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THE EVOLUTION OF INNOVATION NETWORKS: THE CASE OF A GERMAN AUTOMOTIVE NETWORK

Tobias Buchmann

Andreas Pyka

Universität Hohenheim | Forschungszentrum Innovation und Dienstleistung

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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

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Abstract

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

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1. Introduction

Innovation networks are considered as a means to share increasing R&D costs, gain access to scarce resources and - most 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 internal and external sources. First, scientists and engineers explore new combinations in R&D laboratories and create new knowledge to be exploited. Second, knowledge can be absorbed by accessing external knowledge-bases (firms, universities, government labs, customers). In this second case, internal units have to process the absorbed knowledge (Cohen & Levinthal 1990). Innovation is accordingly the result from internal expertise and external stimuli. In particular, in knowledge intensive industries firms have a hard time relying solely on the internal generation of knowledge. Their access to external knowledge becomes of paramount importance. "Tapping external sources of know-how becomes a must" (Tsang 2000, p. 225).

The door opener to access knowledge is interaction between actors. A suitable way to analyse firm interactions is the network perspective. Networks are characterized by a specific structure which is the result of the emergence and dissolution of ties between firms over time (Wasserman & Faust 1994). These ties serve as channels for the flow of knowledge between actors and allow for knowledge diffusion and mutual learning in the network (Buchmann & Pyka 2012a). The 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 (Huggins 1997, Scott 1996, Snijders 2001). To construct the networks we return to the basic idea of interfirm networks: The elementary building blocks are nodes, in our case the 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.

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 no longer considered to be purely a public good, but as a local, tacit, firm specific, complex and hence as a (partly) private good. Technological spillovers are no longer freely available (Pyka, Gilbert & Ahrweiler 2009) and knowledge is no longer regarded "as it were in the air" (Marshall 1920, p. 271) as in the standard models of growth, but it has to be acquired actively by internal 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 are increasingly attracting scientific attention. Scholars of various disciplines such as physics (Dorogovtsev, Mendes & Samukhin 2000, Barabasi & Albert 2002, Bianconi & Barabási 2001) 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 evolution of innovation networks (Jackson & Watts 2002, Cowan & Jonard 2003, Pyka, Gilbert & Ahrweiler 2007, Ter Wal 2009, Balland, De Vaan & Boschma 2012, Balland 2012, Gilbert). The empirical understanding of innovation network evolution is however still preliminary. Further research is needed to, for instance, better grasp the role of industry specificities shaping innovation network evolution. Most studies in the field of network research are of a static nature and apply descriptive analysis techniques (Baum, Shipilov & Rowley 2003) taken from the repertoire of social network analysis (SNA). These approaches are mostly based on 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. A key characteristic of networks is however their evolution with continuously emerging and dissolving ties between the actors (Ter Wal & Boschma 2009). An important 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 for identifying the driving factors (Snijders 2001).

In this article we present results from a study of evolutionary change patterns of an interfirm 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. We test several factors which reflect preferences for initiating and terminating collaboration. In particular, we suggest the following factors to be relevant drivers of network evolution: transitivity, geographical proximity, absorptive capacity, technological proximity, experience with cooperation and the degree 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. Along with that, 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 OEMs and numerous suppliers that can be component manufacturers (often SMEs) or big multinational enterprises which assemble and integrate 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, including R&D. Additionally, increased complexity of product and processes is another prevalent challenge 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 reliably manner. Taken together, this means that the different parts have to be developed within a comprehensive framework on shared platforms. Collaboration in research projects can be seen as an answer to this challenge as no single actor can provide for all relevant competences. Staiger and Gleich (2006) found through expert-interviews (qualitative) evidence for the strategic collaboration approach. 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 the industry, a relational view of these networks is a valuable approach (Dyer 1996, Dyer & Nobeoka 2000).

In the following section we outline how innovation networks can be assessed 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 consist of at least two nodes ('organisations') and linkages between the nodes ('based on collaborative agreements'). Formation of new cooperations as well as termination of existing cooperations influences the growth, fragmentation and thereby the internal structure of the innovation network. From an aggregate network perspective this leads to constantly changing structures. Consequently, modeling innovation networks requires an inherently dynamic framework. 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 in imperfect markets and innovate confronted with strong uncertainty (Knight 1921). Innovation problems are ill-defined from the subject and object sides (Heiner 1983). These imperfect conditions - uncertainty and bounded rationality - are the major ingredients of an *experimentally organized economy* (Eliasson 1991). Due to the uncertainty and non-linearities, guidelines and directions for future development remain unknown (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. Simultaneously, the environment is changed by agents' actions. As such, economic development is largely driven by endogenous processes of self-transformation (Witt 2006).

The application of evolutionary concepts in a network context has only recently begun to happen. 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 seek to contribute to this field of literature of evolutionary network modeling. Our core question deals with the determinants of the emergence and dissolution of a tie between actors. From the firm's perspective this question addresses the guidelines that determine the decision to cooperate and to select a cooperation partner. While 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. Gulati and Gargiulo (1999, p. 1440) conclude: "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".

We apply the 'stochastic actor-based model for network dynamics' (Snijders 1996, Snijders 2001) suited for statistical inference analysis based on longitudinal network data. This type of model has the advantage of capturing network dynamics simultaneously driven by a combination of different factors. The model allows for testing hypotheses about driving factors and for estimating parameters while controlling for other factors. Consequently, stochastic actor-based models for network dynamics enable us to analyze the process of network evolution and to disentangle a diverse set of potential driving factors in this complex process. Standard regression models are clearly inappropriate for this type of network data since the independence of observations is explicitly excluded in the network case, for example, the formation or dissolution of a tie depends on the formation or dissolution of other ties in the network.

In the following sections we introduce the hypothesized independent variables determining the evolution of the analyzed innovation network of German automotive firms.

3.1. Transitivity

Transitivity is a structural effect which refers to the positioning of actors in a network. It describes a tendency of the partners (*j, k*) of an actor (*i*) to initiate a collaboration which leads to 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 behavior (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 behavior. For instance, if actor *j* collaborates with actor *k* and actor *i* collaborates with actor *k*, alter *k* is a reliable source of information about the trustworthiness and reputation of actor *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). 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).

It follows that firms sharing a common cooperation partner are more likely to collaborate compared to other actors which do not have a partner in common (H1). Transitivity is measured by the number of transitive triplets an actor is involved in (Formula 1)

$$T_i = \sum_{j<k} x_{ij} x_{ik}\, x_{jk} \tag{1}$$

3.2. Geographical distance

Despite the wide diffusion of communication technologies which shrink 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 German automotive firms is shown (based on the sample).

The geographical clustering of firms influences the interaction patterns (e.g. Weterings & Boschma 2009, Hoekman, Frenken & Van Oort 2009). Shorter distances provide more opportunities to meet which helps to develop trust, 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. By no means, is this, however, a sufficient condition for the formation of ties on its own. 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).

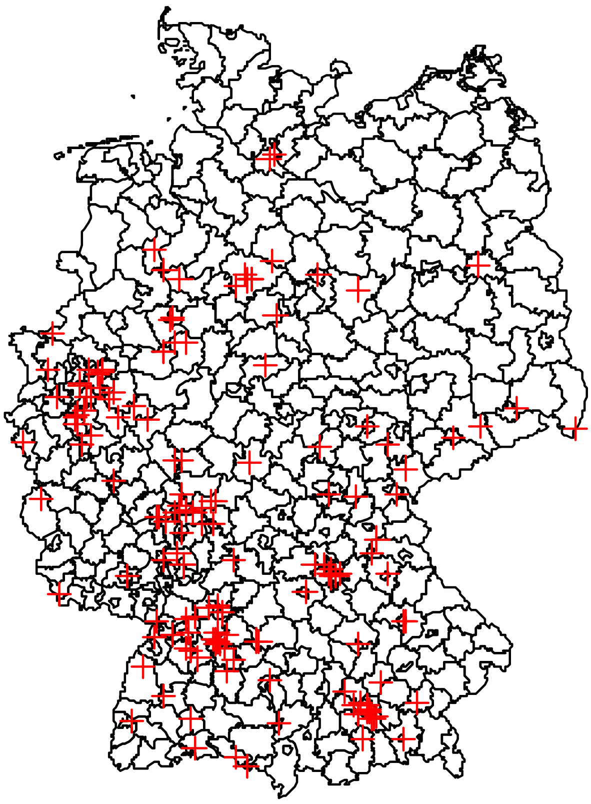


Figure 1: Geographical distribution of (considered) automotive firms in Germany

It follows that firms which are located in relative spatial proximity to one another 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 internet navigation service Google Maps and logarithmized with the natural logarithm (Formula 2).

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

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 evolution, two considerations are relevant: First, firms have advantages in learning if the new knowledge is close to their existing knowledge-base, whereas, it is rather difficult to learn in fields which are completely different. Second, the characteristics of an actor's knowledge-base change only incrementally due to the fact that learning takes place preferably in areas that are related and somewhat similar to already explored areas (Cohen & Levinthal 1990). Zahra and George (2002) stress that sophisticated absorptive capacities allow

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

firms to build up the required knowledge for developing other organizational capabilities and for broadening their knowledge-base. 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).

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

3.4. Technological proximity

Besides geographical proximity, also technological proximity among actors matters for cooperation. Here we refer to the concept of "cooperation partner similarity" (McPherson, Smith-Lovin & Cook 2001) in a network context. According to this concept similar actors have a higher probability to form a link. Similarity may refer to a variety of dimensions. Firms can be similar with regard to technological, knowledge-related, organizational or financial characteristics, or even 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-bases 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 underlying knowledge-bases. This understanding is similar to the concept of cognitive proximity as described by Boschma (2005), 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 for developing new ideas based on the acquired knowledge. Transferred to the dyadic level, hypothesis H4a suggests 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 between firms in the knowledge 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 years prior to the observation point. In a first step, a vector is calculated which places 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 firms has in the N patent classes. For instance, if N was only two (e.g. B60 and B29) and a firm has 40% of its patents in class B60 and 60% in B29 the vector would be (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 two firms *i* and *j* is calculated as formula (4) suggests:

$$w_{techdis\,ij} = \sqrt{\sum_{c=1}^{N} (p_i^c - p_j^c)^2} \tag{4}$$

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 as well as preference for further collaboration. This reflects that from outside it is rather difficult to scan a firm's valuable resources, in particular its knowledge-base. 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 partners, initiate collaborations and manage successfully the partnerships (e.g. Makadok 2001). Experienced firms have implemented collaboration management routines 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). With formula (5) we measure the experience of a firm ($v_{expi(t)}$) with the frequency of participation in subsidized R&D projects with partners ($NbR\&D_{projectsi(t:1998)}$) both from within and outside of the automotive sample starting with the year 1998 which is five years prior to the first observation.

$$v_{expi(t)} = NbR\&D\ projects_{i(t:1998)} \tag{5}$$

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. Brusoni & Prencipe (2001) summarize the suggestions made by the literature on modularity: First, there is a strong link between knowledge, product and organizational modularity which means that the knowledge encapsulated in a modular product is also modular. Second, modular product architecture facilitates the division of labor inside a firm as well as between firms. Third, modular product architecture reduces coordination efforts in the division of labor. In particular, Arora, Gambardella & Rullani (1997) argue that modularity of knowledge and technologies supports the division of labor in innovative activities. In a stylized way, modularity divides innovation processes in two separate components, namely in (i) the production of new (basic) modules and (ii) their combination for tailor-made technologies and designs to fit market needs. Innovation processes can accordingly be broken down into different tasks and stages. The division of labor in innovation processes may lead to an industry structure in which “specialized upstream suppliers” focus on the production of new modules benefitting from economies of scale, and where the combination of modules is conducted by more downstream firms.

We suggest that not only the size or the relatedness of knowledge-bases matter for the propensity to cooperate but that the decomposability of the knowledge-bases into modular knowledge substructures is also relevant. The feature of modularity of a firm’s knowledge-base is approximated by its degree of clustering. Firms not only try to find a partner which has a similar technological understanding, but they attempt to link technologies. We expect firms which have modular knowledge-bases to be preferably chosen as collaboration partners because this facilitates the combination of knowledge. In particular, 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 of 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 processes as compatible technologies can be identified more easily. Based on these considerations we propose 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 modularity 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 in the same patent (see Saviotti 2009 and Yayavaram & Ahuja 2008 for details). Yayavaram & Ahuja (2008, p. 334) state 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 in the patent portfolio of a firm while the elements A and C may appear together only 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 modularity 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).

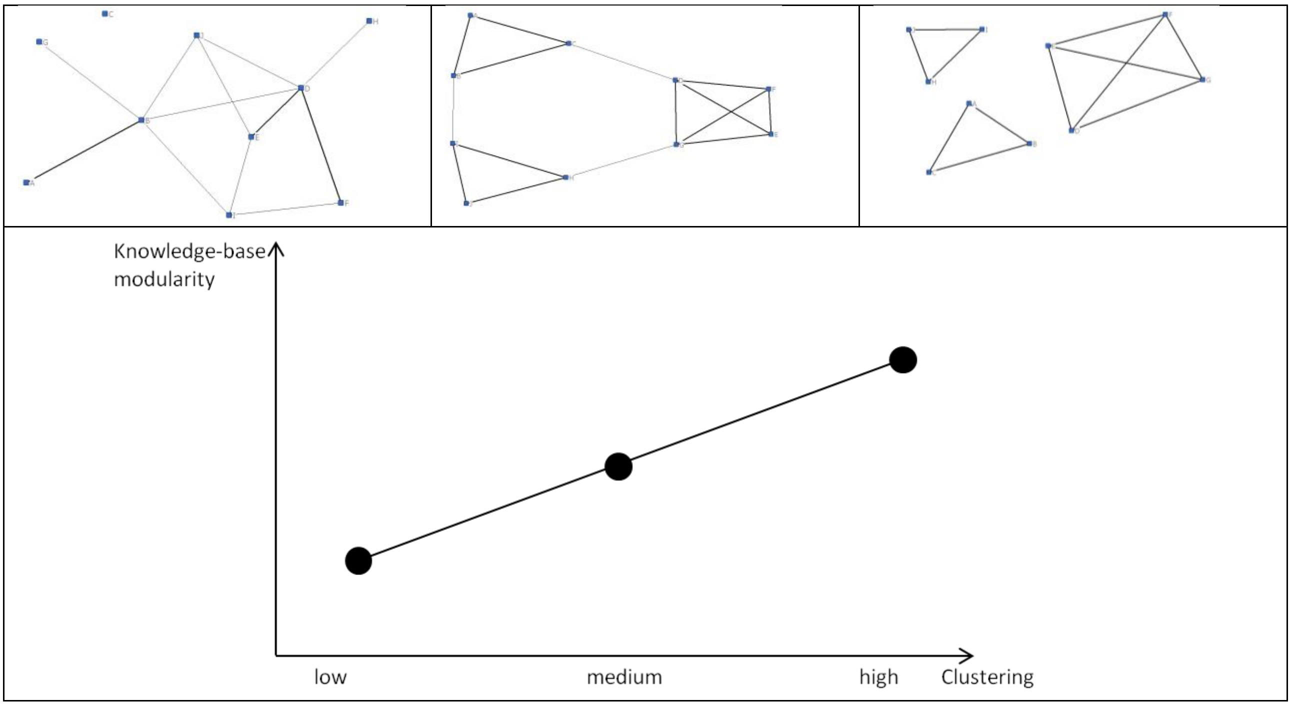


Figure 2: Stylized relation between modularity and clustering

A highly 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). Finally, a non decomposable pattern does not show identifiable clusters but the links seem to be arbitrarily distributed (Figure 2 top left).

As a measure for the level of modularity of a knowledge-base we calculate a slightly modified *clustering coefficient*. The first step in calculating the modularity of the knowledge-bases is to construct the described knowledge network structure. We take IPC sub-classes (4-digit level) as nodes and add a tie between nodes whenever the sub-classes co-occur in a patent. Doing this, we reconstruct the knowledge network from patents for each of the analyzed 153 firms in moving time windows each encompassing five years (1998-2002 to 2002-2006). By neglecting the tie strength (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:

$$cc_i = \frac{n_i}{\frac{k_i * (k_i - 1)}{2}} \tag{6}$$

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:

$$rsc_i = \frac{c_i}{\sum c_i} \tag{7}$$

In a final step, the clustering indicator (ci_i) for each firm's knowledge-base is calculated in (8) by multiplying the clustering coefficients cc_i of each node with the relative shares of the IPC sub-classes (rsc_i) and summing them up to weighted clustering coefficients:

$$v_{modular\ i(t)} = ci_j = \sum cc_{ij} * rsc_{ij} \tag{8}$$

3.7. Control variables

Two important controls have been added to the model, both referring to a capacity effect. Larger firms can coordinate at the same time more cooperation partners than can smaller firms. Accordingly, the model needs to control for firm size. For measuring size we distinguish three categories, 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. The required information is taken from the companies' websites and from excerpts from the commercial register (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 the industry experience of firms. 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

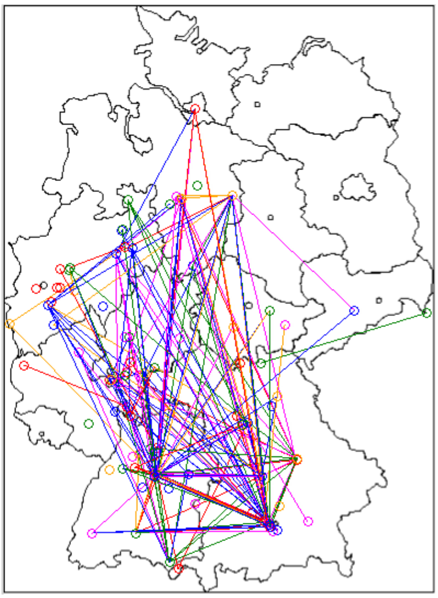
For the empirical research of network evolution, in a first step, we built a sample of German automotive firms. Since our reasoning is led by the knowledge-based view, we selected firms based on the characteristic of their patent portfolio instead of, for instance, applying a standard industry classification such as NACE. A scan of the patent portfolios of the German OEMs and the largest suppliers (OECD June 2010 Regpat database which is a supplemented extraction from Patstat) shows, that the 3-digit IPC class "B60" is strongest in the industry. Thus, we took all firms which filed at least one patent application in this class within the observation period 1998 to 2007 and picked out those which were exclusively operating in the market for commercial vehicles or car accessory kits. Hence, we excluded all firms which were not directly related to the production of passenger cars. We also excluded firms which have not been involved in at least one of the examined research projects. This sampling resulted in 153 firms belonging to the studied network sample.

The networks were observed at six consecutive points in time (2002-2007) resulting in six adjacency matrices representing the state of the network at the observation points. The networks were constructed from the database of the German *Förderkatalog* (*R&D subsidies catalogue*) which contains rich information about research projects supported by the federal government[3]. Only those firms were eventually picked for the analysis which participated in the observation period 1998-2007 at least once in a funded project. The assumption was made that 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 subsidized collective research projects, it has thus far rarely been used to conduct network research (Broekel & Graf 2010).

Information about firms participating in joint subsidized projects documents research activities at an earlier stage compared to patent data. R&D subsidies have become a frequently used instrument of innovation policy to spur collaborative research for a number of reasons: First, due to the sheer scale of some projects, individual firms cannot afford to handle them alone. Second, knowledge transfer from public to private organizations is fostered by the participation of universities and other public research institutes such as the Max Planck and Fraunhofer Institutes. 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 projects. Furthermore, they commit to actively collaborate with the aim to find new solutions (BMBF 2008). That this works out well has been empirically validated by Fornahl, Broekel & Boschma (2011).

To construct networks from the project data, the following information was retrieved: name of the project, starting and end date as well as the name of the receiving/executing organization. The title of the project is important to separate cooperative ("Verbundprojekt" or "Verbundvorhaben") from non-cooperative projects in which single organizations are funded. The database at hand is complementary to other sources such as patent data or publication data (Broekel & Graf 2010). Figure 3 shows the resulting networks for the six observation points (December) 2002-2007 and the regional clustering.

[3] The database is publicly accessible via the website www.foerderkatalog.de



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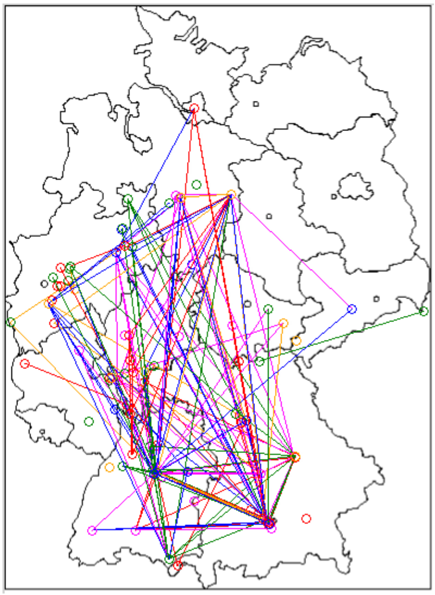

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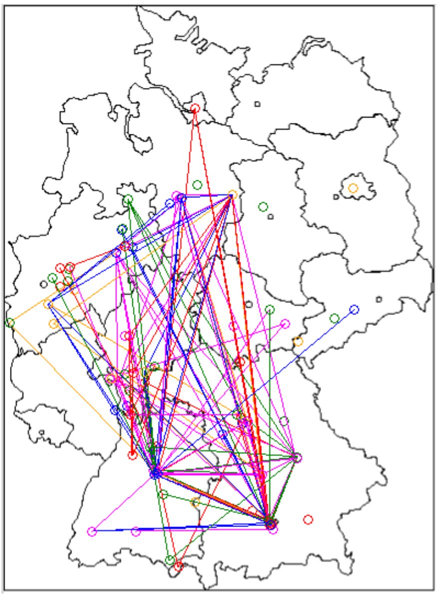
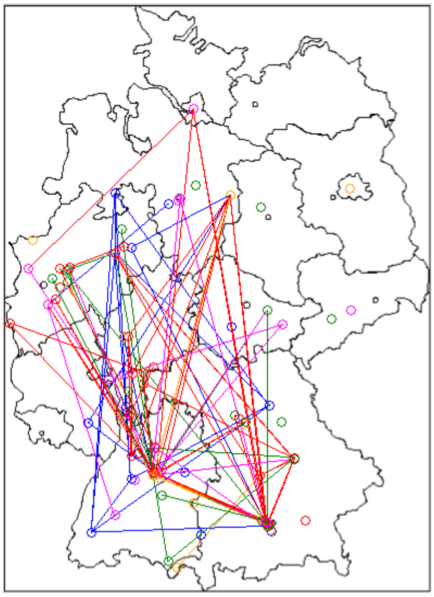
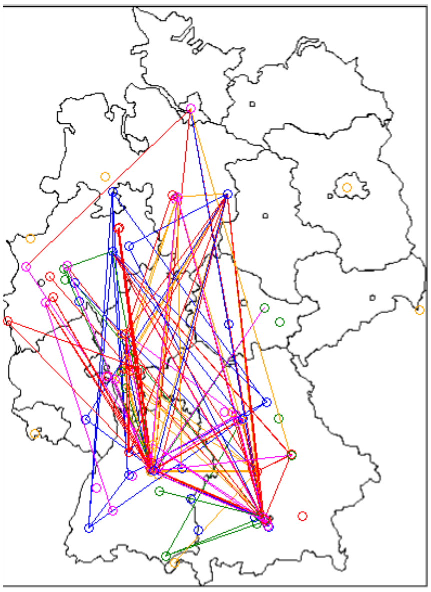


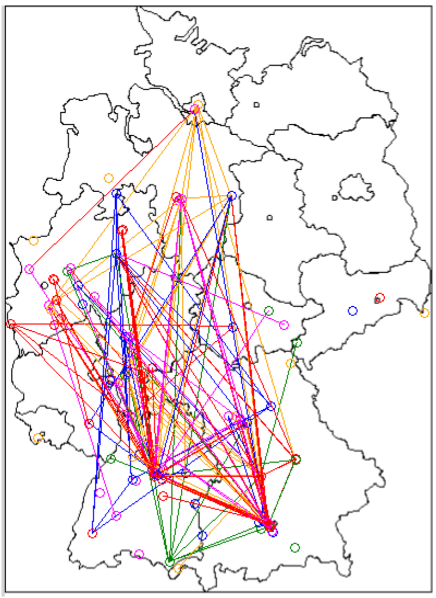
2004



2005



2006



2007

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

A potential shortcoming of our network data is a possible inherent 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 the interpretation of 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, self-organizing networks are characterized by small world properties (Watts & Strogatz 1998) which do not appear frequently in networks created by policy intervention. For instance, small world properties are 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 industry would weaken the 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 approach of Watts and Strogatz (1998) 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. Contrary to random networks, small world networks are characterized by high clustering. 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 critique concerning the usage of data describing publicly funded networks includes the idea that granting schemes preselect eligible firms. In our case, however, 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 only.

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

Table 2 shows a strong increase in the number of established ties in particular between 2004 and 2006. This can be explained to some extent by an increased number of funded research projects due, in turn, to the increasing importance enjoyed by this policy instrument over the years. The number of disrupted as well as the number of stable ties is faltering over the observation period.

Table 2: Link development 2002-2007

Observation	0→1	1→0	1→1	Jaccard Index
2002→2003	14	43	123	0.683
2003→2004	14	39	98	0.649
2004→2005	65	56	55	0.312
2005→2006	120	25	95	0.396
2006→2007	60	47	168	0.611

The density of the network (Table 3) is 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 Centrality	2.258	1.839	1.483	1.611	2.886	3.060
Number of ties	166	137	112	120	215	228

5. The network evolution model

To test our hypotheses with the empirical data of a network in the German automotive industry, we draw on the so-called *stochastic actor-based model for network dynamics* (Snijders 1996, Snijders 2001). The approach is suited to the analysis of longitudinal data of network evolution and goes beyond many other models. In particular, the widespread used econometric application of *scale-free networks* (Barabasi & Albert 1999) is limited, because it considers only one explanatory variable, namely the uneven distribution of the actors' degrees. Even more important, to understand network dynamics, the exclusive focus on the emergence of the network ties is not sufficient. Of course, also the dissolution of network linkages shapes network dynamics. Here we find the decisive advantage of the stochastic actor-based approach for the analysis we have in mind: The stochastic actor-based model explicitly considers formation and dissolution of network ties and allows consulting a broad set of explanatory variables. Because of the high requirements to data availability this approach is so far applied only to a few 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 and Balland, De Vaan & Boschma (2012) investigate the computer games industry. Traditional manufacturing industries such as the automotive industry are not yet analyzed.

In the following paragraphs we briefly summarize the basic mechanism of the approach and refer to Snijders (2005) for details. In the *stochastic actor-based model for network dynamics* actors follow a *myopic stochastic optimization rule* in their decisions to enter, to stay in or to quit a cooperation. Network ties are considered as states which persist over some periods. This assumption is in line with our data as the projects of the *Foerderkatalog* typically run for at least three years. The probabilities for the actors' decisions in the network depend on exogenous individual characteristics as well as on the current state of the network and possible change options. In a typical Markovian assumption, only the present state of the network influences the actors' decisions. This does not exclude path and history dependencies because the independent variables inherently contain historic information; e.g., experience with cooperation and absorptive capacity which are cumulative measures. The time parameter (t) is continuous. For the estimation of parameters it is however assumed that we observe the network at discrete points in time.

That is, the change process is broken down into unobserved so-called *ministeps* that are simulated. Furthermore, we selected the unilateral initiative and reciprocal confirmation version of the model which is closest to reality. This indicates that the actor *i* propose a tie and the potential partner *j* will accept or deny the request based on the evaluation of its objective function (Van de Bunt & Groenewegen 2007).

Tie changes are probabilistically based on the objective function which expresses how a firm perceives the network and evaluates the different options of change. For meaningful estimation results it is necessary to have a certain amount of change between two consecutive observations of the network. The assumption here is that changes in the network take place in a gradual stepwise manner rather than by sudden "shocks". To ensure gradual change in the networks we calculated the Jaccard index (9) (M_{11} = Number of retained links; M_{10} = Number of interrupted links; M_{01} = Number of formed links).

$$J = \frac{M_{11}}{M_{01}+M_{10}+M_{11}} \tag{9}$$

Based on experience with the stochastic actor-based model, the value of the Jaccard Index should ideally be above 0.3 (Snijders, Van de Bunt & Steglich 2010). This is the case for all observation periods (Table 2). The assumed aim of each actor is to increase the value of this objective function which is determined by the network structure as well as by actor and dyadic covariates. For the process of changing or maintaining ties, we have to consider probabilities which depend on the evaluation of possible changes in the network in terms of ties and covariates. The way the objective function is constructed represents the hypothesized decision rules relevant for the actors. For any possible state of the network the objective function takes a specific value and for change options which yield higher values the probability increases that an actor opts for this network state. Formally the objective function (10) is a linear combination of a set of factors:

$$f_i(x^0, x, v, w) = \sum_k \beta_k s_{ki}\,(x^0, x, v, w) \tag{10}$$

In particular, 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 such as the different proximity categories (w). Functions $s_{ki}()$ are the effects introduced in section 3 and based on theoretical considerations. Effects which depend on the network are called structural or endogenous effects. Effects which depend on external attributes are called covariates or exogenous effects. Weights β_k are the statistical parameters to be estimated; if β_k = 0, corresponding effects play no role for network evolution and if β_k > 0, the probability increases of moving in the direction where the respective effect increases the objective function.

Changing tie variables are the dependent variables in the model and iterative Markov Chain Monte Carlo (MCMC) algorithm based on the method of moments are then used to estimate the parameters (Snijders 2001) of an objective function which contains the effects to be analyzed. The core idea for the estimation of parameters is to find values for the parameters β_k such that the expected value of the statistics s_{ki} equal the observed values. In other words, the aim of the estimation is to fit the expected statistics to the observed statistics by simulating networks which fulfill this condition. For example, we may search for a simulated network which has as many closed triads as the observed network. Due to the complexity of an evolving network the expected values have to be taken from the simulation.

This 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 in order 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 standard errors (Snijders 2001). The MCMC estimations can be interpreted like the results of a logistic regression, which implies that all potentially relevant variables that could influence change processes in the network are controlled for (Balland, De Vaan & Boschma 2012).

6. Estimation results

Model parameters have been estimated with the stochastic actor-based network model as implemented in the SIENA program based on the *R* platform (Ripley et al. 2011). 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)	0.08	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 summarizes the resulting coefficient values 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 suggests 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. The finding is in line with studies performed for other industries. Accordingly, it can be considered a general effect which basically always plays a role in innovation network evolution.

Hypothesis 2 indicates an inverse relationship between the propensity to cooperate 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 despite the fact that is has moved from an explorative phase to a more exploitative phase.

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 cognitive distances and abilities to learn from cooperation partners. With the data at hand, however, this cannot be adequately tested. Moreover, there are various ways of operationalizing the concept of technological distance (see Benner & Waldfogel 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 link.

Additionally, our results indicate that 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.

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 destructive part of Schumpeterian innovation competition. This holds in particular for the automotive industry in Germany, challenged by firms from emerging markets which dominate 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 innovation networks, however, is far from constant and 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. Contributions which analyze static network structures are much more common. With our paper we seek to contribute to the dynamic analysis of innovation networks and investigate 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 our network, composed of publicly funded R&D projects in the German automotive industry, structural as well as individual and dyadic covariates are relevant drivers.

The following main results were obtained: The establishment of cliques plays 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 such as geographical distance, technological distance, cooperation experience are confirmed and explain the cooperation behavior of the sample 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. We regard the preference for modular knowledge-bases as an industry specific property which is related to the automotive product architecture and manufacturing. The high modularity of knowledge in the automotive industry seems to play a very important role for the particular innovation networks which can be found in this industry. Once R&D is increasingly shifted to suppliers and once the industry structures changes is character from a strongly hierarchical architecture towards a more horizontal network organization, knowledge needs to become more modular. In fact, in the automotive industry suppliers are expected to gain even larger shares in the value chain during the next years. This tendency concerns production but also R&D. For R&D the share of the OEMs is expected to drop from 60 % in 2012 to only 47 % in 2025. Beneficiaries are suppliers and in engineering service providers. This trend is accelerated by the paradigmatic move in the power train towards electric engines (Oliver Wyman 2012). Modularity is also an attempt to face the complexity trap. Clearly defined interfaces and communication standards such as the CAN-Bus allow for the coordination of sub-systems. In a nutshell, even though the OEMs have still the lead in product architecture design which requires sound knowledge across all relevant technologies, the trend clearly signifies that lower tier suppliers play a stronger role not only in production but particularly in R&D. Consequently, the knowledge on which technologies are based on is increasingly modularized. This might not be reproduced in other sectors such as ICT, biotech, laser or nanotech which are on our agenda for future research.

Obviously the results are of policy relevance and contribute to the improvement of policy design. The paper also leads to a number of further research questions: E.g. is there a special role played by inventors in the network, which are not necessarily employees of the innovating firms? Other than the impact of geographical distance, absorptive capacities, experience etc., are there additional factors determining the cooperation behavior? 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?

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Fruwirthstr. 12
D-70593 Stuttgart
Phone +49 (0)711 / 459-22476
Fax +49 (0)711 / 459-23360
Internet www.fzid.uni-hohenheim.de