

The Evolution of Innovation Networks:
The Case of the German Automotive Industry¹

Tobias Buchmann & Andreas Pyka

University of Hohenheim, Economics Institute, Innovation Economics (520 i)

Wollgrasweg 23; D-70593 Stuttgart

tobias.buchmann@uni-hohenheim.de; a.pyka@uni-hohenheim.de

November 2012

Abstract

In this paper we outline a conceptual framework for depicting network evolution patterns of interfirm innovation networks and analysing the dynamic evolution of an R&D network in the German automotive industry. We test the drivers of evolutionary change processes of a network that is based on subsidised R&D projects in the 10 years period between 1998 and 2007. For this purpose a stochastic actor-based model is applied to estimate the impact of various network change drivers. Our hypotheses for the description of network dynamics are embedded in the knowledge-based approach of the firm and evolutionary economics thinking. We show that structural positions of firms as well as actor covariates and dyadic covariates describing characteristics of the firms' knowledge bases are influential determinants of network development.

¹ The research for this paper is an outcome of the project "innovation networks for regional development" (INSPIRED) which is financed jointly by DFG and FWF. We also thank the Friedrich-Ebert-Stiftung (FES) which provided Tobias Buchmann with a PhD scholarship.

1. Introduction

Innovation networks are generally considered as a means to share increasing R&D costs, gain access to scarce resources and - even more importantly - to manage complex innovation processes, cope with technological uncertainty and create learning opportunities (Pyka 2002, Buchmann & Pyka 2012a). The innovation process of a firm is fuelled by two distinct sources: First, scientists and engineers explore new combinations in the firms' R&D laboratories and create new knowledge to be exploited. Second, knowledge and new ideas can be externally accessed by linking to other agents (firms, universities, government labs, customers). In this second case, internal units have to process the absorbed knowledge (Cohen & Levinthal 1990). This means that innovation is the result from internal expertise as well as external stimuli. In particular, in knowledge intensive industries firms cannot rely on the internal generation of new knowledge and the access to external knowledge becomes of paramount importance. Or as Tsang expressed it: "Tapping external sources of know-how becomes a must" (Tsang 2000, p. 225).

Each network is characterised by its specific structure which is the result of the emergence and dissolution of ties between actors (firms) over time. The ties serve as channels of knowledge flows among the actors and allow for knowledge diffusion and mutual learning in the network. This process of network tie formation and dissolution, which is in the focus of this paper, constitutes the evolution of the network and is a function of the actors' characteristics and their socially driven behaviours and interaction patterns (Snijders 2001, Scott 1996, Huggins 1997). To construct the networks we return to the basic network idea: The elementary building blocks are nodes (firms) and ties, reflecting R&D agreements. The ties represent interaction patterns that may serve as channels and conduits of implicit and explicit knowledge flows. On a more aggregate level these bi- and multilateral ties span a complex network structure which is embedded in the wider economic system. In this view, an innovation network can be described as an integral part of the regional, national or sectoral innovation system and manifests channels for knowledge flows among the involved actors.

In innovation networks new technological opportunities are created via technological complementarities, recombination and synergies bringing together different technological and economic competencies (Fleming & Sorenson 2001). Knowledge is considered no longer as a pure public good only, but as local, tacit, firm specific and complex. Technological spillovers are no longer freely available (Pyka, Gilbert & Ahrweiler 2009) and knowledge is no longer regarded "in the air" (Marshall 1920) as in the standard models of growth, but it has to be acquired actively by own R&D and by participating in innovation networks. Geroski (1995, p. 85) emphasises this point: "In particular, what often appears to be an involuntary flow of knowledge between firms may be nothing more than a pair of draws from a narrow but common pool shared by a group of agents within a common set of problems." To summarize: Technological spillovers are hardly conceivable without being embedded in innovation networks.

A review of recent theoretical as well as empirical studies in the broad and interdisciplinary field of network research reveals that dynamic aspects of network evolution processes increasingly attract scientific attention. Scholars of various disciplines like physics (Dorogovtsev, Mendes & Samukhin 2000, Barabasi & Albert 2002, Bianconi & Barabási 2001), biology (Krapivsky, Redner & Leyvraz 2000, Vázquez 2003), and sociology (Stokman & Doreian 1997, Steglich, Snijders & West 2006) start to analyse drivers and mechanisms of network growth and change. Also some first contributions in economics address the dynamics of innovation networks (Jackson & Watts 2002, Cowan & Jonard 2003, Ter & Wal 2009, Balland, De Vaan & Boschma 2012, Balland 2012, Gilbert, Ahrweiler & Pyka 2007). However, in particular the empirical understanding of innovation network evolution is still preliminary. Further research is needed to understand network evolution and industry specificities shaping innovation network evolution. Most studies in the field of network research are, however, of a static nature and apply descriptive analysis techniques (Baum, Shipilov & Rowley 2003) like social network analysis (SNA). These approaches are mostly related to snapshots of network data at a certain point in time. Such studies provide valuable insights into the network structures, the roles of actors and advantageous network positions and roles. However, a key characteristic of networks is their evolution with continuously emerging and dissolving ties between the actors (Ter Wal & Boschma 2009). A key question therefore has to be: What are the mechanisms and forces that determine the evolution of networks over time? Actor-based models for network dynamics shed more light on this dynamic process and are, thus, a useful instrument to disentangle the driving factors (Snijders 2001). In this paper we present results from a study of evolutionary change patterns of an interorganisational innovation network in the German automotive industry. We consider actor characteristics (on the individual and dyad level) and social factors to be relevant drivers for network evolution processes. We test a number of factors which influence the propensity to start and to terminate collaboration or to keep the status quo. In particular, we suggest the following factors to be relevant drivers: transitivity, absorptive capacity, technological proximity, geographical proximity, experience with cooperation and the level of knowledge-base modularity.

2. Innovation networks in the German automotive industry

Intensified competition in the global automotive industry and particularly the catching-up of Asian firms forced German producers to significantly improve their cost structure. To escape this pressure, new strategies were developed and implemented. Innovations are identified as the key to success because they allow firms to escape a destructive price competition and to create unique selling propositions. With this an intensified innovation competition emerged as a race for innovation, shortened product life cycles as well as rising safety and quality requirements (Staiger & Gleich 2006).

The basic structure of the automotive industry is characterized by few Original Equipment Manufacturers (OEMs) and numerous suppliers that can be components manufactures (often SMEs) or big multinational enterprises which assemble entire systems that are just in time supplied at the assembly lines of the large

car producers. During the last decade more and more value creation, and with it relevant know-how, has been shifted from the OEMs to specialized suppliers also including R&D. In addition, increased complexity is another challenging topic in the automotive industry. Electronic systems linking various units of a car need to communicate with a common language and be able to interact without interference in a perfect reliable manner. Taken together, this means that the different parts have to be developed within a comprehensive framework resulting in integrated solutions. Collaboration in common research projects can be seen as the answer to this challenge. Staiger and Gleich (2006) found in interviews evidence for the strategic collaboration approach. Most firms even participate in more than just one network. Moreover, networks are seen as a strategic instrument in the long run and thus more than cooperation for just a single project is envisaged.

Due to the network character of the entire production process, the costs as well as the quality of a car can be directly linked to the productivity of the network. Hence, for the analysis and explanation of success and failure of national and regional innovation systems, the relational view of the networks is a valuable approach. The decisive advantage of the network compared to a single firm is that the network incorporates a greater variety of knowledge which offers numerous possibilities for recombination (Dyer 1996, Dyer & Nobeoka 2000).

In the following section we outline how innovation networks can be accessed from an evolutionary economics point of view and which factors are considered to be responsible for the observed dynamics of networks.

3. Network dynamics and determinants of network evolution

Innovation networks are not static but continuously evolve with ties emerging and disappearing. Innovation networks consist of at least two nodes ('organisations') and linkages between the nodes ('collaborative agreements'). Formation of new cooperations as well as termination of existing cooperations influence the growth, fragmentation and therefore the internal structure of the innovation network. From an aggregate network perspective this leads to constantly changing structures. From this follows that in order to model innovation networks and their development an inherently dynamic framework is required.

Evolutionary models are based on the assumption that the object of analysis is continuously changing. Compared to traditional static or comparative-static economic models, evolutionary models capture the causes, underlying mechanisms and consequences of change processes. Economic actors interact on imperfect markets and innovate confronted with strong uncertainty. Innovation problems are ill-defined from the subject and object side (Heiner 1983). These imperfect conditions - uncertainty and bounded rationality - are the major ingredients of an *experimentally organized economy* (Eliasson, G. 1991).

Due to the uncertainty and non-linearities, guideposts for future development remain opaque and vague (Araujo & Harrison 2002). History dependencies and future openness determine decisions and processes which are impossible to be predicted (Arrow 1973). Furthermore, evolutionary change is context specific: the object of analysis cannot be analyzed without taking into account its co-evolving broader environment. The environment provides opportunities and constrains influencing the driving forces of evolutionary change. Simultaneously, the environment is changed by the agents' actions. Although, economic development is largely driven by endogenous processes of self-transformation (Witt 2006), additionally exogenous shocks influence change and might be responsible for surprises.

The application of evolutionary concepts in a network context happened only recently. For instance, Glückler (2007) analyses how tie-selection constitutes evolutionary processes in networks. He argues that network tie selection processes cause retention and variation within network structures. Hite (2008) presents an evolutionary multi-dimensional model of network change that explicitly considers micro-level network change processes. Kudic, Pyka & Günther (2012) analyse network change processes in the German laser industry considering relational, contextual and organizational determinants. With our paper we want to contribute to this literature of evolutionary network modelling. For this purpose, we apply a new methodology which is explicitly focusing on empirical evolutionary network modelling to a data set of a mature however knowledge-intensive industry, namely German car manufacturing.

Our core question deals with the determinants of the emergence and dissolution of a tie between two actors (i, j). From the firm's perspective this question addresses the guidelines that determine the decision to cooperate and to select a cooperation partner. Collaboration serves as a means to cope with technological uncertainties. At the same time it creates a new facet of uncertainty which refers to the decision and choice of becoming involved in joint projects with appropriate partners. Gulati and Gargiulo (1999, p. 1440) stress thus: "while exogenous factors may suffice to determine whether an organization should enter alliances, they may not provide enough cues to decide with whom to build those ties".

In our model we consider four factors to be relevant for relational tie changes:

- (i) the structural position of actors in a network, e.g. in the simplest case when friends of friends become friends and close cliques are formed;
- (ii) the characteristics of actors, e.g. the size of their knowledge-base (actor covariates);
- (iii) and attributes characterizing pairs of actors (dyadic covariates), e.g. their geographical proximities;
- (iv) finally, a residual component which is to be considered to capture other (unknown) influences.

We apply the 'stochastic actor-based model for network dynamics' (Snijders 1996, Snijders 2001) suited for statistical inference like analysis based on longitudinal network data. This type of models has the advantage of capturing network dynamics driven by a combination of different factors. The model also allows for testing hypothesis about possible driving factors and for estimating the parameters while controlling for

other factors. Therefore, stochastic actor-based models for network dynamics enable us to analyze the process of network evolution and to disentangle different driving factors in this complex process. Contrariwise, standard regression models can hardly be applied for network data since the independence of observations is explicitly excluded in the network case. The network properties of one actor are not independent of the other actors' network attributes.

In the following paragraphs of this section we introduce the variables determining the evolution of the analyzed innovation network of the German automotive industry. In section 5 the stochastic actor-based model for network dynamics is introduced.

3.1. Transitivity

Transitivity is a structural effect which refers to the positioning of actors in a network. It describes a tendency for partners (j,k) of an actor (i) to start a collaboration among them which results in the formation of closed triangles. The number of these triangles is supposed to exceed the number of triadic structures in random networks (e.g. Davis 1970, Holland & Leinhardt 1971). The formation of triads is interpreted as an indicator for the formation of interconnected cliques (Skvoretz & Willer 1991). As firms are *bounded rational*, for instance concerning their knowledge about potential partners, they face the risk of opportunistic behaviour (Gulati 1995a). Whenever a firm is looking for a collaboration partner, existing links are valuable and trustworthy sources of information reducing the risk of opportunistic behaviour.

For instance, if alter j collaborates with alter k and ego i collaborates with alter k , alter k is a reliable source of information about the trustworthiness and reputation of alter j . The formation of triads creates social spaces that prevent actors from opportunistic behaviour, allows for the formation of trust and supports the exchange of tacit knowledge (Uzzi 1997). From this follows that firms sharing a common cooperation partner will more likely collaborate compared to other actors which do not have a partner in common. Groups of strongly interconnected actors – with a large number of redundant ties – generally show a high level of mutual trust (Buskens & Raub 2002, Walker, Kogut & Shan 1997). Reagans and McEvily (2003) show that strong social cohesion around a relationship reinforces the willingness and motivation to invest time, energy and effort in sharing knowledge with others. Trust in dense parts of the network facilitates intensive exchange of knowledge (Zaheer & Bell 2005). In our study we expect firms which already have a cooperation partner in common, to have a higher propensity to form a cooperation among each other (H1). Transitivity is measured by the number of transitive triplets an actor is involved in (Formula 1)

$$T_i = \sum_{j < k} x_{ij} x_{ik} x_{jk} \quad (1)$$

3.2. Geographical distance

Despite the wide diffusion of communication technologies which shrinks perceived distances, geographical distances still play a role when it comes to the propensity to cooperate and to select a cooperation partner (Leamer & Storper 2001). In various industries we find tendencies for an uneven distribution of firms in

space. This holds in particular for high-tech industries (Audretsch & Feldman 1996). In figure 1 the clustered geographical dispersion of the German automotive industry is shown.

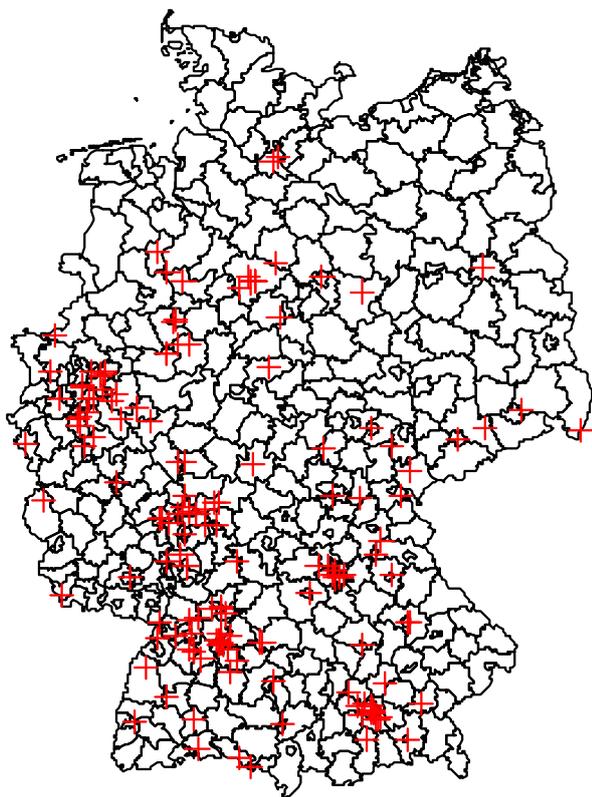


Figure 1: Geographical distribution of automotive firms in Germany

The geographical clustering of firms influence interaction patterns (e.g. Weterings & Boschma 2009, Hoekman, Frenken & Van Oort 2009). Shorter distances provide more opportunities to meet which helps to develop trust as a prerequisite for the willingness to exchange knowledge, in particular tacit knowledge (Howells 2002). Face-to-face interaction facilitates learning processes and interactive learning. According to Glückler (2007) there are two channels by which distance exerts influence: First, short distances positively affect the formation of interfirm networks. Note, however, that it is not the geographical distance as such which influences network formation. Instead, the possibilities and preferences of agents to communicate matter (Storper & Venables 2004). Also, the infrastructure and possibilities to travel faster are to be taken into account (Marquis 2003). Thus, there is a potential relation between geographical distances and the possibilities and propensities to form fruitful agreements of interaction which, however, is by far not compulsory. Second, locations may play a role by providing opportunities to access specific and locally bounded resources (e.g. specialized workforce) and regional unequal distributed opportunities for economic development (Sayer 1991, Bathelt & Glückler 2005).

It follows that firms which are located in relative spatial proximity have a higher propensity to cooperate compared to other pairs (H2). In order to form a pairwise distance matrix, geographical distances between

all pairs of actors ($dist_{ij}$) have been retrieved by a specific search routine from the web navigation service Google Maps and logarithmized with the natural logarithm (Formula 2).

$$w^2_{geodis\ ij} = \ln(dist_{ij}) \quad (2)$$

3.3. Absorptive capacity

Absorptive capacity reflects the ability to evaluate, assimilate and exploit knowledge from external sources (Cohen & Levinthal 1990). If a firm has already accumulated knowledge in the same or related fields it is easier for it to recognize, evaluate, assimilate and apply external knowledge. Thus “learning is cumulative, and learning performance is greatest when the object of learning is related to what is already known” (Cohen & Levinthal 1990, p. 131). For our case of testing the drivers of network dynamics two considerations are relevant: first, firms do have advantages in learning new things in fields which are close to their knowledge-base, while it is rather difficult in fields which are completely different. Second, the characteristics of an actor’s knowledge-base changes only incrementally due to the fact that learning takes only place in fields that are related and somewhat similar to already explored fields (Cohen & Levinthal 1990). Zahra and George (2002) stress that dynamic absorptive capacities allow firms to build up the required knowledge to develop other organizational capabilities and to broaden their knowledge-base in time. Consequently, we expect firms which have higher levels of absorptive capacity to also have a higher propensity to collaborate as they face more opportunities to benefit from external knowledge (H3). The absorptive capacity ($v_{absorpcai(t)}$) is approximated by taking the natural logarithm of the number of patents ($NbPatents_{i(t:t-5)}$) a firm applied for in the five years prior to the observation point. Accordingly absorptive capacities of actors increase with the accumulated patenting activity with diminishing rates (Formula 3).

$$v_{absorpcai(t)} = \ln(NbPatents_{i(t:t-5)}) \quad (3)$$

3.4. Technological proximity

Besides geographical proximity also technological proximity among actors matters for cooperation. Here we refer to the notion of cooperation partner similarity (McPherson, Smith-Lovin & Cook 2001) in a network context. According to this concept, similar nodes have a higher probability to form a tie. However, similarity can refer to various dimensions. Partner could be similar with regard to technological, knowledge-related, organisational or financial characteristics or comparable in terms of reputation and status. For instance, Gulati (1995b) and Rothaermel and Boeker (2008) demonstrate that status similarity increases the rate of tie formations in interorganizational networks. As we focus on innovation networks the similarity of the technological knowledge-base is of outmost importance. The notion of technological proximity refers to “shared technological experiences and knowledge-bases” (Knoben & Oerlemans 2006). Thus, it does not express the similarity of technological equipment, processes etc., but reflects the similarity of the

² For all dyadic covariates $S_{idyadic} = \sum_j ij(w_{ij} - \bar{w})$

underlying knowledge-bases. This understanding is somewhat similar to the concept of cognitive proximity as described by Boschma (2005) even though cognitive proximity is more comprehensive.

Knowledge-base similarity facilitates learning. In addition, it sharpens the senses for the perception of emerging technological trends (Zeller 2004). From Cohen and Levinthal (1990) it can be inferred that effective learning of an organization necessitates a certain degree of similar problem perception and assimilation of new knowledge but at the same time some degree of diversity is useful to develop new ideas based on the acquired knowledge. This idea transferred to the dyadic level suggests hypothesis H4a that cooperating firms must, for effective learning, have similar knowledge-bases which reflect a common understanding of problems and increases the capacity to absorb each other's knowledge (Colombo 2003). On the other hand, invention and innovation can be understood as a new combination of existing knowledge which would require the combination of more different knowledge-bases which is our hypothesis H4b. Not surprisingly, Nooteboom et al. (2007) find a U-shaped curve for an optimal cognitive distance which is, as mentioned earlier, conceptually close to the technological distance.

For the calculation of distances of firms in technological space, we apply the Euclidean distance (E) measure based on a firm's patent portfolio which encompasses all EPO patents filed not more than 5 year prior to the observation point. In a first step, a vector is calculated which puts each firm in an N-dimensional vector space. The number of dimensions N results from the number of 3-digit IPC classes in which all firms filed patents (priority filling). The firm vector p is given by the relative share of patents a firm has in the N patent classes. For instance, if N is only two (e.g. B60 and B29) and a firm has 40% of its patents in class B60 and 60% in B29 the vector is $(p^{B60}, p^{B29}) = (0,4; 0,6)$. In a second step, differences between vectors representing distances in the technology space are calculated. Thus the technological distance ($w_{techdisij}$) between firms i and j is calculated as formula (4) suggests:

$$w_{techdisij} = \sqrt{\sum_{c=1}^N (p_i^c - p_j^c)^2} \quad (4)$$

3.5. Experience with cooperation

A further factor we examine is the firm's experience with cooperation. We assume for Hypothesis H5 that a large record of collaborative activities signals a larger attractiveness for further collaboration. This reflects that from outside it is rather difficult to scan a firm's valuable resources, in particular the knowledge. Thus, a firm which has been often involved in cooperative projects signals to be a valuable partner with a good reputation and established routines of collaboration. Cooperation capabilities are specific and not transferable resources which can enhance a firm's ability to identify partner, initiate collaborations and manage successfully the partnerships (e.g. Makadok 2001). Experienced firms have implemented collaboration management functions whose task is to coordinate the portfolio of different types of alliances (Kale, Dyer & Singh 2002). Developing experience is time consuming because firms are forced to adapt internal routines (Powell, Koput & Smith-Doerr 1996). However, it is worth the effort as it not only enables

a firm to become effectively embedded in a formal innovation network but also paves the ground for likewise important informal collaboration (Pyka 2000). In formula (5) we measure the experience of a firm ($v_{expi(t)}$) with the frequency of participation in the subsidised R&D projects with partners ($NbR\&D_{projectsi(t:1998)}$) from within or outside the automotive sample in the years 1998 to 2007.

$$v_{expi(t)} = NbR\&D_{projectsi(t:1998)} \quad (5)$$

3.6. Knowledge-base modularity

Finally, modularity constitutes a basic evolutionary principle (Pyka 2002). It has been mostly studied with respect to product architecture and organizational structures (see for instance Sanchez & Mahoney 1996, Baldwin & Clark 2000, Schilling 2000, Ethiraj & Levinthal 2004). Modularity effects concerning the knowledge structure, however, so far have been of minor interest. Some studies identify a relation between the structure of the organizational knowledge-base and innovation related outcomes. Ahuja and Katila (2001), for instance, show that the size of the knowledge base is positively correlated with innovative productivity. Lane and Lubatkin (1998) find that the degree to which two knowledge-bases overlap influences positively the ability of mutual learning in cooperation.

With respect to the modularity of knowledge-bases, we suggest that not only the size or the relatedness matter for the propensity to cooperate but also that the decomposability of the knowledge-bases into modular knowledge substructures. The feature of modularity of a firm's knowledge-base is approximated by its degree of clustering and decomposability. The core argument is that firms not only try to find a partner from which they can learn or which has a similar technological understanding, but they attempt to link technologies. This combination of technologies is way easier if the technologies have a modular structure. A decomposable knowledge-base enables researchers to conduct recombinant search processes without getting trapped in complexity and endless combinatorial possibilities (Yayavaram & Ahuja 2008). The recombinatorial possibilities become rapidly very large even with rather modest sized knowledge-bases. Firms that search for an appropriate cooperation partner to combine elements of their own knowledge-base with elements or a partner's knowledge-base are confronted with a high level of complexity, an overload of possibilities and uncertainty at the same time. Thus, modularity reduces time and costly search process as compatible technologies can be identified more easily. From these considerations we propose our hypothesis H6: the propensity of two firms to cooperate rises with the possibility to structure their knowledge-base in a modular way.

To analyze the decomposability of a firm's knowledge-base we consider it as a network of knowledge elements (IPC classes) that are linked by patents (affiliation or co-occurrence network). We further assume that a link emerges between technology classes once they are mentioned on the same patent (see Saviotti 2009 and Yayavaram & Ahuja 2008 for details). Yayavaram (2008, p. 334) states that "the set of couplings or ties together with the strength of the ties constitute the structure of a firm's knowledge base." The

connection of knowledge elements is not only dichotomous but varies in its intensity. For instance, two knowledge elements (IPC classes) A and B may appear ten times together on patents of a firm while the elements A and C may only appear together once. Consequently, for our network representing the knowledge-base of firms we use the frequency of co-occurrences as weights for the ties. The degree of decomposability is reflected by a continuum of structures. From a non-modular to a highly modular knowledge-base the links between knowledge elements become more equally distributed (Figure 2).

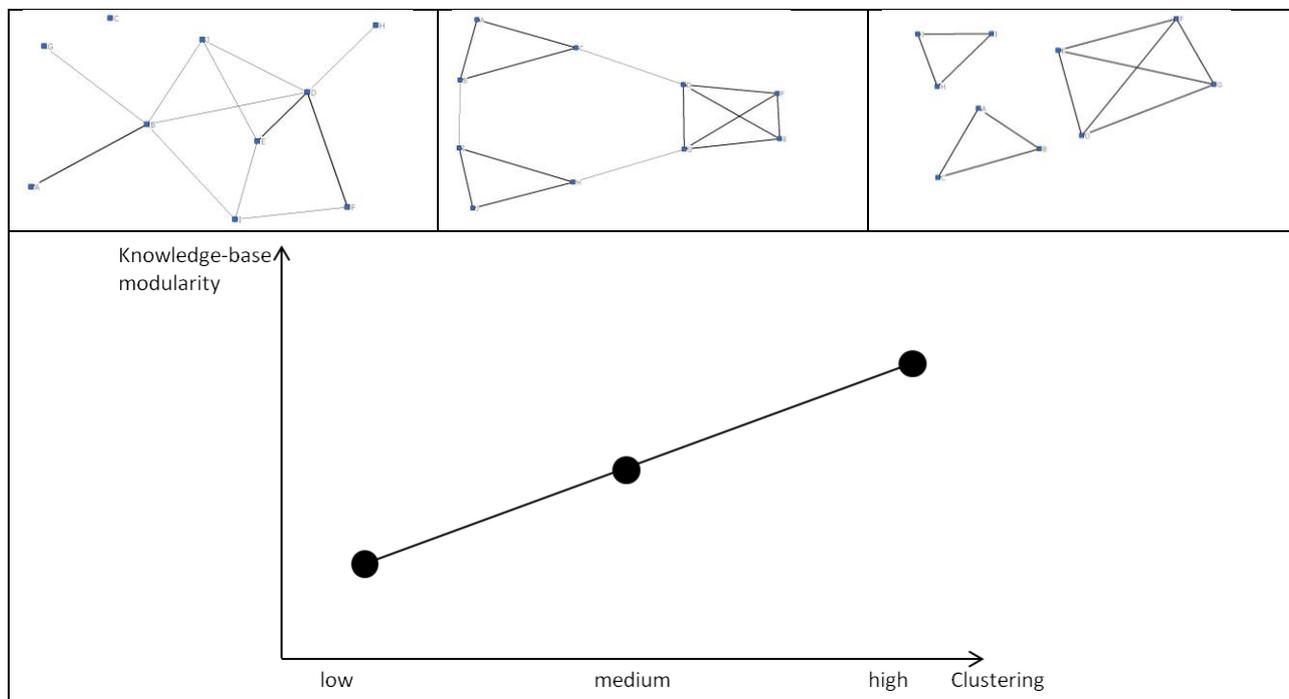


Figure 2: Relation between modularity and clustering

A high modular knowledge-base is characterized by some knowledge elements forming a dense cluster and different clusters being independent (Figure 2 top right). Nearly decomposable structures (Simon 1962) show some elements forming groups through dense links and some links between these clustered knowledge elements (Figure 2 top middle). Baldwin & Clark (2000), Schilling (2000) and Weick (1976) suggest that nearly decomposable structures benefit from a high potential for recombination, persistence and adaptability. Yayavaram and Ahuja (2008) and March (1991) highlight that nearly decomposability allows for a balanced search between depth and breadth. Finally, a non decomposable pattern does not show identifiable clusters but the links seem to be arbitrarily distributed (Figure 2 top left).

The coupling of knowledge elements is caused by three distinct motives:

- (i) there is a natural interdependence between some knowledge elements which mutually influence each other;
- (ii) search routines of firms may be directed to the coupling of certain knowledge elements while other elements are used more independently;

(iii) finally, innovation processes are often recombinant, i.e. coupling different so far unrelated knowledge elements.

As a measure for the level of modularity of a knowledge-base we calculate a slightly modified clustering coefficient. The first step to calculate the modularity of the knowledge-bases is to construct a knowledge network structure. For this purpose, we take IPC sub-classes (4-digit level) as nodes and add a tie between nodes whenever the IPC sub-classes co-occurred in a patent. Doing this, we reconstruct the knowledge network from patents for each of the analyzed 153 firms in two time windows encompassing five years (1998-2002; 2002-2006). By neglecting the tie strengths (dichotomization of the adjacency matrix), we then calculate the clustering coefficient (cc) for each node of a firm's knowledge-base network.

The clustering coefficient for node (IPC sub-class) i with k_i ties (CC_i) is defined in formula 6:

$$CC_i = \frac{n_i}{\frac{k_i * (k_i - 1)}{2}} \quad (6)$$

The calculation includes n_i , the number of ties between the k_i neighbours of node i . The denominator represents the maximum number of ties which are possible between the k_i neighbours of node i .

In order to weight the IPC sub-classes which appear more often in the patent portfolio we calculate in (7) the share (RSC_i) of an IPC sub-class (C_i) relative to all IPC sub-classes in the portfolio such as:

$$RSC_i = \frac{C_i}{\sum C_i} \quad (7)$$

In a final step, the clustering indicator (CI_j) for each firm's (j) knowledge base is calculated in (8) by multiplying the clustering coefficients CC_i with the relative shares of the IPC sub-classes (RSC_i) and summing up the weighted clustering coefficients:

$$CI_j = \sum CC_{ij} * RSC_{ij} \quad (8)$$

3.7. Control variables

Two important controls have been added to the model, both referring to a capacity effect. Larger firms can coordinate more cooperation partners at the same time than smaller firms. Accordingly, the model needs to control for firm size. For measuring the size, three categories have been created, namely large firms, medium sized firms and small firms. Threshold levels are applied for the number of employees and/or the annual turnover for the years 2002-2010. Data are taken from the companies' websites and "Handelsregister" excerpts (accessed via LexisNexis). For the categorization the usual classification is chosen:

- Category 1 (Large): > 249 employees; turnover \geq 50 Mio. €
- Category 2 (Medium): 50-249 employees; turnover < 50 Mio. €
- Category 3 (Small): 10-49 employees; turnover < 10 Mio. €

The second control variable is experience of firms in the industry. Likewise, older firms are more experienced and can manage a higher number of collaborative projects. To approximate experience we apply the natural logarithm of firm age.

4. Data sources and descriptive analysis

For empirical research of network evolution, the first challenge is to select the firms which are (potentially) part of the network. This opens the discussion about the boundaries of the network (e.g. Laumann, Marsden & Prensky (1983)). We aim for studying publicly funded research networks in the German automotive industry. While it is relatively easy to filter German firms by their location (address), the approach for covering an industry is more contentious. Since our reasoning is led by a knowledge-based view of the firm, we start to build the sample based on a firm's patent portfolio instead of applying a standard industry classification like NACE. A scan of the patent portfolios (OECD June 2010) Regpat database (which is a supplemented extraction from Patstat) of the German Original Equipment Manufacturers (OEMs) and the largest suppliers shows that the 3-digit IPC class B60 is dominant in the industry. Thus, we pick all firms which filed at least one patent application in this class within the observation period 1998 to 2007 and pick out those which were exclusively operating in the market for commercial vehicles or car accessory kits. This way we exclude all firms which were not directly related to the production of passenger cars. We also exclude firms which have not been involved in at least one of the examined research projects. This sampling resulted in 153 firms belonging to the network sample.

For the simulation implementation, networks are observed at six consecutive points in time (2002-2007) resulting in six adjacency matrices reflecting the state of the network at the observation points. It is generally challenging to find sources about interfirm networks, in particular for longitudinal network studies. In our case, the networks are constructed from the database of the German *Förderkatalog (R&D subsidies catalogue)* which contains rich information about research projects supported by the federal government. The database is publicly accessible via the website www.foerderkatalog.de. Only those firms are eventually picked for the analysis which participated in the observation period 1998-2007 at least one time in a funded project. In the model a tie emerges between any two actors i and j if they participated in the same project. Despite the fact that the database contains rich information about subsidised collective research projects, it has been hardly used to conduct network research thus far (Broekel and Graf 2010).

Information about firms participating in joint subsidised projects documents research activities at an earlier stage compared to patent data. R&D subsidies have become a frequently used instrument of innovation

policy makers to spur collaborative research for a number of reasons. First, due to the sheer scale of some projects they cannot be afforded by single firms. Second, knowledge transfer from public to private organisations is fostered by the participation of universities and other public research institutes such as Max Planck and Fraunhofer. The projects listed in the “Förderkatalog” are considered to contribute to knowledge transfer (Broekel & Graf 2010). The participants have to sign agreements explicitly stipulating that gained knowledge within the project will be freely shared among the participants. They even have to grant free access to their know-how and IPRs within the scope of the project. Furthermore, they commit to actively collaborate with the aim to find new solutions (BMBF 2008). That this has worked out well and is not to be considered a lip-service only is empirically shown (Fornahl, Broekel & Boschma 2011).

To construct networks from the project data, the following information were retrieved: name of the project, starting and end date, name of the receiving/executing organisation. In addition, we find information about the grant, the location of the receiving/executing organisation and a classification number which divides funded technologies into different classes like biotechnology, energy etc. The title of the project is important to separate cooperative (“Verbundprojekt” or “Verbundvorhaben”) from non cooperative projects in which single organisations are funded. However, the title is not in all cases a clear indication for a joint project. The database at hand is complementary to other sources like patent data or publication data, in particular when it comes to longitudinal network studies (Broekel & Graf 2010) these other data sources provide valuable information.

A possible drawback of our network data is the political determination, i.e. networks are to some extent designed by political decisions to support certain key technologies that are considered as relevant for the improvement of the competitiveness of the national economy. Innovation networks generated by policy instruments might differ from emerging networks without external stimulus and confine results (Schön & Pyka, 2012). Because publicly funded networks dissolve per definition after the funding period, windfall profits are likely and long lasting linkages for knowledge transfer and learning might not appear. In many cases the self-organizing networks are characterized by small world properties (Watts & Strogatz 1998) which do not appear frequently in networks created by policy. For instance, small world properties were found by Uzzi and Spiro (2005) for a network of Broadway musical artists, by Newman (2001) for networks of scientific coauthoring in seven different scientific disciplines, by Fleming, King and Juda (2007) for patent collaboration networks, by Davis, Yoo and Baker (2003) for the network of US company directors and by Pyka, Gilbert and Ahrweiler (2007) for innovation networks in the biopharmaceutical industries. Finding small world attributes in our innovation networks in the automotive industries would weaken this objection towards publicly funded networks.

Small world networks are characterized by two features: (i) a high level of local clustering and (ii) a short average path length between network actors. To test for small world characteristics, we draw on the Watts and Strogatz (1998) approach which compares the observed network’s path length and clustering

coefficient with the respective properties of a random network with the same size and same number of ties. In contrast to random networks, small world networks are characterized by low clustering and low path lengths. To quantify the comparison the small world quotient (Q) is applied. It is defined as the ratio of the (global) clustering coefficient (CC) divided by the ratio of the average path length (PL). Measuring the path length makes only sense in networks where all actors have at least one tie. Therefore, the largest component is extracted from the full network. If the small world quotient is greater than 1.0 then the network can be characterized as small world network. Table 1 shows that Q is in fact for all observed networks larger than 1.0.

Furthermore, the critic concerning the usage of data describing publicly funded networks includes the idea that granting schemes preselect eligible firms. However, in our case the data covers research processes at a very early stage, something which cannot be achieved with patent data representing successful outcomes of the research processes. Broekel & Graf (2010) argue that in fields of limited knowledge appropriability, i.e. potential high technological spillovers, there is a strong need for public subsidies in order to create incentives to invest. Accordingly, technology fields which meet these “criteria” are better covered by subsidy data than by patent data.

Table 1: Small World test

	Network observation 2002	Network observation 2003	Network observation 2004	Network observation 2005	Network observation 2006	Network observation 2007
Nodes (largest component)	56	52	46	50	59	66
Ties	326	270	222	236	426	452
CC	0,74	0,64	0,61	0,63	0,72	0,73
PL	2,42	2,55	2,66	2,62	2,60	2,59
	Random	Random	Random	Random	Random	Random
CCr	0,11	0,10	0,11	0,1	0,13	0,11
PLr	2,45	2,53	2,52	2,60	2,25	2,36
CC / CCr	6,73	6,40	5,55	6,30	5,54	6,64
PL / PLr	0,99	1,01	1,05	1,01	1,16	1,10
Q	6,81	6,35	5,26	6,25	4,79	6,05

Figure 3 and table 2 show a strong increase in the number of established ties between the observation years 2000-2004 and 2001-2005 and in particular between the years 2001-2005 and 2002-2006. This can to some extent be explained by an increased number of subsidised research projects because this policy instrument gained in importance over the years. The number of disrupted as well as the number of stable ties is faltering over the observation period.

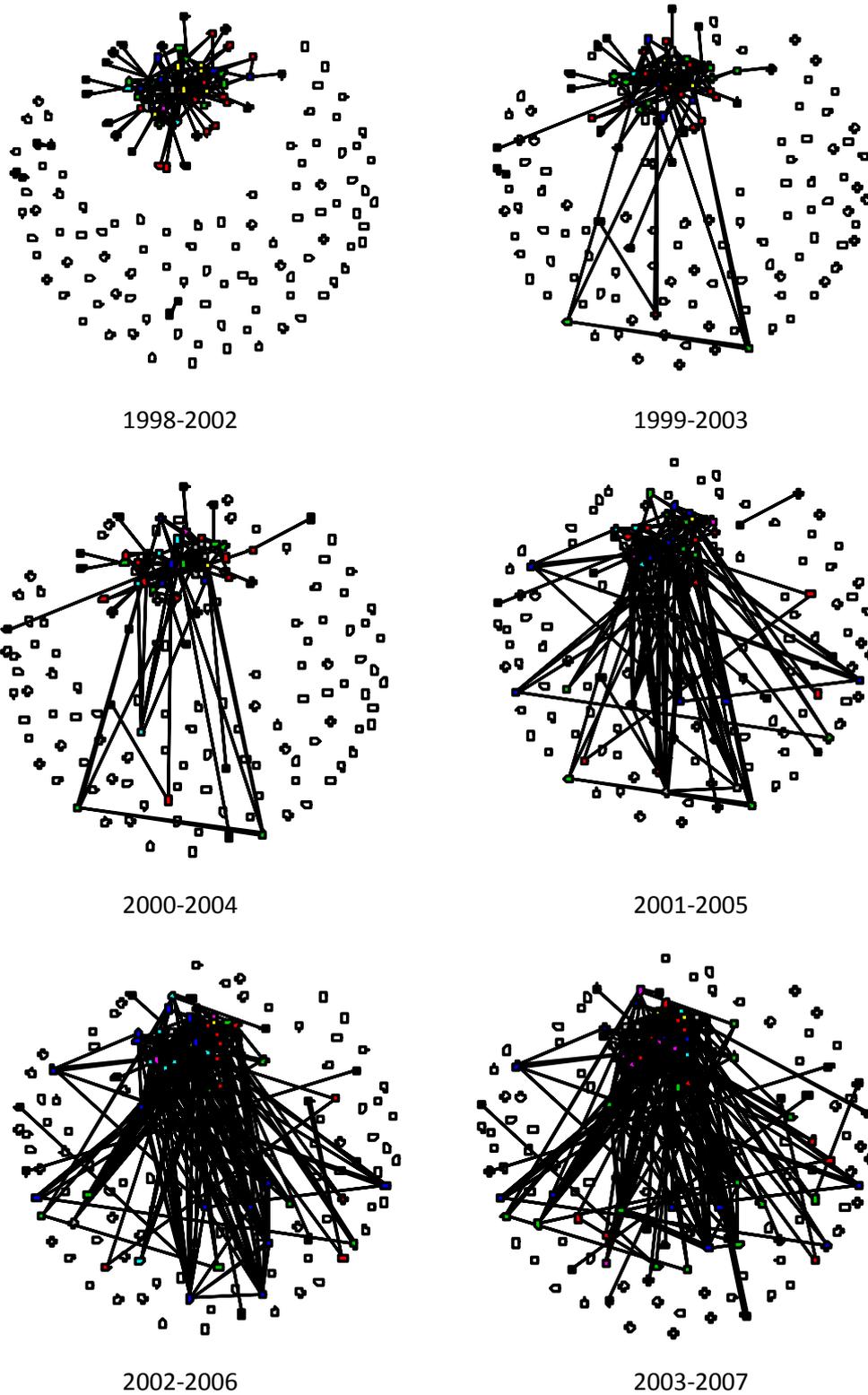


Figure 3: Evolution of the automotive R&D innovation network (2002-2007)

In order to receive proper simulation results it is necessary to have a certain amount of change between two consecutive waves. The assumption here is that changes in the network take place in a gradual stepwise way rather than by sudden “shocks”. To ensure gradual change in the network data the Jaccard

index (Table 2) has been calculated (10) (M_{11} = Number of pertained links; M_{10} = Number of interrupted links; M_{01} = Number of formed links).

$$J = \frac{M_{11}}{M_{01} + M_{10} + M_{11}} \quad (10)$$

Based on experience with the application of the stochastic actor-based model of network evolution, the value of the Jaccard Index should ideally be higher than 0.3 (Snijders, Van de Bunt & Steglich 2010). This is the case for all observation periods which makes the data a good basis for simulation.

Table 2: Link development 2002-2007

Observation	0→0	0→1	1→0	1→1	Jaccard Index
1→2	10846	14	43	123	0.683
2→3	11174	14	39	98	0.649
3→4	11149	65	56	55	0.312
4→5	11085	120	25	95	0.396
5→6	11050	60	47	168	0.611

The density of the network (Table 3) is overall relatively low. It is slightly diminishing from 2002 to 2004 and then rising again to the final year 2007. Likewise, the average degree centrality which indicates the average number of established cooperative relations is decreasing in the first half and increasing again in the second half. This tendency is confirmed by the number of ties which have been formed in the network.

Table 3: Density measures 2002-2007

Observation	2002	2003	2004	2005	2006	2007
Density	0.015	0.012	0.010	0.011	0.019	0.020
Average Degree	2.258	1.839	1.483	1.611	2.886	3.060
Centrality						
Number of ties	166	137	112	120	215	228

5. The stochastic actor-based model of network evolution

The *stochastic actor-based model for network dynamics* (Snijders 1996) allows for the analysis of longitudinal data describing network development and goes beyond the widespread models of network evolution like e.g. *scale-free networks* of Barabasi and Albert (1999). The econometric application of scale free networks is limited because of two reasons: First, the evolution of scale-free networks assumes as an explanatory variable only the uneven distribution of the degrees of the actors in the network, other factors

shaping network evolution are not considered. Second, for understanding network dynamics it is not sufficient to focus exclusively on the emergence of the network ties. Network dynamics are shaped to the same extent by the dissolving of network linkages. The termination of network ties is explicitly considered in the stochastic actor-based model.

In the stochastic actor-based model network ties are not understood as events but as states which persist for some time. In our case of publicly funded R&D networks this is a realistic assumption as the projects typically run for at least three years. The stochastic actor-based model is Markovian in the sense that the current state of the network determines its further evolution. It follows a *myopic stochastic optimization rule* (Snijders 2005). Thus, past events have no direct influence on the future which can be seen as a violation of a cornerstone of evolutionary thinking. However, history still matters, because independent variables inherently reflect historic information. This is the case for the experience with cooperation, technological distances (if we assume path dependences), absorptive capacity and transitivity which is based on structures that emerged in the past.

The basic approach demands the simulation of a large number of artificial networks which results in a sample distribution of networks. The simulated networks then are compared with the observed network. This allows for the estimation of parameters and standard errors to test the hypotheses. In this approach (entire) networks are random variables (X) and have a probability distribution which is complex, thus it cannot be approximated e.g. by a normal distribution. The actually observed network (x) is assumed to be drawn from the population of all possible networks that are simulated based on a model that includes the effects which are tested as drivers of network evolution.

The basic denotation is in line with standard network analysis. Networks are represented by an $n \times n$ adjacency matrix $X(t_m) = X_{ij}(t_m)$ for $m = 1, \dots, M$. $X_{ij}(t)$ takes the values 0 if there is no link at time t between i and j or 1 otherwise. The diagonal of the matrix takes the value 0; $X_{ii}(t) = 0$ for all i . An additional matrix, the composition change matrix, accounts for changes in the sample of firms. It includes information about firms that enter or leave the network within the observation period because they are only founded after the start of the observation or because they were dissolved, for instance due to an acquisition or exit.

It is important to highlight that changes in tie variables are the dependent variables in the model. Modelling network evolution is only meaningful if we have at least two observations, thus M must take a value ≥ 2 . The time parameter t is continuous. For the estimation of parameters it is however assumed that we observe the network at least at two discrete points in time which gives it the character of a panel analysis. The algorithm applied in the model can be traced back to earlier publications of Holland and Leinhardt (1977), Wasserman (1980) and Leenders (1995). Yet, these prior models are rather limited in the structural effect that can be modelled. The assumption of continuous time is advantageous for modelling tie

dependencies with tie formations that mutually depends on one another. Imagine the following example: At $t=0$, in a group of three firms no firm cooperates. At $t=1$ the three firms started to cooperate and thus form a triangle. In a model with only discrete time the emergence of the triangle structure could not be explained, it just happened. In contrast, a continuous time model allows for a step by step, or better tie by tie emergence of the observed triangle structure, for instance due to a transitive closure mechanism.

An actor which gets the possibility to change a tie is randomly chosen. Only one tie in the network can be changed per iteration of the algorithm (Snijders 2001, Holland & Leinhardt 1977). That is, the change process is broken down into the smallest possible components, called *mini steps*. This means that actors do not coordinate tie changes but follow each other tie by tie and react to the stepwise changed network structure. This assumption is somewhat debatable with respect to innovation networks that are based – without doubt - on some kind of coordination or negotiation. In this sense the algorithm has to be considered as purely technical, which, however, allows for disentangling the importance of the various effects tested for in the model.

The change process consists of two stochastic sub-processes. First, the frequency actors get the opportunity to change a tie (change opportunity process) may depend on the position (centrality) of an actor and on other covariates like experience or it is represented by a constant probability function. Second, the tie change process which is determined by a probability function is again influenced by the network position and the covariates of the ego but also of the other actors in the network. This simulation model has the same underlying principles as other agent- or actor-based models. However, as the model is used for statistical inference, it has to fulfil special requirements. First, we must be able to estimate the parameters from the data in order to get a sound fit. Second, parsimony is a prerequisite, i.e. there should not be any other fine details in the model else than what can be estimated from the data (Snijders, Van de Bunt & Steglich 2010).

As proposed by Snijders (2001) the parameters of the model are estimated based on simulations with one exemption. The network state of the first observation is not simulated but used as initial structure from which on the change to the second observation is simulated. In other word, we model the change between two consecutive observation points but we do not model the first observation. Parameters of the objective function (referring to the tested effects) are obtained by applying an iterative Markov Chain Monte Carlo (MCMC) algorithm (based on the method of moments). The stochastic approximation algorithm simulates the evolution of the network and estimates parameters that minimize the deviation between observed and simulated networks. During the iterations, the initial parameters of the model are incrementally adjusted with the aim to find the best fit between simulated and observed networks. The final value of the parameter determines the goodness of fit of the model and the standards errors. The MCMC estimations can be interpreted like the results of a logistic regression which means that it has be controlled for all

potentially relevant variables that could influence change processes in the network (Balland, De Vaan & Boschma 2012).

The change of network ties is determined by the objective function which expresses how the firm perceives the network and evaluates the different change options. The aim of each actor is to increase the value of the objective function which is determined by the ego-network, i.e. its direct (or indirect) ties and the covariates of the other actors which are part of the network. For the processes of changing or keeping ties, we have to consider the probabilities which are in turn dependent on the evaluation of possible changes in the network in terms of ties and covariates. The way the objective function is constructed represents the rules we assume to be relevant from the view of an actor when it makes choices. For any possible state of the network the objective function takes a certain value. For higher values the probability increases that the actor opts for this possible network state. Formally the objective function (9) is a linear combination of a variety of components which are called *effects* and are explained in section 3 for our case.

$$f_i(x^0, x, v, w) = \sum_k \beta_k s_{ki}(x^0, x, v, w) \quad (9)$$

The value of the objective function f_i for actor i depends on the current state (x^0), a potential future state (x) of the network as well as on actor attributes (v) and dyadic attributes like the different proximity categories (w). Functions $s_{ki}(x)$ are the effects that are based on previously explained theoretical considerations and can be tested in the model. Weights β_k are the statistical parameters, if $\beta_k = 0$, corresponding effects play no role in network evolution; if $\beta_k > 0$ there is higher probability of moving in the direction where the respective effect is higher. Effects depending on the network are called structural or endogenous effects. Effects depending on external attributes are called covariates or exogenous effects.

So far the *stochastic actor-based network model* has been applied to several industries: Ter Wal (2009) studies network evolution in the German biotechnology industry; Balland (2012) covers the navigation by satellite industry (GNSS); Giuliani (2010) applies the algorithm in a study on a Chilean wine cluster; Balland, De Vaan & Boschma (2012) investigate the computer games industry. These studies cover industries which have relatively recently emerged as well as an agricultural industry. Traditional manufacturing industries like the automotive industry are so far not analysed.

6. Estimation results

The model parameters have been estimated with the stochastic agent based-network model as implemented in the SIENA programme based on the R platform. The unilateral initiative and reciprocal confirmation version of the model is selected. This indicates that the actor i initiates a tie and the potential partner j has to accept the request based on the evaluation of its own objective function. Simulation runs have been repeated 1000 times. A first parameter indicating the goodness of fit of the simulated model is the t-value of convergence. It indicates the deviation of observed network data from simulated values

(Balland, De Vaan & Boschma 2012). Convergence is excellent if the t-value is smaller than 0.1, which we find for all variables of the objective function.

Table 4: Estimation results

Variable	Value (sd)	P	Hypotheses
Density	-2.0448*** (0.0420)	< 0,01	
Transitive triads	0.4142*** (0.0210)	< 0,01	H1 Confirmed
Geographical distance	-0.1369*** (0.0279)	< 0,01	H2 Confirmed
Absorptive capacity	0.1105*** (0.0298)	< 0,01	H3 Confirmed
Technological distance	-0.3345* (0.1879)	0.07	H4a Confirmed
Cooperative experience	0.0120*** (0.0017)	< 0,01	H5 Confirmed
KB Modularity	0.4970*** (0.1914)	< 0,01	H6 Confirmed
Industry experience	0.3587 (0.1232)	< 0,01	Confirmed
Firm size	0.0811 (0.0846)	0.34	Rejected

Significance levels: $p < 0,1^*$; $p < 0,05^{**}$, $p < 0,01^{***}$

Table 4 summarises the resulting coefficients for the model estimated with the simulation model. All tested effects are at least weakly significant except the capacity effect measured by firm size. Hypothesis 1 which postulates a high cliquishness among network partners is confirmed. This indicates a significant endogenous network effect leading to the formation of cohesive triadic subgroups caused by trusted partnerships. This is in line with studies performed for other industries. Accordingly, this can be considered a general effect which always plays its role in innovation network evolution.

Hypothesis 2 suggests an inverse relationship between cooperation and geographical distance. The parameter for geographic distance is negative and highly significant. This indicates that ties emerge more frequently between firms that are located in relative geographical proximity compared to more distant firms. From this follows that geographical distance is an important factor in the automotive industry.

Hypothesis 3 deals with the positive effects of absorptive capacities with respect to the propensity to collaborate. Our calculations confirm that firms with broad absorptive capacities are likely to benefit more from cooperation and therefore more intensely engage in networks. Firms which have a larger knowledge-base have more incentives to cooperate as they are better capable of making use of the other firm's knowledge base they get access to.

For the technological distance we find a negative parameter value which suggests that there is a tendency for firms with similar knowledge-bases to cooperate (Hypothesis H4a). However, the parameter is not

strongly significant in the tested model. This result might support Noteboom's et al. (2007) suggestion of the u-formed relationship between technological distances and abilities to learn from cooperation partners. With the data at hand, however, this cannot be adequately tested. There are various ways of operationalizing the concept of technological distance (see Benner & Waldfoegel 2008) and this factor provides room for further investigation.

A further tested variable is the experience in cooperation. The results confirm the hypotheses H5 suggesting that firms with more experience in cooperation are more open to participate in collaboration projects.

Finally, the modular structure of the knowledge-base seems to be crucial for the attractiveness of becoming a collaboration partner. Our estimations therefore confirm hypothesis H6 about the beneficial effects of a modular knowledge structure which facilitates recombinatorial research and with it possibilities to benefit from sharing knowledge in innovation networks. More structured knowledge-bases are easier to be linked. It also hints at the industry structure which is characterised by suppliers which often assemble entire modules which become integrated by the OEMs.

Furthermore, more experienced firms (approximated by firm age) also built up better capabilities in handling collaborative projects as the parameter is highly significant. The impact of firm size on collaboration, however, is not visible. There is no clear effect supporting either small or large firms with respect to their collaboration activities. This result is a potential policy issue. While small firms are often supported in their cooperation activities in order to remedy their potential resource deficiencies, the data does not provide evidence that small firms have a higher propensity to cooperate or become involved in cooperation projects.

7. Conclusion

The objective of this paper is to outline conceptual considerations of dynamic and knowledge-based aspects for the analysis of innovation network evolution. Competitive pressure forces firms to continuously develop new ideas, invent new technologies and bring new products to the market in order to survive the creative destruction part of Schumpeterian innovation competition. This holds in particular for the automotive industry in Germany that has become challenged by firms from emerging markets in Asia which dominate markets in terms of price competition. In this competition for new technological solutions competences and knowledge are the success factors. New knowledge is the basis for new ideas that can be transformed into innovation. This knowledge obviously can be acquired internally in the companies R&D laboratories. However, relying on internal knowledge generation is no longer sufficient. Participating innovation networks which allow for access to external knowledge and applying innovation cooperation as

a strategic tool to acquire necessary knowledge which cannot easily be developed in-house opens up rich opportunities to complement and recombine the own knowledge-base.

Innovation networks are characterized by certain structures which support knowledge exchange and learning to different extents. The structure of the innovation networks, however, is by far not constant but evolves with emerging and dissolving ties between actors. So far in the literature only a few approaches exist which focus on the dynamics of innovation networks and contributions to analyse network structures are prevailing. In our paper we want to contribute to the dynamic analysis of innovation networks and ask for the drivers and mechanisms that determine the change process. For this purpose, we apply a stochastic actor-based model which simulates network evolution between observation periods and can be used for the estimation of parameters which reflect the impact of certain variables. For the network we built from publicly funded R&D projects in the German automotive industry, structural as well as individual and dyadic covariates as relevant drivers.

The following main results are obtained: The establishment of cliques play an important role in the evolution of innovation networks and the formation of triadic structures can be widely observed. The factors emphasized in the literature like geographical distance, technological distance, cooperation experience are confirmed and explain the cooperation behaviour of firms in the automotive industry in Germany. Also firms with high levels of absorptive capacity tend to be more often involved in the innovation networks. Knowledge base modularity exerts the strongest effect on cooperation behaviour and indicates to be a source for industry specificities. The high modularity of knowledge in the automotive industry seems to play an outstanding role for the particular innovation networks which can be found in this industry. This might not be reproduced in other sectors like ICT, Biotech, Laser or nanotech which are on our agenda for future research.

The paper leads to a number of further research questions. Obviously the results are of policy relevance and are suited to improve policy designs. Is there a special role played by inventors in the network, which not necessarily are employees of the innovating firms. Despite the observed impact of geographical distance, absorptive capacities and experience are there other factors determining the cooperation behaviour? What role is played by cultural distances which become more relevant in international cooperation or institutional distances, which might matter in networks comprising public and private actors?

8. References

- Ahuja, G. & Katila, R. 2001, "Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study", *Strategic Management Journal*, vol. 22, no. 3, pp. 197-220.
- Araujo, L. & Harrison, D. 2002, "Path dependence, agency and technological evolution", *Technology Analysis & Strategic Management*, vol. 14, no. 1, pp. 5-19.
- Arrow, K.J. 1973, "Information and Economic Behavior" in *Collected Papers of Kenneth J. Arrow, Vol. 4.*, Belknap, Cambridge, Massachusetts.
- Audretsch, D.B. & Feldman, M.P. 1996, "Innovative clusters and the industry life cycle", *Review of Industrial Organization*, vol. 11, no. 2, pp. 253-273.
- Baldwin, C.Y. & Clark, K.B. 2000, *Design rules: The power of modularity*, The MIT Press.
- Balland, P.A. 2012, "Proximity and the evolution of collaboration networks: evidence from research and development projects within the global navigation satellite system (GNSS) industry", *Regional Studies*, vol. 46, no. 6, pp. 741-756.
- Balland, P.A., De Vaan, M. & Boschma, R. 2012, "The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987–2007", *Journal of Economic Geography*, vol. 12.
- Barabasi, A.L. & Albert, R. 1999, "Emergence of scaling in random networks", *Science*, vol. 286, pp. 509-512.
- Barabasi, A.L. & Albert, R. 2002, "Statistical mechanics of complex networks", *Reviews of modern physics*, vol. 74, no. 1, pp. 47-97.
- Bathelt, H. & Glückler, J. 2005, "Resources in economic geography: from substantive concepts towards a relational perspective", *Environment and Planning A*, vol. 37, no. 9, pp. 1545-1563.
- Baum, J.A.C., Shipilov, A.V. & Rowley, T.J. 2003, "Where do small worlds come from?", *Industrial and Corporate Change*, vol. 12, no. 4, pp. 697-725.
- Benner, M. & Waldfogel, J. 2008, "Close to you? Bias and precision in patent-based measures of technological proximity", *Research Policy*, vol. 37, no. 9, pp. 1556-1567.
- Bianconi, G. & Barabási, A.L. 2001, "Competition and multiscaling in evolving networks", *EPL (Europhysics Letters)*, vol. 54, no. 4, pp. 436-442.
- BMBF 2008, "Merkblatt für Antragsteller/Zuwendungsempfänger zur Zusammenarbeit der Partner von Verbundprojekten", vol. Bundesministerium für Bildung und Forschung, BMBF-Vordruck 0110/10.08.
- Boschma, R. 2005, "Proximity and innovation: a critical assessment", *Regional Studies*, vol. 39, no. 1, pp. 61-74.
- Broekel, T. & Graf, H. 2010, "Structural properties of cooperation networks in Germany: From basic to applied research", *Jena Economic Research Papers*, vol. 78.
- Buchmann, T. & Pyka, A. 2012a, "Innovation networks", *Handbook on the Economics and Theory of the Firm*, in *Handbook on the economics and theory of the firm*, eds. M. Dietrich, J. Krafft, Edward Elgar, Cheltenham, pp. 466-484.

- Buchmann, T. & Pyka, A. 2012b, "Netzwerkindikatoren zur Bewertung der innovativen Leistungsfähigkeit", *Zeitschrift für Controlling und Innovationsmanagement*, vol. Sonderheft 1, pp. 22-28.
- Buskens, V. & Raub, W. 2002, "Embedded trust: Control and learning" in *Embedded trust: Control and learning*, eds. E. Lawler & S. Thye, Emerald Group, pp. 167-202.
- Cohen, W.M. & Levinthal, D.A. 1990, "Absorptive capacity: a new perspective on learning and innovation", *Administrative Science Quarterly*, vol. 35, no. 1, pp. 128-152.
- Colombo, M.G. 2003, "Alliance form: a test of the contractual and competence perspectives", *Strategic Management Journal*, vol. 24, no. 12, pp. 1209-1229.
- Cowan, R. & Jonard, N. 2003, "The dynamics of collective invention", *Journal of Economic Behavior and Organization*, vol. 52, no. 4, pp. 513-532.
- Das, T.K. & Teng, B.S. 2000, "A resource-based theory of strategic alliances", *Journal of management*, vol. 26, no. 1, pp. 31-61.
- Davis, J.A. 1970, "Clustering and hierarchy in interpersonal relations: Testing two graph theoretical models on 742 sociomatrices", *American Sociological Review*, vol. 35, no. 5, pp. 843-851.
- Davis, G.F., Yoo, M. & Baker, W.E. 2003, "The small world of the American corporate elite, 1982-2001", *Strategic organization*, vol. 1, no. 3, pp. 301-326.
- Dorogovtsev, S.N., Mendes, J.F.F. & Samukhin, A.N. 2000, "Structure of growing networks with preferential linking", *Physical Review Letters*, vol. 85, no. 21, pp. 4633-4636.
- Dyer, J.H. 1996, "Specialized supplier networks as a source of competitive advantage: Evidence from the auto industry", *Strategic Management Journal*, vol. 17, no. 4, pp. 271-291.
- Dyer, J.H. & Nobeoka, K. 2000, "Creating and managing a high-performance knowledge-sharing network: the Toyota case", *Strategic Management Journal*, vol. 21, no. 3, pp. 345-367.
- Eliasson, G. 1991, "Modeling the experimentally organized economy: Complex dynamics in an empirical micro-macro model of endogenous economic growth", *Journal of Economic Behavior & Organization*, vol. 16, no. 1, pp. 153-182.
- Ethiraj, S.K. & Levinthal, D. 2004, "Modularity and innovation in complex systems", *Management Science*, vol. 50, no. 2, pp. 159-173.
- Fleming, L. & Sorenson, O. 2001, "Technology as a complex adaptive system: evidence from patent data", *Research Policy*, vol. 30, no. 7, pp. 1019-1039.
- Fleming, L., King, C. & Juda, A.I. 2007, "Small Worlds and Regional Innovation", *Organization Science*, vol. 18, no. 6, pp. 938-954.
- Fornahl, D., Broekel, T. & Boschma, R. 2011, "What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location", *Papers in Regional Science*, vol. 90, no. 2, pp. 395-418.
- Geroski, P. 1995, "Markets for technology: knowledge, innovation and appropriability" in *Handbook of the economics of innovation and technological change*, ed. P. Stoneman, Blackwell, Oxford, pp. 90-131.

- Giuliani, E. 2010, "Network dynamics in regional clusters: The perspective of an emerging economy", *Papers in Evolutionary Economic Geography (PEEG)*, [Online], vol. 10, no. 14.
- Glückler, J. 2007, "Economic geography and the evolution of networks", *Journal of Economic Geography*, vol. 7, no. 5, pp. 619-634.
- Gulati, R. 1995a, "Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances", *Academy of management journal*, vol. 38, no. 1, pp. 85-112.
- Gulati, R. 1995b, "Social structure and alliance formation patterns: A longitudinal analysis", *Administrative Science Quarterly*, vol. 40, pp. 619-652.
- Gulati, R. & Gargiulo, M. 1999, "Where Do Interorganizational Networks Come From?", *American journal of sociology*, vol. 104, no. 5, pp. 1398-1438.
- Hall, R. 1993, "A framework linking intangible resources and capabilities to sustainable competitive advantage", *Strategic Management Journal*, vol. 14, no. 8, pp. 607-618.
- Heiner, R.A. 1983, "The origin of predictable behavior", *The American Economic Review*, vol. 73, no. 4, pp. 560-595.
- Hite, J. 2008, "The evolution of strategic dyadic network ties: Strategically navigating bounded agency within multidimensional and dynamic dyadic relationships", *Network strategy: Advances in strategic management*, vol. 25, pp. 133-170.
- Hoekman, J., Frenken, K. & Van Oort, F. 2009, "The geography of collaborative knowledge production in Europe", *The Annals of Regional Science*, vol. 43, no. 3, pp. 721-738.
- Holland, P.W. & Leinhardt, S. 1971, "Transitivity in structural models of small groups", *Comparative Group Studies*, vol. 2, pp. 127.
- Holland, P.W. & Leinhardt, S. 1977, "A dynamic model for social networks", *The Journal of Mathematical Sociology*, vol. 5, no. 1, pp. 5-20.
- Howells, J.R.L. 2002, "Tacit knowledge, innovation and economic geography", *Urban Studies*, vol. 39, no. 5-6, pp. 871-884.
- Huggins, R. 1997, "Competitiveness and the global region: the role of networking" in *Innovation, networks, and learning regions?*, ed. J. Simmie, Jessica Kingsley Publishers, London, pp. 97-119.
- Jackson, M.O. & Watts, A. 2002, "The Evolution of Social and Economic Networks", *Journal of Economic Theory*, vol. 106, no. 2, pp. 265-295.
- Kale, P., Dyer, J.H. & Singh, H. 2002, "Alliance capability, stock market response, and long-term alliance success: the role of the alliance function", *Strategic Management Journal*, vol. 23, no. 8, pp. 747-767.
- Knoben, J. & Oerlemans, L.A.G. 2006, "Proximity and inter-organizational collaboration: A literature review", *International Journal of Management Reviews*, vol. 8, no. 2, pp. 71-89.
- Krapivsky, P.L., Redner, S. & Leyvraz, F. 2000, "Connectivity of growing random networks", *Physical Review Letters*, vol. 85, no. 21, pp. 4629-4632.
- Lane, P.J. & Lubatkin, M. 1998, "Relative absorptive capacity and interorganizational learning", *Strategic Management Journal*, vol. 19, pp. 461-477.

- Laumann, E.O., Marsden, P.V. & Prensky, D. 1983, "The boundary specification problem in network analysis" in *Applied network analysis*, eds. R.S. Burt & M.J. Minor, Sage Publications, Newbury Park, pp. 18- 34.
- Leamer, E.E. & Storper, M. 2001, "The economic geography of the internet age", [Online], NBER Working Paper 8450 .
- Leenders, R.T.A.J. 1995, "Models for network dynamics: A Markovian framework", *The Journal of Mathematical Sociology*, vol. 20, no. 1, pp. 1-21.
- March, J.G. 1991, "Exploration and exploitation in organizational learning", *Organization science*, vol. 2, no. 1, pp. 71-87.
- Marquis, C. 2003, "The pressure of the past: Network imprinting in intercorporate communities", *Administrative Science Quarterly*, vol. 48, pp. 655-689.
- Marshall, A. 1920, *Principles of economics: an introductory volume*, 8th edn, Macmillan, London.
- McPherson, M., Smith-Lovin, L. & Cook, J.M. 2001, "Birds of a feather: Homophily in social networks", *Annual review of sociology*, vol. 27, pp. 415-444.
- Newman, M.E.J. 2001, "The structure of scientific collaboration networks", *Proceedings of the National Academy of Sciences*, vol. 98, no. 2, pp. 404-409.
- Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V. & Van den Oord, A. 2007, "Optimal cognitive distance and absorptive capacity", *Research Policy*, vol. 36, no. 7, pp. 1016-1034.
- OECD June 2010, "REGPAT database".
- Powell, W.W., Koput, K.W. & Smith-Doerr, L. 1996, "Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology.", *Administrative Science Quarterly*, vol. 41, no. 1, pp. 116-145.
- Powell, W.W., White, D.R., Koput, K.W. & Owen-Smith, J. 2005, "Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences", *American journal of sociology*, vol. 110, no. 4, pp. 1132-1205.
- Pyka, A. 2000, "Informal Networks and Industry Life Cycles", *Technovation*, vol. 20, pp. 25-35.
- Pyka, A. 2002, "Innovation networks in economics: from the incentive-based to the knowledge-based approaches", *European Journal of Innovation Management*, vol. 5, no. 3, pp. 152-163.
- Pyka, A., Gilbert, N. and Ahrweiler, P. 2007, Simulating Knowledge-Generation and Distribution Processes in Innovation Collaborations and Networks, *Cybernetics and Systems*, Vol. 38 (7), 667-694.
- Pyka, A., Gilbert, N. and Ahrweiler, P. 2009, Agent-Based Modelling of Innovation Networks – The Fairytale of Spillover, in: Pyka, A. und Scharnhorst, A. (Hrsg.), *Innovation Networks – New Approaches in Modelling and Analyzing*, Springer: Complexity, 2009, 101-126
- Pyka, A. & Hanusch, H. 2006, *Applied evolutionary economics and the knowledge-based economy*, Edward Elgar, Cheltenham u.a.
- Reagans, R. & McEvily, B. 2003, "Network structure and knowledge transfer: The effects of cohesion and range", *Administrative Science Quarterly*, vol. 48, no. 2, pp. 240-267.

- Rothaermel, F.T. & Boeker, W. 2008, "Old technology meets new technology: complementarities, similarities, and alliance formation", *Strategic Management Journal*, vol. 29, no. 1, pp. 47-77.
- Sanchez, R. & Mahoney, J.T. 1996, "Modularity, flexibility, and knowledge management in product and organization design", *Strategic Management Journal*, vol. 17, Winter Special Issue, pp. 63-76.
- Saviotti, P. 2009, "Knowledge networks: Structure and dynamics", in *Innovation Networks*, eds. A. Pyka, A. Scharnhorst, Heidelberg, Springer Verlag, pp. 19-41.
- Sayer, A. 1991, "Behind the locality debate: deconstructing geography's dualisms", *Environment and Planning A*, vol. 23, no. 2, pp. 283-308.
- Schilling, M.A. 2000, "Toward a general modular systems theory and its application to interfirm product modularity", *Academy of management review*, vol. 25, no. 2, pp. 312-334.
- Schön, B. & Pyka, A. (2012), A taxonomy of innovation networks, FZID discussion paper, #42/2012
- Scott, A.J. 1996, "Regional motors of the global economy", *Futures*, vol. 28, no. 5, pp. 391-411.
- Simon, H.A. 1962, "The architecture of complexity", *Proceedings of the American Philosophical Society*, vol. 106, no. 6, pp. 467-482.
- Skvoretz, J. & Willer, D. 1991, "Power in exchange networks: Setting and structural variations", *Social psychology quarterly*, vol. 54, pp. 224-238.
- Snijders, T.A.B. 1996, "Stochastic actor-oriented models for network change", *Journal of Mathematical Sociology*, vol. 21, no. 1-2, pp. 149-172.
- Snijders, T.A.B. 2001, "The statistical evaluation of social network dynamics", *Sociological methodology*, vol. 31, no. 1, pp. 361-395.
- Snijders, T.A.B. 2005, "Models for longitudinal network data" in *Models and Methods in Social Network Analysis*, eds. P.J. Carrington, J. Scott & S. Wasserman, Cambridge University Press, pp. 215-247.
- Snijders, T.A.B., Van de Bunt, G.G. & Steglich, C.E.G. 2010, "Introduction to stochastic actor-based models for network dynamics", *Social Networks*, vol. 32, no. 1, pp. 44-60.
- Staiger, T.J. & Gleich, R. 2006, "Innovationsnetzwerke in der Automobilindustrie", *Zeitschrift für Controlling und Innovationsmanagement*, , no. 3, pp. 34-39.
- Steglich, C., Snijders, T.A.B. & West, P. 2006, "Applying SIENA: An Illustrative Analysis of the Coevolution of Adolescents' Friendship Networks, Taste in Music, and Alcohol Consumption.", *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, vol. 2, no. 1, pp. 48-56.
- Stokman, F.N. & Doreian, P. 1997, "Evolution of social networks: Processes and principles" in *Evolution of Social Networks*, eds. P. Doreian & F.N. Stokman, Routledge, New York, pp. 233-250.
- Storper, M. & Venables, A.J. 2004, "Buzz: face-to-face contact and the urban economy", *Journal of economic geography*, vol. 4, no. 4, pp. 351-370.
- Ter Wal, A.L.J. 2009, "The spatial dynamics of the inventor network in German biotechnology. Geographical proximity versus triadic closure.", *Utrecht: Department of Economic Geography*, .

- Ter Wal, A.L.J. & Boschma, R.A. 2009, "Applying social network analysis in economic geography: framing some key analytic issues", *The Annals of Regional Science*, vol. 43, no. 3, pp. 739-756.
- Tsang, E.W.K. 2000, "Transaction cost and resource-based explanations of joint ventures: A comparison and synthesis", *Organization Studies*, vol. 21, no. 1, pp. 215-242.
- Uzzi, B. 1997, "Social structure and competition in interfirm networks: The paradox of embeddedness", *Administrative Science Quarterly*, vol. 42, no. 1, pp. 35-67.
- Uzzi, B. & Spiro, J. 2005, "Collaboration and Creativity: The Small World Problem", *American Journal of Sociology*, vol. 111, no. 2, pp. 447-504.
- Vázquez, A. 2003, "Growing network with local rules: Preferential attachment, clustering hierarchy, and degree correlations", *Physical Review E*, vol. 67, no. 5, pp. 056104.
- Walker, G., Kogut, B. & Shan, W. 1997, "Social capital, structural holes and the formation of an industry network", *Organization Science*, vol. 8, no. 2, pp. 109-125.
- Wasserman, S. 1980, "A stochastic model for directed graphs with transition rates determined by reciprocity", *Sociological methodology*, vol. 11, pp. 392-412.
- Watts, D.J. & Strogatz, S.H. 1998, "Collective dynamics of 'small-world' networks", *Nature*, vol. 393, pp. 440-442.
- Weick, K.E. 1976, "Educational organizations as loosely coupled systems", *Administrative Science Quarterly*, vol. 21, no. 1, pp. 1-19.
- Weterings, A. & Boschma, R. 2009, "Does spatial proximity to customers matter for innovative performance?: Evidence from the Dutch software sector", *Research Policy*, vol. 38, no. 5, pp. 746-755.
- Witt, U. 2008, "What is specific about evolutionary economics?", *Journal of Evolutionary Economics*, vol. 18, no. 5, pp. 547-575.
- Witt, U. 2006, "Evolutionary concepts in economics and biology", *Journal of Evolutionary Economics*, vol. 16, no. 5, pp. 473-476.
- Yayavaram, S. & Ahuja, G. 2008, "Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability", *Administrative Science Quarterly*, vol. 53, no. 2, pp. 333-362.
- Zaheer, A. & Bell, G.G. 2005, "Benefiting from network position: firm capabilities, structural holes, and performance", *Strategic Management Journal*, vol. 26, no. 9, pp. 809-825.
- Zahra, S.A. & George, G. 2002, "Absorptive capacity: A review, reconceptualization, and extension", *Academy of management review*, vol. 27, no. 2, pp. 185-203.
- Zeller, C. 2004, "North Atlantic innovative relations of Swiss pharmaceuticals and the proximities with regional biotech arenas", *Economic Geography*, vol. 80, no. 1, pp. 83-111.