990 to 26.56 % in 1993. The following years are characterized by an alignment of the network actors' betweenness centralities over time. In 2002 the inequalities among network actors in terms of their brokerage activities reach a minimum with an index value of 6.73 %. In subsequent years the index increases again until the network finally reaches a betweenness centralization of 15.76 % in 2010.

8.3 Exploring the Emergence of Large-Scale Network Properties

This section addresses large-scale network properties. Real world networks differ from random networks in many respects. Accordingly, we check for the existence and emergence of three types of network properties – scale-free distribution, small-world phenomenon, and core-periphery structure – to demonstrate that the structural configuration of the German laser industry network exhibits fairly different patterns than randomly generated reference networks. Finally, we visualize the network topology at four distinct points in time.

8.3.1 Degree Distribution and Scale-Free Network Structure

In random networks the placement of links is purely random which means that the resulting system is characterized by nodes that have approximately the same number of links (Barabasi and Bonabeau 2003, p. 52). In contrast, real-world networks typically show very different large-scale patterns. In a seminal paper on large-scale network properties Barabasi and Albert (1999, p. 510) suggest that "[...] large networks self-organize into a scale-free state." This, however, implies that some actors attract ties at a higher rate than others. The reasons for this can be manifold. For instance, some actors have simply more to offer than others or show a higher capability in establishing or sustaining interorganizational partnerships. In this context, sociologists have highlighted the importance of reputation, status (Podolny 1994) and interorganizational endorsement effects (Stuart et al. 1999). However, these actors are usually called "hubs" (Newman 2010, p. 245) and have a much higher degree than the majority of other network actors.

The exploration of a network's degree distribution provides a simple but powerful diagnostic indicator of whether tie formation in a network is equiprobable (simply random) for all pairs of nodes or systematically biased (Powell et al. 2005, p. 1151). In other words, the existence of these network hubs should be reflected in the overall degree-distribution of the network. "Unlike the tail of a random bell curve whose distribution thins out exponentially as it decays, a distribution generated by a popularity bias has a "fat" tail for the relatively greater number of nodes that are highly connected" (Powell et al. 2005, p. 1151).

Figure 8.7 illustrates the degree distribution of the German laser industry innovation network (above) and a randomly generated Erdös-Renyi network (below). In order to analyze the large-scale properties of the German laser industry innovation network we have generated a random network which is comparable in terms of network size and network density. This procedure was repeated several times to obtain reliable average degree values.

The abscissa represents the degree k and the ordinate measures the fraction of nodes in the network p(k) for each degree value. The right-skewed distribution indicates that the German laser industry innovation network consists of a few

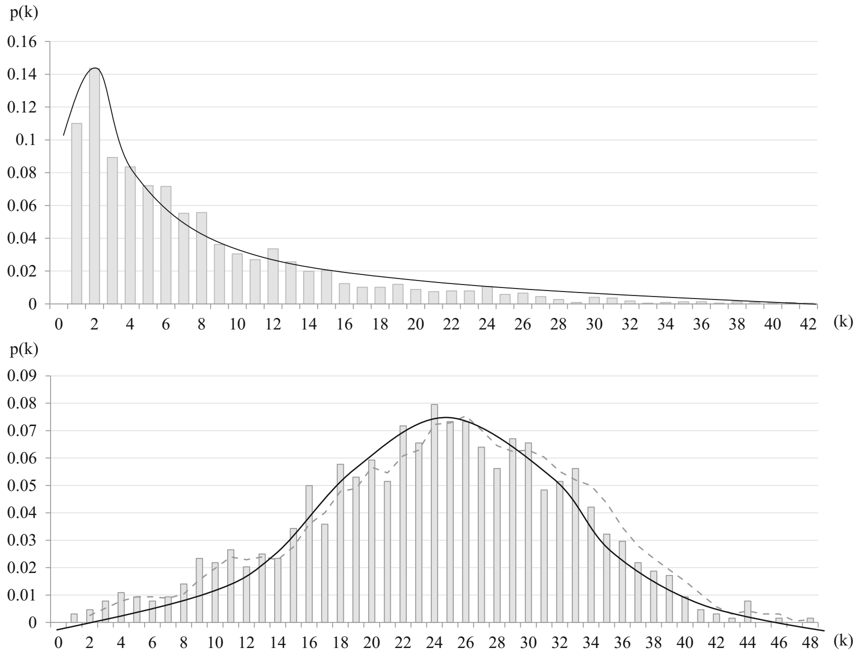


Fig. 8.7 Degree distribution – German laser industry innovation network vs. random network (Source: Author's own calculations and illustrations)

extremely well-connected actors (with a degree of up to 46) whereas the majority of network actors are rather sparsely connected (with a nodal degree of 1 or 2).

We follow the procedure proposed by Newman (2010, pp. 247–260) to detect power-law behavior in networks.[5] The logarithm of the degree distribution p(k) is a linear function of the degree k with a negative sloping gradient and a constant y-intercept which can be written as a logarithmic equation by simply taking the exponential of both sides (Newman 2010, p. 247). This leads to a function p(k) that is defined by the degree k with a negatively defined constant exponent α, which is known as the "exponent of the power law", and a constant multiplier C (Newman 2010, p. 248). A simple histogram or scatter graph of the degree distribution plotted on a log-log scale provides the easiest way to detect power law behavior in real world networks. A true power-law distribution monotonically decreases over its entire range and appears in the log-log plot as a negatively sloping straight line (Newman 2010, p. 249). Figure 8.8 provides the log-log scatter plots of the degree distributions for the German laser industry network and for a comparable Erdös-Renyi random network.[6]

[5] These types of networks are called scale-free networks (Barabasi and Bonabeau 2003, p. 52).

[6] To provide a solid benchmark for the real world network, we proceeded as follows: First we calculated the network size and density measures of each real world network on a yearly basis.

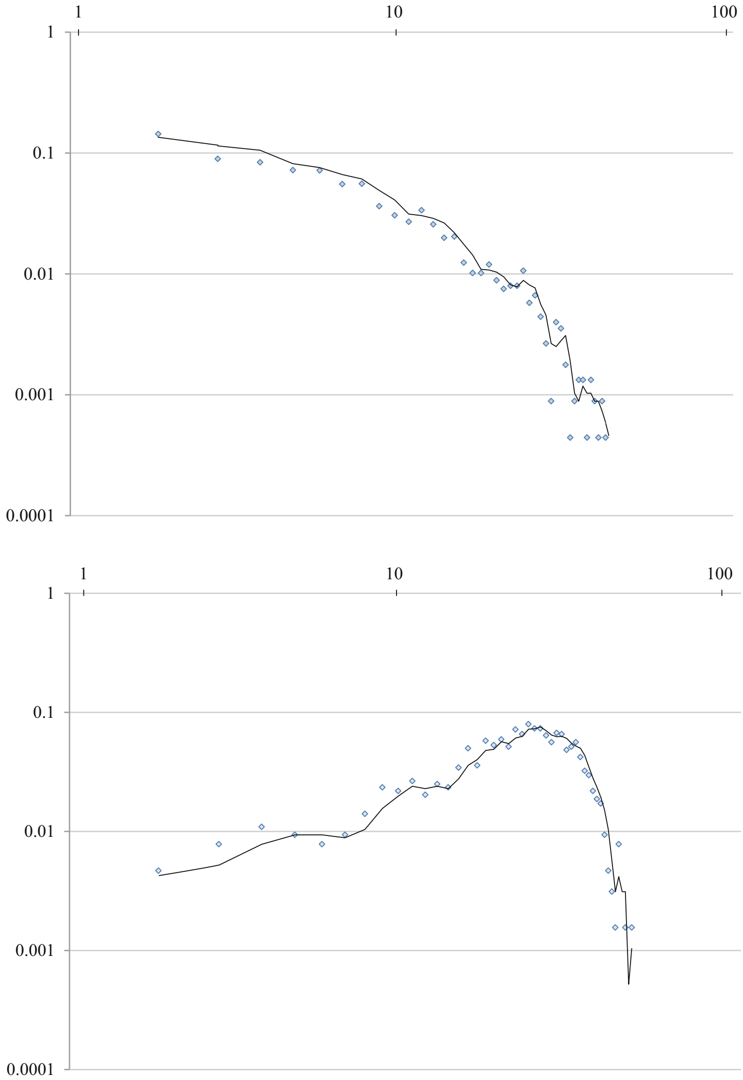


Fig. 8.8 Power law and sale free patterns – German laser industry innovation network versus random networks (Source: Author's own calculations and illustrations)

Then we used the Erdös-Renyi procedure implemented in UCI-Net 6.2 (Borgatti et al. 2002) to generate random networks on an annual basis. Each annual random network corresponded exactly to its real-world equivalent in terms of network size and network density. Finally the annual degree distributions for both the real world network and the random network were accumulated and the results were plotted on a log-log scale.

We aggregated all log degrees (abscissa) and the log node fraction in the network (ordinate) over all time periods. Even though the German laser industry innovation network shows no perfect power law behavior, we can clearly detect the tendency towards the emergence of a straight line in the log-log plot. In other words, the degree distribution of our real world network reveals systematically different structural patterns compared to a purely random network. This indicates a pronounced tendency towards the emergence of scale-free properties. Our analysis reveals quite similar structural patterns as were reported by Powell and his colleagues (2005) for the degree distribution of the interfirm network (one-mode network: DBFs – DBFs) and the interorganizational network (two-mode network: DBFs – universities) for the US biotech industry.

8.3.2 Small-Word Properties

Now we turn our attention to small-world network properties. Even though the underlying idea of small-world networks can be traced back to a series of network experiments conducted by Stanley Milgram and his team in the late 1960s, it took nearly 30 years before scholars were able to quantify the concept (Watts and Strogatz 1998).

Milgram (1967) showed in his letter-passing experiment that people in the United States are separated, more or less, by six degrees of separation (i.e. letters that have been sent even reach far-off targets after roughly six distinct steps on average). He concluded that a small-world network is characterized by a short path length despite a high level of clustering (Uzzi et al. 2007, p. 78). Small-world properties have some far-reaching implications for innovation networks. As we will discuss in more detail later (cf. Chap. 11), it is plausible to assume that macro-level network properties affect firm innovativeness. However, in this section, we apply the method proposed by Watts and Strogatz (1998) to check for the existence of small-world properties in the German laser industry innovation network. According to this methodological approach, two conventional network measures can be used[7]: the overall clustering coefficient and average path length clustering (Uzzi et al. 2007, p. 78).

We proceeded as follows to check for the existence of small-world properties in the German laser industry network. First we generated a total of 21 Erdös-Renyi random networks for the period under observation, one network for each year.[8] In order to ensure comparability between real world and random networks, both the size and the density parameters were adapted to the actual proportions of the real networks. In general, random networks are characterized by a short average path length and a low clustering tendency as neighboring nodes have the same

[7] For details on the calculation and interpretation of both measures, see Sect. 5.2.3.

[8] To gain a more robust random benchmark this procedure has to be repeated several times. However, this may be dispensed with for the purpose of this analysis.

probability of being connected as non-neighboring nodes (Uzzi et al. 2007, p. 79). Then, based on the procedure proposed by Watts and Strogatz (1998), we calculated "clustering" and "reach" measures for both the annually constructed German laser industry networks and for the annually constructed Erdös-Renyi networks. Finally, we calculated the "clustering coefficient ratio", the "path length ratio" (Watts and Strogatz 1998) and the "small-world Q" (Uzzi and Spiro 2005) to compare network properties.

The "clustering coefficient ratio" is defined as the real world network clustering coefficient divided by the random network clustering coefficient. The "path length ratio" is defined as the real world average path length divided by the random network average path length. The small world Q is defined as the "clustering coefficient ratio" divided by the "path length ratio" (Watts and Strogatz 1998; Uzzi and Spiro 2005; Uzzi et al. 2007).[9]

Standard procedures implemented in UCI-Net 6.2 (Borgatti et al. 2002) were applied to calculate both the overall clustering coefficient and the weighted overall clustering coefficient. In accordance with Schilling and Phelps (2007, pp. 1117–1118) we chose the latter measure here since the weighted clustering coefficient provides exactly the same measure as the transitivity index of each transitive triple (Borgatti et al. 2002).

According to Watts and Strogatz (1998) and with reference to Uzzi et al. (2007, p. 79) small-world networks have to fulfill at least one of the following two conditions: (**I**) a "clustering coefficient ratio" that is many times greater than 1.0 and a "path length ratio" that is approximately 1.0 or (**II**) a "small-world Q" that is much greater than 1.0.

The threshold values are not exactly specified as they can differ slightly for different types of real world networks. In our case we chose a threshold value of 2.5 for both the "clustering coefficient ratio" and the "small-world Q" and a band of accepted "path length ratio" values ranging from 0.7 to 1.3. Areas between minimum and maximum thresholds are shaded in light gray.

Figure 8.9 shows the "clustering coefficient ratio" (cf. Fig. 8.9, top), the "path length ratio" (cf. Fig. 8.9, center) and the "small-world Q" (cf. Fig. 8.9, bottom) for the German laser industry network between 1990 and 2010. The illustrations show that the conditions specified above are fulfilled with very few exceptions (e.g. year 1990).

In summary, our data clearly shows an increasing tendency towards small-world properties over time.

Concerns were expressed that, unlike unipartite networks, bipartite[10] networks significantly exaggerate the network's true level of clustering and understate the true path length (Uzzi and Spiro 2005, p. 453). Based on the pioneering work of Watts and Strogatz (1998) a new interpretation of small-world indicators for

[9] For further details, see Sect. 5.2.3.

[10] Bipartite networks are based on the assumption that all members of a team form a fully connected clique (Uzzi and 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.

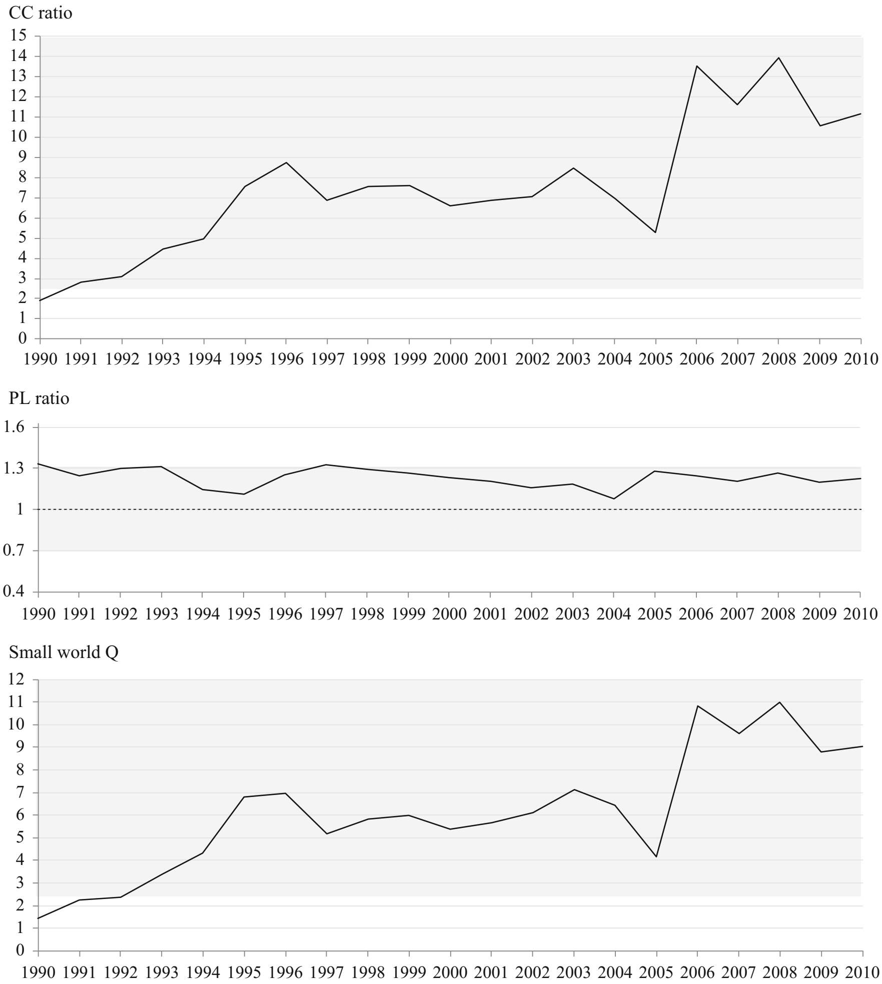


Fig. 8.9 Small-world properties in the German laser industry innovation network (Source: Author's own calculation and illustration)

bipartite networks was proposed by Newman et al. (2001). They showed that the "path length ratio" in bipartite networks are interpreted in the same way as unipartite networks (Uzzi and Spiro 2005, p. 454). In contrast, according to Newman et al. (2001) and Uzzi and 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 and Spiro 2005, pp. 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 increasing tendency towards comparably high clustering coefficient ratios over time, confirms our initial findings. We put our data to the test to check for the issue addressed above. Appendix 3 provides the results of an additional consistency test that is based on an alternative network data decomposition procedure. The additional calculations reveal nearly the same large-scale network patterns as reported above. On the whole, our initially reported findings were largely confirmed.

8.3.3 Core-Periphery Structure

As we have shown in Sect. 7.1.1, the overall German laser industry network consists of an average of 3.6 components with a standard deviation of 2.33. However, the question remains as to what the size proportions of these components look like and how these proportions change over time. The following core-periphery analyses goes way beyond a simple component-based analysis. The previously presented explorations substantiate the assumption that real world networks show quite unique structural patterns.

Several authors have suggested that interorganizational networks typically display core-periphery structures (Rank et al. 2006; Amburgey et al. 2008; Muniz et al. 2010). The identification of core-periphery structures in real world networks is important for several reasons. For instance, Rank and her colleagues (2006, p. 76) have argued that actors in the core of a network have a favorable position for negotiating with peripheral actors. In addition they have argued that these actors have better access to critical information and knowledge (ibid). Consequently, in this section we check for the emergence and existence of a core-periphery structure in the German laser industry innovation network.

In its most basic sense, the core-periphery concept is based on the notion of "[. . .] a dense, cohesive core and a sparse, unconnected periphery" (Borgatti and Everett 1999, p. 375). In addition, the core of the network occupies a dominant position in contrast to the subordinated network periphery (Muniz et al. 2010, p. 113). Several formalizations of the concept have so far been proposed. We argue that using single indicators runs the risk of providing a somewhat biased picture of the actual network structure. Thus, in order to identify a core-periphery structure in longitudinal network data, we propose the simultaneous use of four distinct indicators, each of which addresses different network characteristics.

According to Doreian and Woodard (1994, p. 269) a core of a network is simply a more cohesive and richly connected area of the network, relative to the overall structure of the entire network. Technically spoken, 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).

To start with, we focus on a concept that basically draws an actor-based *k*-core analysis. Amburgey et al. (2008) have applied this concept to conduct a *k*-core decomposition at the overall network level in order to analyze the emergence of a core-periphery structure in the biotech industry. The basic idea behind the 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 modes in the subgraph” (Wasserman and Faust 1994, p. 266). 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. For instance, a subgroup consisting of network actors with a *k*-core of $k = 6$ indicates that all of these actors have at least six direct linkages to other network actors. Amburgey et al. (2008) have argued that the exploration of the coreness strata (i.e. coreness layers for $k = 1\ldots$n) allows us to check over time for the existence and emergence of a core-periphery structure. This approach provides a very valuable initial look at the network’s core-periphery structure.

However, when focusing on “connectedness” as one of the most important features of networks (Wasserman and Faust 1994, p. 109) the measure creates a distorted picture for the following reasons. Firstly, and most importantly, 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. Secondly, the *k*-core concept concentrates exclusively on the tie dimension. This means that the size distribution of the core component versus peripheral components remains ignored. In other words, the proportion of nodes that fills the main component is not captured by the concept.

Consequently we argue that additional measures are needed to substantiate and complement a coreness analysis. The next two measures are as simple as the previous one but they provide a quite different view of the same phenomenon. Newman (2010, p. 235) shows that the majority of real world networks are not fully connected and the main component usually fills more than 90 % of the whole network. Our data confirms this finding and indicates that peripheral components are not only considerably smaller but also quite heterogeneous in terms of size and structure. In other words, we can distinguish between at least two elementary types of components in real world networks – the main component and peripheral component(s). Based on these considerations, two simple ratios – M-P tie ratio & M-P node ratio – can be calculated which allow us to quantify the proportion of ties or nodes that fill the main component versus peripheral components. The values for both ratios range between 0 and 1. These two ratios do not claim to provide comprehensive core-periphery indicators. Instead they give a valuable initial idea of size and density proportions between the fully connected main component and the scattered periphery of a network.

The last of our four core-periphery indicators was originally proposed by Borgatti and Everett (1999). They introduced two different concepts – discrete model and continuous model – that can be used to conduct a coreness analysis based on directed or undirected as well as valued or non-valued graphs. The underlying idea of the core-periphery identification procedures is based on a comparison of a hypothetically optimal core-periphery structure in an artificially generated network with a network structure that has actually been observed in a real-world network. Borgatti and Everett (1999, pp. 377–378) argued that an optimal core-periphery structure is characterized by a few core nodes that are adjacent to other core nodes, core nodes that are adjacent to some periphery nodes, and a notable proportion of periphery nodes that are not connected with other periphery nodes. As real-world networks are very unlikely to fit this theoretically optimal pattern, Borgatti and Everett (1999, pp. 377–378) have proposed an algorithm that measures how well the real-world network structure approximates the optimal core-periphery structure. The discrete model categorizes all network nodes into two classes – core nodes and peripheral nodes – whereas the procedure implemented in the continuous model simultaneously matches a core-periphery model to the overall network and estimates the coreness parameters of each actor in the network (Borgatti and Everett 1999; Borgatti et al. 2002). The parameter ρ is a measure of the network coreness. The measure ranges from 0 to 1 whereas large values indicate a high fit between an optimal core-periphery structure and an empirically observed network.

Figure 8.10 illustrates the calculation results for all four core-periphery indicators for the German laser industry innovation network between 1990 and 2010. As before, we chose a time-discrete approach and calculated all four indicators on an annual basis.

Figure 8.10a displays the k-core decomposition results. In contrast to Amburgey et al. (2008) we did not plot and interpret each k-core strata layer separately. Instead we grouped all network actors into three groups based on their k-core values: high ($k \geq 8$), medium ($8 > k > 4$) and low ($4 \geq k > 0$). We argue that a high spread between the first and the last group indicates the existence of a core-periphery structure at a given point in time. Our k-core decomposition analysis indicates that between 1994 and 1997, and between 2002 and 2010 there was a pronounced tendency towards having a core-periphery structure.

Figure 8.10b and c shows the M-P tie ratio and the M-P node ratio indicating the proportion of ties as well as nodes that fill the main component. Both ratios considerably decrease between 1994 and 1997, and between 2004 and 2008. In addition, a closer look at the M-P node ratio points to the fact that between 1998 and 2002 a notable proportion of nodes are located in peripheral components.

Figure 8.10d illustrates the results of a core-periphery analysis according to the approach proposed by Borgatti and Everett (1999). For the purpose of this study we have applied the continuous core-periphery model for undirected graphs. The estimation procedures implemented in UCI-Net 6.2 (Borgatti et al. 2002) were used to calculate coreness values on an annual basis. Figure 8.10d reports the gini-based core-peripheriness measure. Large values indicate a tendency towards a core-periphery structure. Results reveal that the German laser industry innovation network approximated a hypothetically optimal core-periphery structure quite

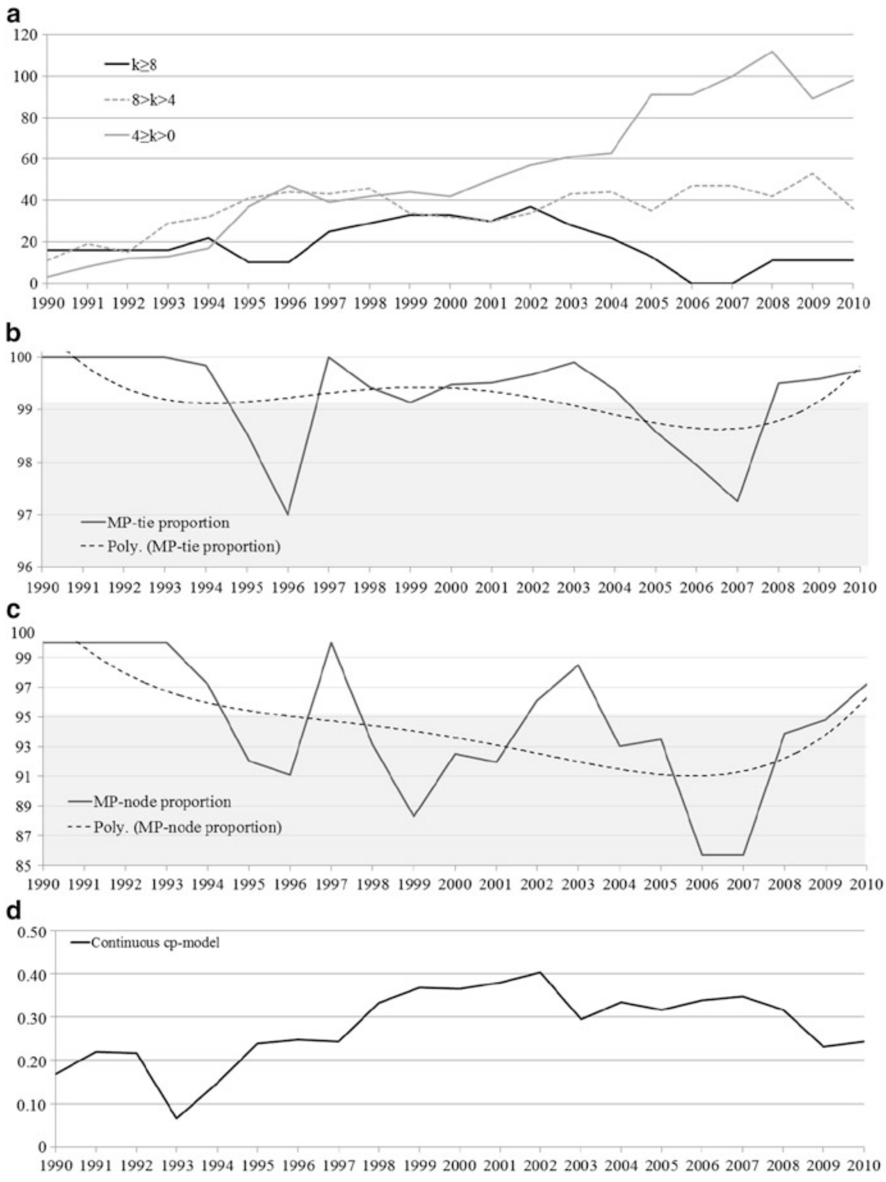


Fig. 8.10 Core-periphery structure in the German laser industry – a comparison of four indicators (Source: Author's own calculations and illustration)

well between 1994 and 2008. Surprisingly, the model indicates that the highest core-peripheriness occurred between 1999 and 2002.

In summary, our analysis gives us good reasons to assume that the German laser industry innovation network exhibited a comparably pronounced core-periphery structure during three time periods – (I) 1994–1997, (II) 1999–2002 and (III) 2004–2008. In all three time periods at least two out of four indicators substantiate this finding. In addition, the long-term trends indicate the tendency toward an increasing coreness of the German laser industry network over time. At first glance, the *k*-core analysis fails to indicate the pronounced core-peripheriness between 1999 and 2002 indicated by the continuous model of Borgatti and Everett (1999). However, a closer look at the dotted gray line in Fig. 8.10a (medium group, with k-core values: $8 > k > 4$) reveals a structural transition between 1998 and 1999. Obviously, there seem to be some hidden structural processes that strengthen the periphery at that time. It is interesting to note that the comparably simple M-P node ratio points to the second time period and reveals patterns that would have maybe remained unseen if only degree-based indicators were used. To conclude, both node-related and tie-related indicators should be used in a complementary manner to check for the existence and emergence of a core-periphery structure over time.

8.3.4 Exploration of Network Change Patterns Over Time

The last step in an exploratory network analysis is visualization (De Nooy et al. 2005, pp. 5–6). Figure 8.11 gives us snap-shots of the German laser industry innovation network at four distinct points in time (i.e. 1991, 1995, 1999 and 2007).[11] The visualization of the network over time gives us an initial idea of the network topology and provides valuable insights in terms of characteristic network change patterns over time.

To start with we take a closer look at the network structure in 1991 (cf. Fig. 8.11a). In this early stage of development the network consists of one component. Thus, the network is fully connected. Nevertheless, the network structure is by no means homogeneous. We can generally identify one densely connected area in the network whereas the majority of the network actors are relatively sparsely connected. This finding is in line with the comparably high degree centralization index of about 17.5 % in 1991 as reported earlier.

Only a few years later the picture changes considerably (cf. Fig. 8.11b). In 1995, the network consists of three distinct components. The main component is by far the largest. The size proportions among the peripheral components are quite heterogeneous. We have a dyadic component on the one hand, and a multi-node component that consists of five LSMs and PROs on the other. As we will see later (cf. Chap. 9) this has some important implications for the theoretical conceptualization of evolutionary network change processes. In addition, the network plot reveals the existence of several densely connected areas – hot spots – within the main component of the network. It turns out that initially central actors, such as LSM287,

[11] We used NetDraw 2.0 to visualize the network (Borgatti 2002).

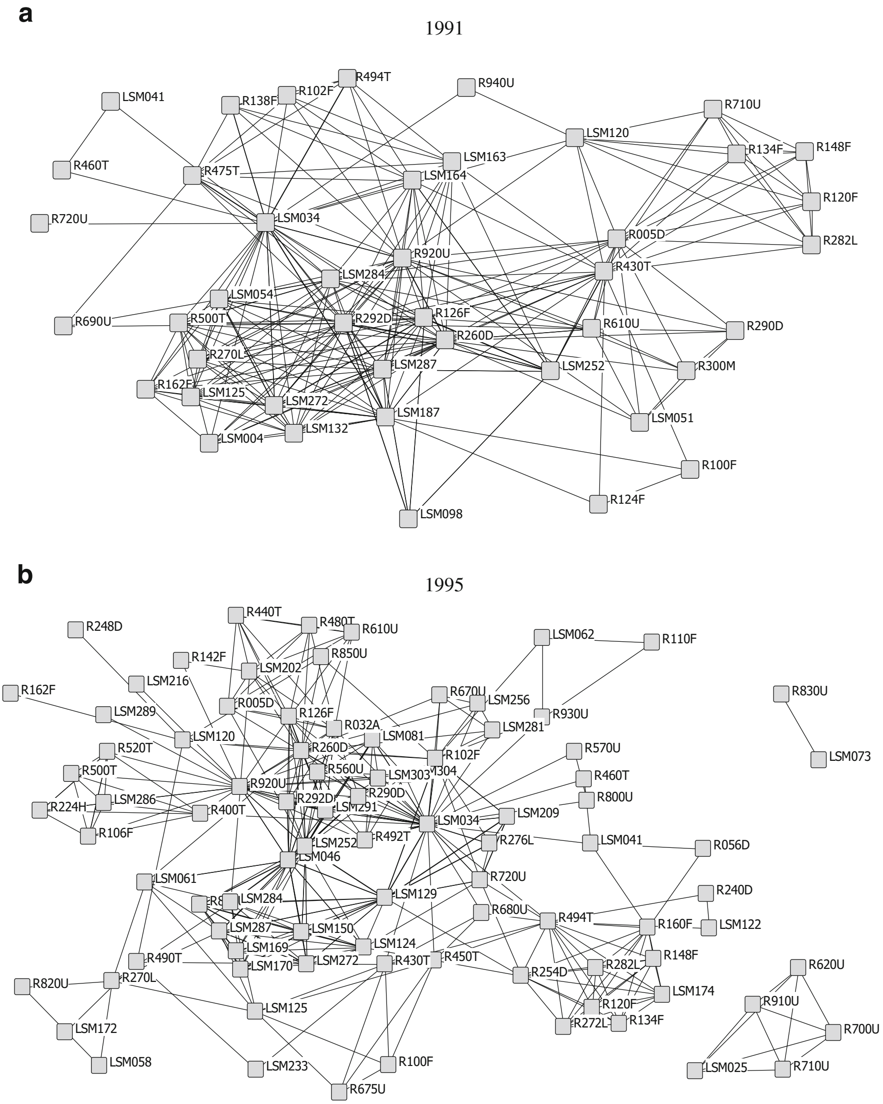


Fig. 8.11 The evolution of the German laser industry innovation network, 1991 & 1995 (Source: Author's own calculations and illustrations)

LSM272, R126F, R920U, R260D, were able to further develop their position in terms of their nodal degrees.

Two patterns in 1999 are striking (cf. Fig. 8.12a). Firstly, the number of components has grown considerably and the main component continues to dominate in terms of size. Now the periphery consists of two dyadic and three triadic components. Furthermore it is interesting to note that the previously identified

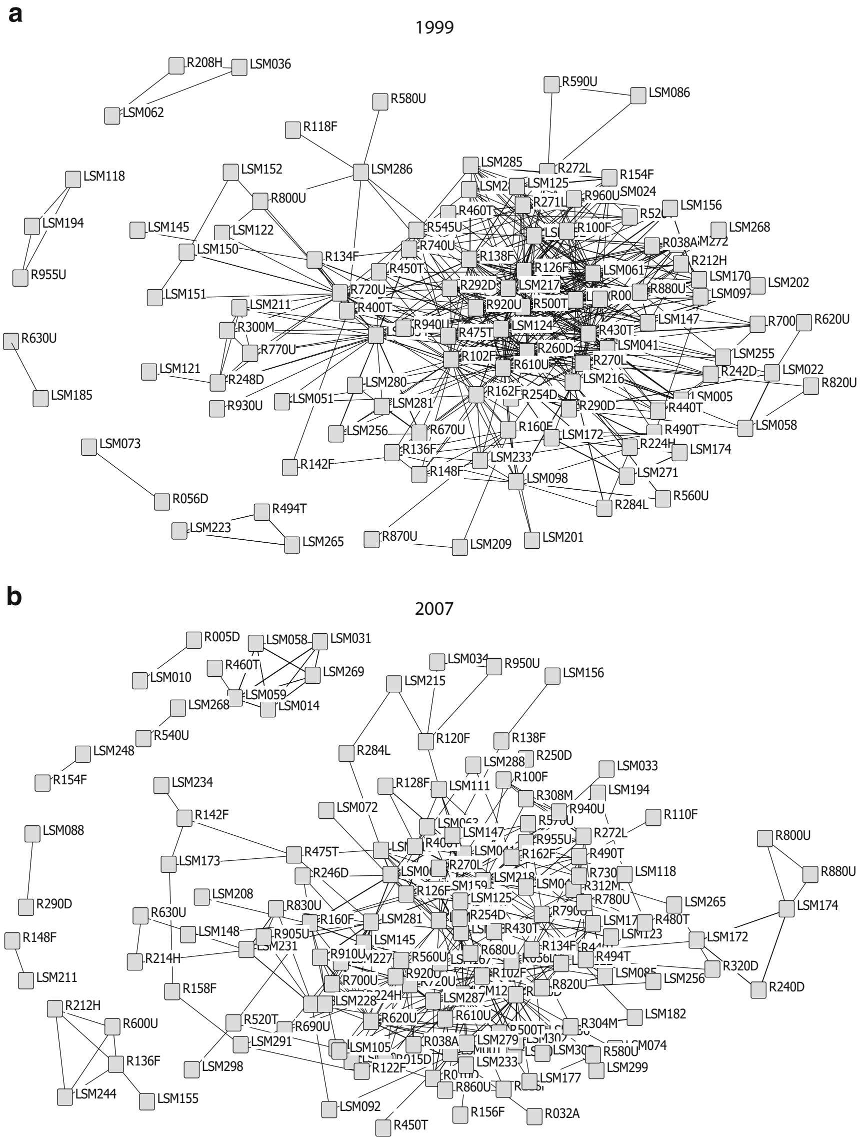


Fig. 8.12 The evolution of the German laser industry innovation network, 1999 & 2007 (Source: Author's own calculations and illustrations)

peripheral multi-node component has meanwhile been integrated into the main component. In other words, between 1995 and 1999 at least one of the five LSMs or PROs in the multi-node component was able to establish a bridging tie to an actor within the main component. Secondly, we can observe an increasing concentration tendency in the main component. Some nodes are quite loosely linked to the main component whereas others are embedded in the core of the main component and show an above-average nodal degree. This observation clearly supports the results of our core-periphery analysis (cf. Sect. 8.3.3). Not surprisingly, the initially identified high-degree actors are still positioned at the core of the network. But what is perhaps more interesting are the high-degree nodes in the network that entered the scene later. For instance, the firms LSM124 and LSM061 entered the industry in 1994 and 1995, respectively. This indicates that some nodes seem to reach the core of the network much faster than others.

Finally, the last network plot (cf. Fig. 8.12b) illustrates the network topology in 2007. The network structure is clearly more fragmented than it was in 1999. In addition, we can observe a large number of peripheral components. These components are quite heterogeneous in terms of size. More precisely, we see five dyadic components and two multi-node components consisting of five and six nodes respectively. Moreover, it is remarkable that neither of the peripheral network organizations identified in 1999 are still in the network periphery in 2007.

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