Chapter 11
Small World Patterns and Firm Innovativeness

Innovation is the central issue in economic prosperity.
(Michael E. Porter 1980)

Abstract In this section we switch analytical perspective and take a closer look at the systemic or overall network level. As outlined before (cf. Sect. 8.3), an in-depth understanding of large-scale network patterns is important for several reasons. On the one hand, previous studies have demonstrated that networks with comparably short path lengths and a high level of clustering – so-called "small-world" networks – can facilitate the exchange of information, ideas and knowledge in networks (Fleming, L., C. King, A. I. Juda. 2007. Small worlds and regional innovation. *Organ. Sci.* 18(6) 938-954). This, however, substantiates the assumption that systemic level network properties are likely to affect the embedded firms in their efforts to innovate. On the other hand, systemic level studies have some far-ranging implications, not only for firms but also for policy makers, by providing an informative basis for the evaluation of cooperation-related innovation policies at the national and supra-national level. In a nutshell, the aim of the third empirical part of this study is to shed light on the relationship between specific types of large-scale network properties at the macro-level and firm-level innovation outcomes at the micro-level. This investigation is organized as follows. After a short introduction in Sect. 11.1 we outline selected theoretical concepts. Next, we continue by providing the graph theoretical underpinnings of small-world properties in Sect. 11.2. Then, we introduce our conceptual framework and derive a set of testable hypotheses. In Sect. 11.3 we provide a short overview of data and methods used for this analysis. After these preparatory steps, we continue with a description of the empirical model and present our estimation results in Sect. 11.4. Finally, after a brief discussion of our main findings we conclude with some critical remarks.

M. Kudic, *Innovation Networks in the German Laser Industry*,
Economic Complexity and Evolution, DOI 10.1007/978-3-319-07935-6_11

11.1 On Small-World Characteristics in Innovation Networks

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

Only recently have economists, sociologists and management scholars started to address the "small-world" phenomenon (for a comprehensive review see: Uzzi et al. 2007). Milgram's findings have some far-reaching implications for innovation networks. The experiment implies that the network topology itself is likely to affect the exchange of knowledge in innovation networks. This, however, substantiates the assumption that large-scale properties at the overall network level affect the innovative performance of network actors at the micro-level. It is all the more astonishing that large-scale network properties have been widely neglected in the field of interorganizational alliance and network research over the past decades.[1] One possible explanation is that it took scholars about 30 years to quantify Milgram's initial idea. Watts and Strogatz (1998) have shown that the "small-world" phenomenon can be empirically analyzed by using relatively simple network measures which were originally designed for unipartite networks (cf. Sect. 8.3.2). Some years later a reconceptualization for bipartite networks was proposed by Newman and colleagues (2001). Quite recently, a few excellent empirical studies were conducted which explicitly analyzed the relationship between "small-world" properties and the creation of novelty and innovation (Uzzi and Spiro 2005; Fleming et al. 2007; Schilling and Phelps 2007).

One of the first studies on collaboration, creativity and small worlds was conducted by Uzzi and Spiro (2005). The authors analyzed the relationship between small-world properties in the Broadway musical industry and creativity in terms of the financial and artistic performance of musicals produced from 1945 to 1989. This setting is remarkable for two reasons. Firstly, the network measures were constructed based on bipartite network data. In other words, groups of artists were treated as fully connected cliques. To handle the data properly, novel statistical techniques (Newman et al. 2001) were applied to detect and interpret small-world properties which were explicitly designed for the analysis of bipartite

[1] Most notable exceptions are the studies by Baum et al. (2003), Corrado and Zollo (2006), Uzzi and Spiro (2005), Fleming et al. (2007), Schilling and Phelps (2007) and Cassi and Zirulia (2008).

networks. Finally, it is interesting to note that Uzzi and Spiro (2005) measured performance outcomes at the team level and not the actor level. They reported a parabolic small-world network effect in a sense that performance increased initially and then decreased after a certain point.

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

The most comprehensive study on small worlds and firm innovativeness was provided by Schilling and Phelps (2007). They analyzed the patent performance of 1,106 firms in 11 industry-level alliance networks based on a comprehensive panel dataset. The findings of the study provide support for the small-world hypothesis by showing that networks with comparably short path lengths and high clustering have a significant impact on the innovativeness of the firms involved. The authors came to the conclusion that local density and global efficiency can exist simultaneously, and in particular, the combination of these two network characteristics enhances innovation (Schilling and Phelps 2007, p. 1124). Despite these interesting findings the study has some limitations. The most notable is that the authors had to make assumptions about alliance duration due to a lack of information on alliance termination dates. They assumed that alliance relationships last for 3 years on average. In the worst case, this could result either in a systematic underestimation or overestimation of small-world network properties.

All of these studies provide us with valuable insights into the small-world phenomenon. However, this discussion also reveals that recent empirical findings have so far been rather mixed and inconclusive. In addition, we still lack an in-depth understanding of how large-scale network properties affect firm innovativeness. In other words, we have to open up the black box in order to understand the mechanisms or transmission channels through which firm innovativeness is affected by systemic-level network properties. Thus, the aim of this investigation is twofold. From a theoretical point of view, we draw upon a reconceptualization of the absorptive capacity concept proposed by Zahra and George (2002) to provide the missing link between overall network characteristics and a firm's innovative performance. From an empirical point of view, we put the "small-world" hypothesis to the test according to which small-world networks are assumed to enhance an embedded firm's creativity and its ability to create novelty in terms of innovation. More precisely, we analyze the relationship between distinct large-scale patterns (i.e. "weighted clustering coefficient" ***or*** "avg. path-length") and firm innovativeness on the one hand, and small-world properties (i.e. "weighted clustering coefficient" ***and*** "avg. path-length") and firm innovativeness on the other.

11.2 Small-World Networks and Absorptive Capacity

11.2.1 Graph Theoretical Basis of the "Small-World" Phenomenon

Small-world networks are characterized by two structural particularities: a high level of clustering and short average path lengths. The theoretical conceptualization and quantification of the small-world phenomenon can be traced back to the pioneering work of Watts and Strogatz (1998). The authors argued that a compression of real-world networks and randomly generated networks should reveal some systematic differences with regard to network clustering and reachability. They proposed using two simple graph theoretical concepts – "cluster coefficient" and "average distance" – and calculating two ratios – "clustering coefficient ratio" (CC ratio) and "path length ratio" (PL ratio) – in order to check for the existence of small-world properties (cf. Sect. 8.3.2). Quantitative network analysis methods provide a rich toolbox for calculating these indicators (cf. Wasserman and Faust 1994; Borgatti et al. 2013).

The actor-specific clustering coefficient varies from 0 to 1.0 whereby high values indicate that many of the actor's direct contacts are connected to each other (Wasserman and Faust 1994). The overall clustering coefficient is an indicator that allows the connectedness and crowding in a network to be quantified. This measure is simply defined as the average of all individual clustering coefficients for a well-specified population of network actors. In contrast, the weighted overall clustering coefficient is defined as the weighted mean of the clustering coefficient of all the actors, each one weighted by its degree (Borgatti et al. 2002). The shortest path between two network actors is referred to as a geodesic whereas the length of the geodesic between a pair of network actors is referred to as the geodesic distance (Wasserman and Faust 1994, p. 110). The average path length captures the reachability among all network actors in a connected graph or subgraph. The measure can be defined as "[. . .] the average number of intermediaries, that is, the degrees of separation between any two actors in the network along their shortest path of intermediaries" (Uzzi et al. 2007, p. 78).[2]

Watts and Strogatz (1998) concluded that real-world networks with a CC ratio much higher than 1.0 and a PL ratio of about 1.0 have a small-world character. A related indicator is the so-called "small-world Q" (defined as: the CC ratio divided by the PL ratio), where Q values that are much greater than 1.0 indicate the small-world nature of a real-world network (Uzzi et al. 2007, p. 79). Newman et al. (2001, 2002) have shown that the "path length ratio" in bipartite networks has basically the same interpretation as in unipartite networks (Uzzi and Spiro 2005, p. 454). In contrast, the "clustering coefficient ratio" has to be interpreted differently in the

[2] For further details on the calculation and interpretation of these two measures, see Sects. 5.2.3 and 8.3.2.

sense that a coefficient ratio of about 1.0 indicates within-team clustering whereas a higher clustering coefficient ratio indicates an increase in between-team clustering (Uzzi and Spiro 2005, pp. 454–455).

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

11.2.2 Potential and Realized Absorptive Capacity: The Missing Link

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

The originally proposed "absorptive capacity" concept by Cohen and Levinthal (1989, 1990) has significantly enhanced our understanding of a firm's ability to identify, exploit and assimilate external knowledge and apply it for commercial ends. Cohen and Levinthal (1989) focused initially on the costs of acquiring new technological knowledge and on the incentives for learning that determine the firm's willingness to invest in creating and establishing absorptive capacity. Later the authors enriched the construct by emphasizing the relevance of individual learning processes and incorporating the notion that learning is a cumulative process (Cohen and Levinthal 1990). Furthermore, they adapted insights from research on individual cognitive structures and individual learning processes. They applied these findings to the organizational level and emphasized that an organization's absorptive capacity is path-dependent, builds on prior investments in individual absorptive capacity and depends on an organization's internal communication processes and its ability to share knowledge (Lane et al. 2006, p. 838). In addition, they pointed to the fact that previously accumulated knowledge enables the firm to predict and appraise new technological trends and developments in a timely way. Since then the concept has attracted a great deal of attention.[3] Several scholars have proposed insightful reconceptualizations of Cohen and Levinthal's original concept (Lane and Lubatkin 1998; Van Den Bosch et al. 1999; Zahra and George 2002).

For the purpose of this analysis we draw upon the concept proposed by Zahra and George (2002). This reconceptualization builds upon the distinction between "capabilities" and "dynamic capabilities". By starting from the dynamic capability perspective (Teece et al. 1997; Katkalo et al. 2010) they suggest a separation of the original absorptive capacity concept into potential absorptive capacity and realized absorptive capacity and introduce an efficiency factor η that captures the interrelationship between these two constructs (Zahra and George 2002, p. 194). They argue that four capabilities[4]– i.e. knowledge acquisition, assimilation, transformation and exploitation – are combinative in nature and build upon each other. These four capabilities make up a firm's absorptive capacity that has to be regarded as a dynamic capability pertaining to knowledge creation and utilization that enhances a firm's innovative performance and ability to gain and sustain a knowledge-based competitive advantage (Zahra and George 2002, p. 185). They define absorptive capacity as "[. . .] a set of organizational routines and processes by which firms acquire, assimilate, transform, and exploit knowledge to produce a dynamic organizational capability" (Zahra and George 2002, p. 186).

Figure 11.1 illustrates a slightly refined version of Zahra and George's (2002) model. The absorptive capacity construct, at the core of the model (cf. Fig. 11.1 center), is divided into potential absorptive capacity (PACAP), which includes knowledge acquisition and assimilation, and realized absorptive capacity (RACAP), that consists of knowledge transformation and exploitation capabilities. This absorptive capacity construct connects the antecedents, i.e. external knowledge sources, knowledge complementarities and experiences (cf. Fig. 11.1, left) with firm-level outcomes, i.e. firm innovativeness and sustainable competitive advantages (cf. Fig. 11.1, right). In addition, the model accounts for several moderating effects: "activation triggers", "social integration mechanisms", and "regimes of appropriability". An efficiency factor η is integrated into the model that captures a firm's ability to transform and exploit external knowledge sources in order to gain a sustainable competitive advantage. This factor reflects the extent to which a firm can make commercial use of potentially available knowledge. In other words, RACAP approaches PACAP in firms with a high efficiency factor (Zahra and George 2002, p. 191). This model paves the way for a dynamic conceptualization of absorptive capacity and provides several interesting implications for systemic level network studies. Below we argue that a simple extension of the model

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

[4] Zahra and George (2002) draw upon Winter (2000, p. 983) who defines capabilities as "[. . .] a high-level routine that, together with its implementing input flows, confers upon an organization's management a set of decision options for producing significant outputs of a particular type."

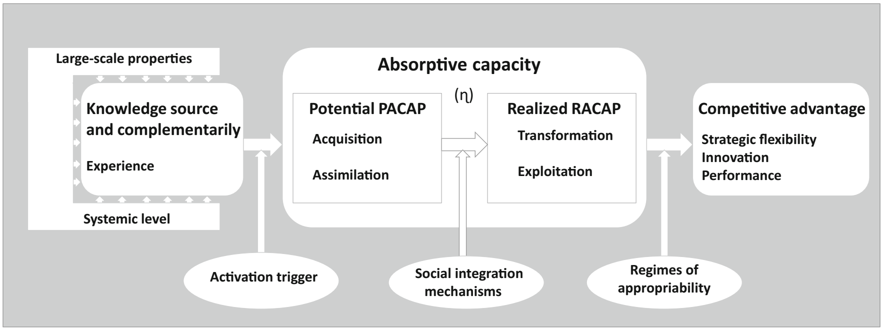


Fig. 11.1 Conceptual framework – an adapted model of potential and realized absorptive capacity (Source: Zahra and George (2002, p. 192), extended and modified)

provides the missing link for understanding how large-scale properties at the overall network level affect innovation outcomes at the firm level.

In doing so, we have to take a closer look at the first element of the framework (cf. Fig. 11.1, left). According to the model originally proposed by Zahra and George (2002, p. 191) there is a direct link between external knowledge sources and complementarities and a firm's PACAP. These external knowledge sources encompass, among other things, various structural forms of interorganizational relationships such as R&D consortia, alliances, or joint ventures.[5] Thus cooperative relationships to external partners can serve as a vehicle for accessing new information and knowledge. However, it is important to note that not only direct but also indirect interorganizational linkages have to be considered in this context (Gulati 1998). As a consequence, we apply here not a relational but rather a structural network embeddedness perspective (cf. Sect. 2.5.4). One particular feature of a network is that a particular firm can even reach far distant organizations that are spread throughout the entire network space by second or third tier ties. This means that a firm that is a part of the industry's innovation network has potential access to an extensive pool of external technological knowledge sources spread throughout the entire network. Thus, in line with previous systemic-level studies (Uzzi and Spiro 2005; Fleming, et al. 2007; Schilling and Phelps 2007), we argue that actual access to information and the knowledge stocks of other firms is likely to be affected by the structure of the network in question. The network topology itself plays a key role in the permeability of the network. In contrast to previous research, we believe that an extension of the absorptive capacity concept outlined above and an in-depth exploration of structural network characteristics adds extra value to our understanding of how large-scale properties at the systemic level affect a firm's efforts to innovate (cf. Fig. 11.1, left). Or to put it differently, given that network topologies can facilitate but also hamper the flow of information and knowledge

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

among actors in an innovation network, the question arises as to what these structural network patterns look like.

11.2.3 Large-Scale Network Properties: Opening Up the Black Box

Networks can exhibit quite heterogeneous structural patterns. Figure 11.2 illustrates four fairly different network topologies. To start with, we look at a typically random network. It is important to note that the emergence of these networks is not very likely under realistic conditions. Nonetheless, we explicitly consider and discuss all four cases in order to develop our theoretical arguments.

The first network example is characterized by a rather fragmented network structure that consists of five components (cf. Fig. 11.2, I). The structural configuration of the network shows no significant peaks in term of the actors' nodal degrees. The minimum degree is one and the maximum degree is two. Network actors within a component are not directly but rather are indirectly connected to other actors in the same component. The benefits of a firm in participating in such a fragmented, randomly distributed network are rather limited. The reasons for this are straightforward. Firstly, the pool of potentially accessible knowledge sources is limited by the size of the component in which the firm is embedded. Secondly, the geodesic distances to most other actors are infinite due to the high degree of fragmentation. Thus, knowledge transfer processes are likely to be hampered by the component's size or even entirely prevented by the overall network structure.

These issues lead to our second network example. Figure 11.2 (II) illustrates a fully connected but randomly distributed network structure. Like before there are no systematic biases in the degree distribution at the overall network level. The main difference is that the network consists of only one large component. This, however, has some important implications with regard to knowledge diffusion processes. Theoretically, we would expect that a firm's participation in such a

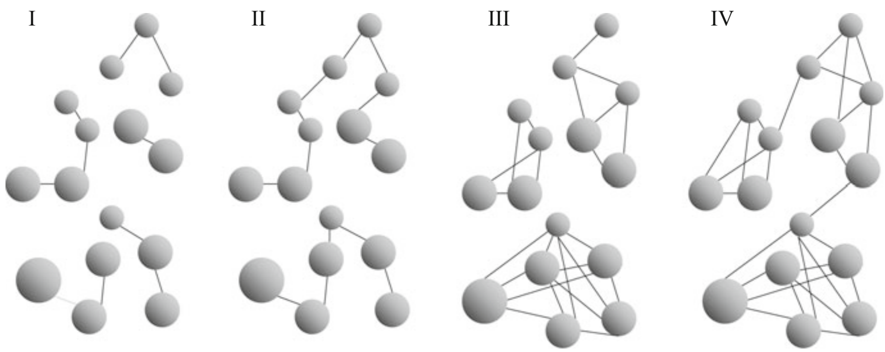


Fig. 11.2 Illustration of network topologies (Source: Author's own illustration)

network broadens the scope and variety of potentially accessible information and knowledge sources. One could argue that the firm's chance of identifying and actually accessing external knowledge sources that fit with its own set of capabilities increases with the number of potentially accessible knowledge sources. The crucial point is that such an increased set of opportunities would allow a firm to make better use of its knowledge exploitation capabilities. According to Zahra and George (2002) this would be reflected in a higher efficiency factor η and lead to a higher firm-level innovation outcome at subsequent points in time. In fact the actual situation looks somewhat different. The likelihood of successfully exchanging knowledge between two indirectly connected network actors decreases with the number of other actors that lie on the geodesic between them. A closer look at our network example illustrates this point (Fig. 11.2, II). In this case we have up to 11 intermediates between the most distant actors in the network.

Next, we turn our attention to a somewhat more realistic network structure. By now, it is well-recognized that some nodes attract ties at a higher rate than others. This is reflected in real-world networks by the emergence of a strongly biased degree distribution at the overall network level. These types of networks are also known as power law distributed or scale free networks (cf. Sect. 8.3.1). Real-world network topologies can differ significantly in terms of their structural features.

Our third network example consists of three components (two peripheral and one main component) and the nodal degrees range from one to five (cf. Fig. 11.2, III). The network is disconnected and clustered. The nodes within these components are well-connected themselves but have no linkages to actors in other areas of the network. We start our line of argument by focusing on the network's main component (cf. Fig. 11.2, III, bottom). A firm's involvement in a highly interconnected main component of a disconnected network has some considerable advantages. Firstly, all main component firms are connected to one another. A main component firm can reach most other actors in the same component in only a few steps. Short paths are likely to facilitate potential knowledge transfer and learning processes. Most innovation researchers would agree that a decreasing path length is positively related to firm innovativeness (Fleming et al. 2007, p. 941).

Secondly we turn our attention to clustering within connected network components. A high degree of interconnectedness allows a focal firm to achieve cooperation-related synergy effects. These effects can result from direct but also from indirect linkages among a focal actor's directly connected partners (White 2005; Hoffmann 2005). Redundant knowledge transfer channels allow firms to circumvent potentially emerging knowledge transfer barriers. It has been argued that clustering promotes collaboration, resource pooling and risk sharing (Fleming et al. 2007, p. 940).[6]

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

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

H1 Short average path length in the overall network level is positively related to its innovative performance at later points in time.

H2 A high degree of clustering at the overall network level is positively related to its innovative performance at later points in time.

Last but not least, we address small-world properties of innovation networks. It becomes apparent that the previously discussed real-world network in itself encounters barriers in information and knowledge transfer. As already stated above, the network consists of several densely interconnected components which are not connected to one another. This leads us to take a look at the last network example. Figure 11.2 (IV) illustrates a highly clustered but fully connected real-world network. The simultaneous occurrence of cohesive subgroups and short paths in a network has some interesting implications.

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

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

H3 A firm's participation in a small-world network (characterized by short average path lengths and a high level of clustering) is positively related to its innovative performance at later points in time.

11.3 Data, Variables and Descriptive Statistics

11.3.1 Data Sources

Four main data sources were used to construct a longitudinal panel dataset: patent data, industry data, geographical data and network data (cf. Sect. 4.2).

Patent data was used to measure innovative performance at the firm level. We are not the first to use patent data as an innovation proxy (Jaffe 1989; Jaffe et al. 1993). Previous studies provide us with important insights into the pros and cons of using patents to measure innovation performance.[7] In accordance with contemporary research (Schilling and Phelps 2007), we used annual patent counts as a proxy for innovation output. Our database (cf. Sect. 6.1.2) includes patent applications as well as patents granted by the German Patent Office and by the European Patent Office. DEPATISnet (the German Patent and Trade Mark Office's online database) and *ESPACEnet* (the European Patent Office database) were employed to cross check the results from our initial data gathering procedure. For the purpose of this analysis we used the annual count of patent applications [*pacnt*] as an endogenous variable.

Industry data came from a proprietary dataset containing the entire population of German laser source manufacturers between 1969 and 2005 (Buenstorf 2007). Based on this initial dataset we used additional data sources to gather information about firm entries and exits after 2005. We chose the business unit or firm level for the purpose of this analysis.[8] In addition, we identified 145 universities and public research organizations with laser-related activities by using two complementary methods – the expanding selection method and the bibliometric approach.[9]

Network data was gathered from two official databases on publicly funded R&D collaboration projects – the *Foerderkatalog* database and *CODRIS* database.[10] The first database contains information on more than 110,000 ongoing or completed subsidized research projects. The second raw data source was an extract from the *CORDIS* project database which includes a complete collection of R&D projects for all of the German companies funded by the European Commission. This database extract encompasses a project dataset with over 31,000 project files and an organization dataset with over 57,100 German organizations and roughly 194,000 international project partners. In total, we were able to identify, for the entire population of 233 German laser source manufacturers, 570 R&D projects with up to 33 project partners from various industry sectors, non-profit research organizations and universities.

[7] Section 4.2.4 provides a detailed discussion on the measurement of innovation and describes the patent data sources and data gathering procedure used for the purpose of this study.

[8] For a detailed description of industry data used for this study, see Sect. 4.2.1.

[9] Both methods are described in detail in Sect. 4.2.

[10] For a detailed description of both cooperation data sources (*CORDIS* and *Foerderkatalog*) and the methods used to construct annual networks, see Sect. 4.2.3.

11.3.2 Variable Specification

The data sources described above were used to construct interorganizational innovation networks and calculate network indicators on a yearly basis. We calculated weighted clustering coefficients *[nw_wclust]* and average path length *[nw_areach]* on an annual basis (cf. Sect. 5.2.3, Eqs. 5.10 and 5.11). An interaction term was calculated to capture the small-world properties of the network *[inter_sw]*. Several additional control variables were calculated. We measured firm-specific cooperation activities with two cooperation count measures based on the *Foerderkatalog* data *[coopcnt_fk]* and *CORDIS* data *[coopcnt_c]* respectively, as well as a combined cooperation count indicator *[coopcnt_fkc]* consisting of the sum of both. Moreover, we accounted for cooperation funding by including a variable that measures the firm's amount of cooperation funding received annually *[coopfund_fkc]* in 1,000 euros. We also included a linear firm age measure *[firmage]* as well as a squared term *[firmage_sq]* to account for firm maturity. In addition, two network level variables were included to control for the structural network characteristics at the overall network level. The first variable captured the size of the overall network *[nw_size]* defined as the proportion of firms with at least one dyadic partnership in a given year. The second variable measured the connectedness of the overall network *[nw_density]*. Standard algorithms implemented in UCI-Net 6.2 were used to calculate the network measures (Borgatti et al. 2002).

11.3.3 Descriptive Statistics

Next, we take a brief look at the variable description and basic summary statistics (cf. Table 11.1). In total, we have 2,645 firm-year observations in the time between 1990 and 2010. The average number of observations per firm amounts to 11.35. Table 11.2 reports the correlation coefficients for all variables in our empirical models.

Based on the data sources described above we conducted an initial exploratory analysis to get an idea of what the overall network topology looks like. Figure 11.3 (top) displays the weighted overall clustering coefficients and the average overall path length for both the German laser industry innovation network and a randomly generated Erdös-Renyi network that is comparable in terms of size and density.[11] Network measures are calculated on an annual basis and the period under observation is from 1990 to 2010. All measures are calculated using UCI-Net 6.2 (Borgatti et al. 2002). The corresponding CC ratios, the PL ratios and the small-world

[11] The construction of the reference network is described in Sect. 8.3.2.

Table 11.1 Descriptive statistics – clustering, reach and small-world properties

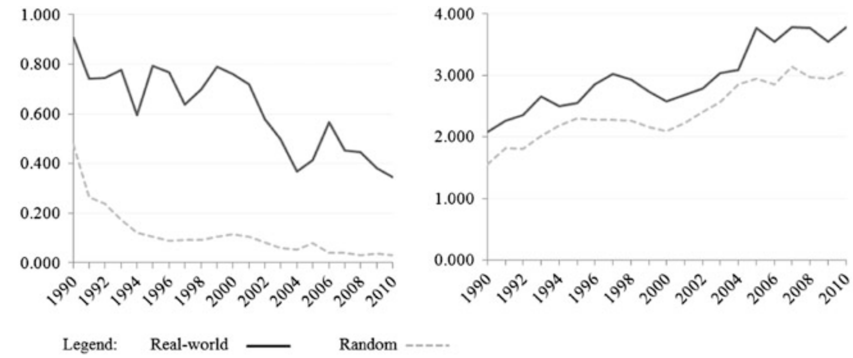
Variable	Variable definition	Summary statistics				
		Obs.	Mean	Std. dev.	Min	Max
Endogenous variables						
papcount	Patent applications (annual count)	2,645	2.662004	17.43323	0	366
pgrcount	Patent grants (annual count)	2,645	0.339130	1.635554	0	28
Control variables						
firmage	Age of the firm	2,645	8.055955	6.800477	0	43
firmage_sq	Age of the firm, squared	2,645	111.1274	177.8146	0	1,849
coopcount	Count of cooperation events (annual)	2,645	0.275992	0.774138	0	8
coopfund	Annual cooperation funding received (in k€)	2,645	132.299	851.8748	0	31.863
nw_size	Network size (overall network level)	2,645	0.381853	0.060200	0.240506	0.472393
nw_density	Network density (overall network level)	2,645	0.088119	0.069955	0.037300	0.440500
Network level properties						
nw_wclust	Weighted clustering coefficient	2,645	0.58152	0.161069	0.345	0.906
nw_areach	Average distance based reach measure	2,645	3.09431	0.504183	2.075	3.786
inter_sw	"Small world" indicator (nw_wclust $\times$ nw_areach)	2,645	1.7324	0.298921	1.14021	2.18748

Source: Author's own calculations

Table 11.2 Correlation matrix – clustering, reach and small-world properties

	Pgr count	Pap count	Firm age	Firm age_sq	Coopcount	Coopfund	Nw_size	Nw_density	Nw_wclust	Nw_areach	Inter_sw
Papcount	1.0000										
Pgrcount	0.6506	1.0000									
Firmage	−0.0566	0.0105	1.0000								
Firmage_sq	−0.0455	−0.0047	0.9276	1.0000							
Coopcount	0.2535	0.2726	0.0101	0.0272	1.0000						
Coopfund	0.3923	0.3114	−0.0279	−0.0100	0.5112	1.0000					
Nw_size	0.0448	0.0670	0.2131	0.1603	0.0442	0.0147	1.0000				
Nw_density	−0.0529	−0.0832	−0.2006	−0.1450	−0.1450	−0.0145	−0.6576	1.0000			
Nw_wclust	−0.0529	−0.0835	−0.2530	−0.1901	−0.0074	−0.0153	−0.4684	0.6934	1.0000		
Nw_areach	0.0637	0.0965	0.2761	0.2062	0.0164	0.0100	0.7154	−0.7499	−0.8255	1.0000	
Inter_sw	−0.0219	−0.0414	−0.1639	−0.1275	0.0026	−0.0141	−0.0656	0.3186	0.8357	−0.4020	1.0000

Source: Author's own calculations



Year	Weighted overall clustering coefficient			Avg. overall path-length (among reachable pairs)			Small-world properties
	Real-world	Random	CC	Real-world	Random	PC	(Q)
1990	0.906	0.477	1.899	2.075	1.560	1.330	1.4279609
1991	0.743	0.263	2.825	2.268	1.820	1.246	2.267051589
1992	0.746	0.240	3.108	2.351	1.810	1.299	2.393059691
1993	0.777	0.175	4.440	2.658	2.020	1.316	3.374266366
1994	0.595	0.120	4.958	2.501	2.180	1.147	4.321937892
1995	0.793	0.105	7.552	2.553	2.300	1.110	6.803946804
1996	0.767	0.088	8.716	2.852	2.280	1.251	6.967837562
1997	0.638	0.093	6.860	3.027	2.280	1.328	5.167258118
1998	0.701	0.093	7.538	2.929	2.270	1.290	5.841731003
1999	0.791	0.104	7.606	2.735	2.160	1.266	6.006750105
2000	0.761	0.115	6.617	2.579	2.090	1.234	5.36267849
2001	0.720	0.105	6.857	2.685	2.220	1.209	5.669592977
2002	0.579	0.082	7.061	2.789	2.410	1.157	6.101452571
2003	0.499	0.059	8.458	3.040	2.560	1.188	7.12221231
2004	0.369	0.053	6.962	3.090	2.860	1.080	6.444037369
2005	0.413	0.078	5.295	3.768	2.950	1.277	4.145401219
2006	0.567	0.042	13.500	3.548	2.850	1.245	10.84413754
2007	0.452	0.039	11.590	3.786	3.140	1.206	9.612201498
2008	0.446	0.032	13.938	3.768	2.970	1.269	10.98576831
2009	0.380	0.036	10.556	3.548	2.950	1.203	8.776462483
2010	0.345	0.031	11.129	3.786	3.080	1.229	9.053729359
Mean	0.6185	0.1157		2.9684	2.4171		
Std. dev.	0.1692	0.1037		0.5386	0.4582		

Fig. 11.3 Weighted overall clustering coefficient and average overall path length

Q values are reported in the illustration below (cf. Fig. 11.3, bottom). The following structural patterns are noteworthy.[12]

Firstly, the German laser industry innovation network shows a relatively high level of clustering and rather short average path lengths overall. Secondly, over time we can observe decreasing weighted clustering coefficients and increasing average path length. This is primarily due to the fact that the German laser industry network has demonstrated a pronounced growth tendency over time. In other

[12] Note that the calculations are based on bipartite network data. This is in line with the study by Uzzi and Spiro (2005). However, the use of bipartite network data generates relatively high clustering coefficients. This should be kept in mind when interpreting the results. For an in-depth discussion on the differences between unipartite and bipartite network data, see Sect. 8.3.2. To ensure robustness of the reported results we calculated both small-world indicators based on an alternative network data decomposition assumption. Additional calculations confirm the small world character of the network (cf. Appendix 3).

words, the number of laser-related organizations that actively participate in the industry's innovation network increases over time. Thirdly, small-world measures indicate the emergence and consolidation of the network's small-world nature. More precisely, a comparison of the real-world network with a randomly generated reference network reveals that the German laser industry innovation network exhibits both higher overall clustering coefficients and longer average path lengths for each year throughout the entire observation period. The annually calculated CC ratios are clearly above 1.0 and increase over time. PC ratios do not exceed the value range between 1.0 and 1.35 and the small-world Q ratio lies significantly above 1.0 and demonstrates, like the CC ratio, a pronounced tendency towards increasing values over time.

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

11.4 Estimation Results and Empirical Findings

11.4.1 Model Specification and Estimation Strategy

As our endogenous variable – annual patent application counts – only accepts nonnegative integer values, we choose a count data model specification for the purpose of this analysis.[13] Following Ahuja (2000), Stuart (2000) and Schilling and Phelps (2007), we estimated panel data count models.[14] Basically, two estimation techniques can be distinguished: the fixed effects and random effects methods. In general, the use of fixed effects models provides some important advantages. The fixed effects estimator is unbiased as it includes dummy variables for the different intercepts and is more robust against selection bias problems than the random effects estimator (Kennedy 2003, p. 304). The problem that occurs with fixed effects models is that all time-invariant explanatory variables are thrown out because the estimation procedure fails to estimate a slope coefficient for variables that do not vary within an individual unit (Kennedy 2003, p. 304). In addition, using only within-variation leads to less efficient estimates and the model loses its explanatory power (Cameron and Trivedi 2009, p. 259). In contrast, random effects estimators make better use of the information values of patent data and generate efficient estimates with higher explanatory power. In addition, random effects estimators can generate coefficient estimates of both time-variant as well as time-invariant explanatory variables (Kennedy 2003, p. 307). The major drawback of the random effects model is that correlations between the error term and the explanatory variables generate biased estimates and thus inconsistent estimation results (Kennedy 2003, p. 306).

[13] For an in-depth discussion on the use of panel data count models, see Sect. 6.1.2.

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

We adopted the following estimation strategy to test our hypotheses. First, we implemented a 2-year time lag structure in our empirical setting. Then, we estimated panel Poisson models in order to obtain an initial idea of the relationship between cooperation counts, network positioning measures and firm-specific patenting activity. As our endogenous variables exhibited strong overdispersion, we then turned to a Negative Binomial model specification with random effects (cf. Sect. 6.2.2). This generalization of the Poisson model allows for overdispersion by including an individual, unobserved effect in the conditional mean (Schilling and Phelps 2007, p. 1119). In the next step, we estimated both fixed effects and random effects models. Usually the Standard Hausman Test (1978) is used to decide which results to interpret. In this analysis, most fixed effects and random effects estimates are consistent. In a final step, we ran consistency checks to ensure the robustness of our results by using a 1-year time lag structure.

11.4.2 Estimation Results

The presentation and discussion of our empirical findings is centered on the Negative Binomial model for panel count data reported in Table 11.3. Robustness of our findings is ensured by additional estimation results reported in Table 11.4. Results from both estimation techniques (fixed effects and random effects) are reported in the tables below.

Table 11.3 includes information on the total of four models. In addition to a baseline model (i.e. BL Model), there is one model that includes the network clustering coefficient (i.e. Model I), one model that comprises the overall average path length indicator (i.e. Model II), and one model that accounts for small-world properties of networks (i.e. Model III). We did not specify a full model that incorporates path-length, clustering and small-world indicators simultaneously because we are primarily interested in testing the relatedness between three distinct and structurally quite different network topologies and firm-level innovativeness. At the same time we face the risk of running into methodological problems when including all three variables in one estimation model. Potential methodological extensions and refinements of the empirical setting are discussed in Sect. 14.2.

The baseline model (cf. Table 11.3, BL Model) provides results for firm-level controls (i.e. firm age & firm age squared), cooperation-related controls (i.e. cooperation counts & cooperation funding) and overall network level control variables (i.e. network size & network density). Results from a random effects specification (time lag, t-2) reveal a positive and significant coefficient for cooperation counts (cf. Table 11.3). This should be viewed with great caution because the fixed effects specification fails to show a positive and significant relationship between cooperation counts and firm innovativeness. The same is true for both the fixed effects and the random effects model with a time lag t-1 (cf. Table 11.4). The situation looks fairly different for overall network control variables, especially in terms of network size. Estimation results (cf. Table 11.3, FE & RE; Table 11.4,

Table 11.3 Estimation results – clustering, reach and small-world properties; patent applications, time lag (t-2)

Variables	Estimation results							
	Baseline model		Model (I)		Model (II)		Model (III)	
	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects
firmage	.01022012	.01024719	.02827257	.02714577	.02608898	.02586384	.02002634	.01947403
firmage_sq	−.00073156	−.00052259	−.00118264	−.00095319	−.00111437	−.00091046	−.00098806	−.00076586
coopcnt	.05714882	.09544829**	.05419512	.09080471 **	.05701504	.09396949 **	.05424240	.09156302 **
coopfund	.00000789	.00001272	.00000904	.00001399	.00000728	.00001199	.00000962	.00001464
nw_size	−3.8560791 ***	−4.0591897 ***	−4.2459032***	−4.4569542 ***	−3.0717744***	−3.1756426 ***	−4.8507463 ***	−5.0871176***
nw_density	−3.9025440***	−3.7342787 ***	−5.4885633***	−5.4673971 ***	−4.5450498 ***	−4.522689 ***	−4.8823746***	−4.7819077 ***
nw_wclust			1.1088603***	1.1611018 ***				
nw_areach					−.28236740 *	−.31326415 *		
inter_sw							.44901422***	.46640724***
_cons	1.4738306***	1.4692506***	1.0165371 **	1.0050505 **	2.0200482 ***	2.0895598 ***	1.100405 **	1.0870732 **
ln_r_cons		−.13420195		−.13538645		−0.1364538		−0.1329913
ln_s_cons		−.97386831 ***		−.97281046 ***		−.96994511 ***		−.97476673 ***
chi^2	24.34534	30.054709	29.330156	35.970943	26.690456	33.130402	30.034183	36.51918
ll	−1,470.5418	−2,093.1967	−1,467.0863	−2,089.2416	−1,469.0602	−2,091.2694	−1,466.9632	−2,089.2587
aic	2,955.0837	4,204.3934	2,950.1725	4,198.4833	2,954.1204	4,202.5388	2,949.9263	4,198.5174
bic	2,991.3389	4,255.573	2,991.607	4,255.3495	2,995.5549	4,259.405	2,991.3608	4,255.3836
N	1,312	2,179	1,312	2,179	1,312	2,179	1,312	2,179

Legend: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Source: Author’s own calculations

Table 11.4 Robustness check – clustering, reach and small-world properties; patent applications, time lag (t-1)

Variables	Estimation results							
	Baseline model		Model (I)		Model (II)		Model (III)	
	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects
firmage	.00994378	.00829882	.03733312 *	.03220746	.00423757	.00460507	.03259915	.02808188
firmage_sq	−.00053489	−.00034804	−.00105358	−.00081466	−.00041663	−.00026863	−.00089849	−.0006686
coopcnt	−.01811569	.01934418	−.01818331	.01694328	−.01846864	.01938771	−.01811078	.01728223
coopfund	.000009877	.00001396	.00001412	.00001792	.00001004	.0000141	.000017	.00002073
nw_size	−2.9475613***	−3.1684482 ***	−3.3421082***	−3.5298766***	−3.2089678***	−3.3685447***	−4.2628185***	−4.468513***
nw_density	−2.8696261***	−2.88051 ***	−4.8546***	−5.0429677 ***	−2.6009588***	−2.6603955***	−4.1461309***	−4.3348133***
nw_wclust			1.5707897***	1.5695806***				
nw_areach					.11411269	.08427262		
inter_sw							.81154585***	.81613743***
_cons	1.0926888***	1.1293445***	.35436373	.4183161	.85300282 *	.94940078 *	.18453871	.2419253
ln_r_cons		−.09498949		−.09417647		−0.0937929		−.08599318
ln_s_cons		−.91609186***		−.91730297 ***		−.91830232***		−.92419009***
chi^2	15.736744	17.259548	30.991406	33.142983	16.399322	17.688214	44.277213	46.67405
ll	−1,674.1401	−2,339.2755	−1,665.8197	−2,330.532	−1,673.8832	−2,339.1265	−1,659.2927	−2,323.8767
aic	3,362.2801	4,696.5511	3,347.6395	4,681.064	3,363.7664	4,698.2529	3,334.5855	4,667.7534
bic	3,399.6523	4,748.645	3,390.3506	4,738.9461	3,406.4775	4,756.135	3,377.2966	4,725.6355
N	1,539	2,412	1,539	2,412	1,539	2,412	1,539	2,412

Legend: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Source: Author's own calculations

FE & RE) provide empirical evidence for a negative relatedness between network size and firm innovativeness.

To start with, the estimation results are robust for both time lags (Table 11.3, time lag t-2; Table 11.4, time lag t-1) and for both estimation techniques (i.e. random effects & fixed effects models). Coefficient estimates for network clustering are positive and highly significant at the 0.01 level (cf. Table 11.3, Model I; Table 11.4, Model I). Estimation results for average path length are negative and show a minor significance at the 0.1 level (cf. Table 11.3, Model II) and no significance in the robustness check (cf. Table 11.4, Model II). Finally, coefficient estimates for the small-world indicator are positive, consistent over all specifications and highly significant at the 0.01 level (cf. Table 11.3, Model III; Table 11.4, Model III). In summary, our estimation results provide strong empirical support for Hypotheses H2 & H3 but only minor support for Hypothesis H1.

11.5 Discussion and Implications

In this section we were primarily interested in testing the relatedness between three distinct, structurally different, network topologies and firm-level innovativeness.

Our results for the overall average path lengths (Hypothesis H1) are as expected and in line with previous empirical findings (Schilling and Phelps 2007; Fleming et al. 2007). Both studies report a negative[15] and, in most cases, highly significant correlation between the average path length at the overall network level and firm innovativeness. Schilling and Phelps (2007) pay little attention to these individual effects. Fleming et al. (2007, p. 949) conclude: "Shorter path length [. . .] correlates with an increase in subsequent patenting." However, in our setting the significance-level for this coefficient is fairly low and a robustness check did not support the initially identified effect.

Our results for the clustering coefficient are in line with our theoretical expectations (Hypothesis H2), however, it is interesting to note that the findings for the individual clustering of the German laser industry innovation network are not in line with previous empirical findings in several respects. Schilling and Phelps (2007, p. 1122) report in four out of six empirical settings a negative but insignificant effect. Similarly, the results of Fleming and colleagues (2007, p. 948) reveal negative and significant coefficient estimates. This is an issue that clearly calls for clarification and further research.

Last but not least, we take a look at a network's small-world properties. Firstly, the descriptive analysis shows that the German laser industry network clearly fulfills the small-world criteria according to Watts and Strogatz (1998). Moreover, results are suggestive of an increasing solidification of small-world properties over

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

time. Secondly, in our estimation, results clearly support Hypothesis H3 and provide empirical evidence for a positive relatedness between a network's small-world nature and a firm's subsequent innovativeness. This is in sharp contrast to the findings of Fleming et al. (2007, p. 949); the authors conclude: "The small world effect is not observed in our data." However, our results are in line with previous findings by Schilling and Phelps (2007) who summarize their findings as follows: "[. . .] networks that have both the high information transmission capacity enabled by clustering, and the high quantity and diversity of information provided by reach, should facilitate greater innovation by firms that are members of the network" (Schilling and Phelps 2007, p. 1124).

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

The limitations of this analysis are the subject of a discussion in Sect. 13.2. In addition, we outline some fruitful avenues for further research into large-scale networks in Sect. 14.2.

References

Ahuja G (2000) Collaboration networks, structural hole, and innovation: a longitudinal study. Adm Sci Q 45(3):425–455

Baum JA, Shipilov AW, Rowley TJ (2003) Where do small worlds come from? Ind Corp Chang 12 (4):697–725

Borgatti SP, Everett MG, Freeman LC (2002) Ucinet for windows: software for social network analysis. Analytic Technologies, Harvard

Borgatti SP, Everett MG, Johnson JC (2013) Analyzing social networks. Sage, London

Buenstorf G (2007) Evolution on the shoulders of giants: entrepreneurship and firm survival in the German laser industry. Rev Ind Organ 30(3):179–202

Burt RS (1992) Structural holes: the social structure of competition. Harvard University Press, Cambridge

Cameron CA, Trivedi PK (2009) Microeconometrics using Stata. Stata Press, College Station

Cassi L, Zirulia L (2008) The opportunity cost of social relations: on the effectiveness of small worlds. J Evol Econ 18(1):77–101

Cohen WM, Levinthal DA (1989) Innovation and learning: the two faces of R&D. Econ J 99 (397):569–596

Cohen WM, Levinthal DA (1990) Absorptive capacity: a new perspective on learning and innovation. Adm Sci Q 35(3):128–152

Corrado R, Zollo M (2006) Small worlds evolving: governance reforms, privatizations, and ownership networks in Italy. Ind Corp Chang 15(2):319–352

Fleming L, King C, Juda AI (2007) Small worlds and regional innovation. Organ Sci 18(6):938–954
Gulati R (1998) Alliances and networks. Strateg Manag J 19(4):293–317
Hausman JA (1978) Specification tests in econometrics. Econometrica 46(6):1251–1271
Hoffmann WH (2005) How to manage a portfolio of alliances. Long Range Plan 38(2):121–143
Jaffe AB (1989) Real effects of academic research. Am Econ Rev 79(5):957–970
Jaffe AB, Trajtenberg M, Henderson R (1993) Geographic localization of knowledge spillovers as evidenced by patent citations. Q J Econ 108(3):577–598
Katkalo VS, Pitelis CN, Teece DJ (2010) Introduction: on the nature and scope of the dynamic capabilities. Ind Corp Chang 19(4):1175–1186
Kennedy P (2003) A guide to econometrics. Blackwell, Oxford
Lane PJ, Lubatkin MH (1998) Relative absorptive capacity and interorganizational learning. Strateg Manag J 19(5):461–477
Lane PJ, Koka BR, Pathak S (2006) The reification of absorptive capacity: a critical review and rejuvenation of the construct. Acad Manag Rev 31(4):833–863
Milgram S (1967) The small-world problem. Psychol Today 1(1):60–67
Newman ME (2010) Networks – an introduction. Oxford University Press, New York
Newman ME, Strogatz S, Watts D (2001) Random graphs with arbitrary degree distributions and their applications. Phys Rev E 64:1–17
Schilling MA, Phelps CC (2007) Interfirm collaboration networks: the impact of large-scale network structure on firm innovation. Manag Sci 53(7):1113–1126
Stata (2007) Stata statistical software: release 10. StataCorp LP, College Station
Stuart TE (2000) Interorganizational alliances and the performance of firms: a study of growth and innovational rates in a high-technology industry. Strateg Manag J 21(8):791–811
Teece DJ, Pisano GP, Shuen A (1997) Dynamic capabilities and strategic management. Strateg Manag J 18(7):509–533
Uzzi B, Spiro J (2005) Collaboration and creativity: the small world problem. Am J Sociol 111 (2):447–504
Uzzi B, Amaral LA, Reed-Tsochas F (2007) Small-world networks and management science research: a review. Eur Manag Rev 4(2):77–91
Van Den Bosch FA, Volberda HW, De Boer M (1999) Coevolution of firm absorptive capacity and knowledge environment: organizational forms and combinative capabilities. Organ Sci 10 (5):551–568
Wasserman S, Faust K (1994) Social network analysis: methods and applications. Cambridge University Press, Cambridge
Watts DJ, Strogatz SH (1998) Collective dynamics of ‘small-world’ networks. Nature 393 (6684):440–442
White S (2005) Cooperation costs, governance choice and alliance evolution. J Manag Stud 42 (7):1383–1413
Winter S (2000) The satisficing principle in capability learning. Strateg Manag J 21:981–996
Zahra SA, George G (2002) Absorptive capacity: a review, reconceptualization, and extension. Acad Manag Rev 27(2):185–203