Abstract

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

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Innovation networks are regarded as a means to share increasing R&D costs, gain access to scarce resources and, even more importantly, to manage complexity, cope with technological uncertainty and create learning opportunities. Each network can be described by its specific structure which is determined by the emergence and dissolution of ties between actors (firms and research organisations). This process which drives the evolution of a network is a function of the actor’s characteristics and their socially driven behaviours and interactions (Snijders 2001, Scott 1996, Huggins 1997, Pyka 2002).

Most studies in the field of network research are in essence of a static nature and apply purely descriptive techniques (Baum et al. 2003), namely standard social network analysis which is based on the graph theoretical concepts (see Wasserman 1994). This kind of analysis is based on snapshots of networks at a certain point in time. However, a key characteristic of networks is their evolution in time with continuously emerging and dissolving ties between the actors (Ter Wal et al. 2008). Stochastic actor-based models for network dynamics enable us to shed more light on this dynamic process and to disentangle the driving factors.

For the investigated case of an innovation network in the German automotive industry, I assumed both, actor characteristics as well as social factors to be relevant drivers for network evolution. The empirical research is theory lead. Based on hypotheses I tested a number of factors which are alleged to influence the tendency to cooperate. In
particular, as relevant factors I considered: absorptive capacity, technological proximity, cultural proximity, geographical proximity and experience with cooperation.

Networking firms (nodes) have been selected by a multi-step procedure, starting with a collection of firms that hold patents in the 3-digit IPC class B60 which I found to be a dominant class in the automotive industry. The networks have been constructed from the database of the German ?Förderkatalog? which contains rich information about research projects supported by the federal government. Only those firms were finally picked for the analysis which participated in the observation period 1998-2007 at least once in a funded project. In the model a tie emerges between any two actors i and j if they participated in the same project.

The evolution of the network is modelled with a stochastic actor-based model (Snijders 1996, 2001). Stochastic methods for the analysis of networks have a number of advantages: (i) even a small component of randomness in a regular pattern makes predictions of the outcome very difficult; (ii) a statistical model can tell us which social process most probably drives the network evolution and which node level characteristics are relevant; (iii) a simulation approach can help us to understand this micro-macro link between the node level, substructures and the network as a whole (Robins et al. 2007).

The simulation results show that for the current model specification cohesion plays a strong role as firms tend to form transitive triads. Also, for the other tested factors I found significant variable values except for the absorptive capacity (which I have to investigate more in depth). Higher levels of geographical proximity as well as technological proximity lead to higher probabilities of forming cooperative ties. Furthermore, same firm culture and more experience with cooperation are additional factors that increase the likelihood of firm to become involved in R&D partnerships.
The key interest of this paper is to outline a conceptual basement for capturing network evolution patterns of interfirm innovation networks; and to analyse the dynamic evolution of an R&D network in the German automotive industry. In particular, I tested a number of hypotheses with regard to the drivers of evolutionary change of a network that is based on subsidised R&D projects within the observation period 1998 to 2007. This was conducted with a stochastic actor-based model in order to simulate network change based on empirical observations. The general line of argument follows a knowledge-based approach of the firm. I demonstrate that structural positions of firms as well as actor covariates and dyadic covariates are determinants of the evolution process.
1. Introduction to network dynamics

A review of recent theoretical as well as empirical studies conducted in the broad field of network research demonstrates that the dynamic aspects of complex network evolution processes have become increasingly addressed. Scholars from various disciplines like physics (e.g. Dorogovtsev, Mendes et al. 2000; Barabasi, Albert 2002; Bianconi, Barabási 2001), biology (e.g. Krapivsky, Redner et al. 2000; Vázquez 2003), sociology (e.g. Stokman, Doreian 1997; Steglich, Snijders et al. 2006) have started to analyse drivers and mechanisms of network growth and change. Some efforts have also been taken in the field of innovation research (e.g. Jackson, Watts 2002; Cowan, Jonard 2003; Ter Wal 2009; Balland 2009). More research is however needed in order to gain a better understanding of evolving innovation networks in various industries.

Innovation networks are generally regarded 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 (Buchmann, Pyka et al. 2011; Pyka 2002). Each network is characterised by its specific structure which is the result of the emergence and dissolution of ties between actors (firms and/or research organisations) over time. This process which drives the evolution of a network is a function of the actor’s characteristics and their socially driven behaviours and interaction patterns (Snijders 2001; Scott 1996; Huggins 1997).

Most studies in the field of network research are essentially of a static nature and apply purely descriptive analysis techniques (Baum, Shipilov et al. 2003), namely standard social network analysis which is based on the graph theoretical concepts (Wasserman, Faust 1994). These approaches are fed with snapshots of network data at a certain point in time. Those studies gave us for instance interesting insights into the network structure, the roles of actors and advantageous positions. However, a key characteristic of networks is their evolution in time with continuously emerging and dissolving ties between the actors (Ter Wal, Boschma 2009). Actor-based models for network dynamics enable us to shed more light on this dynamic process and are, thus, a useful instrument to disentangle the driving factors. In this paper, I present results from an investigation of evolutionary change patterns of an interorganisational innovation network (Pyka, Fagiolo 2005; Pyka 2006) in the German automotive industry. The elementary building blocks of innovation networks are nodes (firms) and ties (based on R&D agreements) symbolising interaction patterns that may serve as channels of implicit and explicit knowledge flows. These basic network elements span on a more aggregate level a complex network structure which is embedded in a wider economic system. Consequently, an innovation network can be described as an integral part of the regional, national or sectoral innovation system.

For the examined case of an innovation network in the German automotive industry, I assumed both actor characteristics as well as social factors to be relevant drivers for the emergence of cooperative relationships.
between firms. The subsequent empirical research to test the alleged factors was led by theoretical considerations. Based on hypotheses I tested a number of factors which supposedly influence the tendency to cooperate. In particular, I suggested the following factors to be relevant drivers: transitivity, absorptive capacity, technological proximity, geographical proximity and experience with cooperation.

1.1. Starting from a knowledge-based approach

The paper follows a knowledge-based approach for the analysis of economic interaction which has in its principal ideas a longstanding tradition in economics. Early proponents of this concept are (Marshall 1920) who recognizes knowledge as the decisive factor in production processes and (Penrose 1959) who identifies the knowledge base of a firm as a key resource. In the 1980s this approach was taken up by (Nelson, Winter 1982) and (Dosi 1988) and it became an element for the establishment of the Neo-Schumpeterian school (Hodgson, Samuels et al. 1994; Hanusch, Pyka 2007; Dopfer 2005) of economic thought. Here, the role of knowledge for economic development and the success of firms is explicitly recognized and constitutes the cornerstone of economic analysis.

The knowledge of a firm is its key resource which brings it in the focus of the analysis (Das, Teng 2000). Accordingly a firm can be described as a „repository of productive knowledge“(Winter 1988). A key feature of knowledge in turn, is its close relation to other firm resources, its specificity as well as its lacking substitutability and the uncertainty in its generation process (Lippman, Rumelt 1982). The derived heterogeneity between firms has proven to be stable over time (Peteraf 1993). A further important element of firm heterogeneity is the diversity of relations with other actors (Marshall 1920). Moreover, knowledge is limited in its imitability and the transfer on markets is inherently difficult, as the information would have to be (partly) revealed in order to evaluate it and build a price. This holds in particular for implicit knowledge, which is based on experience (learning by doing), whose transfer presupposes a high level of trust between the actors (Hall 1993).

Networks are seen as a vital determinant in the industrial creation of novelty and are therefore decisive coordination mechanisms. In networks new technological opportunities are created via technological complementarities, recombination and synergies bringing together different technological and economic competencies. Knowledge is considered no longer as a pure public good but as local, tacit, firm specific and complex. These characteristics hamper technological knowledge from being easily exchanged on markets. Technological spillovers are no longer freely available, knowledge is no longer “in the air” as in the standard models of growth, but it has to be acquired actively by own R&D and/or by participating in innovation networks. Geroski (1995, p. 85) emphasised 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.” In other words, firms have to take action rendering their knowledge base accessible to others in order to fuel the collective innovation process in which they participate. Technological spillovers are hardly conceivable without being embedded
in innovation networks. A major consequence of sticking to the knowledge-based Neo-Schumpeterian approach is the abandonment of the idea of firms being atomistic entities in perfect markets, aiming to only maximise their profits by internally optimising their processes. Instead, firms have to be seen as actors being embedded in complex environments that encompass numerous interconnected actors trying to reach heterogeneous goals and to improve their imperfect knowledge bases (Heiner 1983). From this it can be concluded that the embedment in networks is a prerequisite for the survival of firms in an intense innovation competition.

2.3 The sources of innovation

The innovation process of a firm is fed by two distinct sources. First, scientists and engineers of a firm discover new combinations and create new knowledge which is the cornerstone for the development of new products that can be offered on markets. R&D units have increasingly become permeable and connected to other departments such as marketing or directly to customers (von Hippel 1988, Chesbrough 2003). Second, knowledge and new ideas can be absorbed by channels to other organisations. The internal functions filter and evaluate absorbed information and will design products or processes from the most promising ones (Cohen, Levinthal 1990). Innovation is in this case the result from internal expertise and external stimuli; or as Tsang expressed it: “Tapping external sources of know-how becomes a must” (Tsang 2000, p. 225).

Increasingly complex technologies spur collaborative efforts for new knowledge creation. Hardly any firm can retain a leading role in competition by solely relying on isolated R&D endeavours. Joint R&D projects, strategic alliances and other forms of collective innovation processes allow for the pooling of expertise and know-how (Teece 1992). In addition, R&D cooperation opens channels to get access to additional critical resources. In contrast to the transaction cost approach (Coase 1937) which focuses on cost minimisation, Neo-Schumpeterian economists emphasise the importance of learning opportunities and the knowledge transfer processes in networks (Buchmann, Pyka et al. 2011). Knowledge as the key factor for invention and innovation is a scarce resource. It is hard to imitate, to transfer on markets and to substitute (Peteraf 1993, Barney 1991). Knowledge intense industries like automotive or biotechnologies fostered the movement towards collaborative innovation (Powell, White et al. 2005; Pyka, Saviotti 2005). „Collaborations are a useful vehicle for enhancing knowledge in critical areas of functioning where the requisite level of knowledge is lacking and cannot be developed within an acceptable timeframe or cost” (Madhok 1997, p. 43).

2. Modelling network dynamics

A typical characteristic of networks is that they are not static but continuously evolve as ties emerge and disappear over time. R&D networks consist of at least two nodes (“organisations”) and connections
between these nodes (“collaborative agreements”). Formations of new alliances as well as terminations of existing alliances influence the growth, fragmentation and therefore the internal structure of an interorganisational network. This leads from an aggregated network perspective to the emergence of constantly changing collaborative structures.

### 2.1. The nature of evolutionary network change

Evolutionary models are quite different compared to economic models in the tradition of classical or neoclassical schools of thought. In the latter models all actors share the same information and transactions do not produce additional costs. Products are assumed to be homogenous and market actors interact time-invariant under the assumption of full rationality on completely transparent markets. As a consequence social interactions in general as well as time, space and mutual trust becomes irrelevant. Even though classical and neoclassical models have provided crucial insights in the functioning of markets, new streams of research – such as evolutionary economics – have emerged and questioned the restrictive assumptions in order to improve economic models (e.g. Pyka 2006; Nelson, Winter 1982; Boschma, Frenken 2006; Witt 2008).

We can capture the inherent logic of evolutionary thinking by taking a closer look at general assumptions common to all evolutionary models which allow at the same time a clear separation from the main stream economic paradigm. Firstly, evolutionary models are based on the assumption that the object of analysis is continuously changing. Compared to traditional static or comparative-static oriented economic models it is important to note that evolutionary models seek to capture the causes, underlying mechanisms and consequences of change processes over time. Besides, it is generally accepted within the evolutionary paradigm that economic phenomena – which appear at multiple aggregation levels – can be ascribed to decisions and actions of bounded rational individuals rather than to collectives. The corresponding term “methodological individualism” was outlined by Schumpeter (1909) and further developed by Austrian economists such as Hayek (1948). Thus, from an evolutionary perspective the world is anything but perfect. Individuals interact on imperfect markets and have to make their decisions under uncertainty and asymmetrically distributed information. In a nutshell, inter-temporal processes trigger individual decisions under the conditions of imperfectness, uncertainty and bounded rationality which can be seen as drivers of change and are thus elementary parts of evolutionary models.

A further general assumption is path dependence. That is, past as well as present events and structural change patterns are relevant for future decisions of individual actors (e.g. Magnusson, Ottosson 1997). In this context (Araujo, Harrison 2002) highlight two important characteristics of the concept: (I) economic processes are not able to shake free from the influence of past event and (II) past dependent processes combine with other types of unique and unpredictable processes. Closely related to the previous aspect is the openness of outcomes of evolutionary processes. Due to unpredictable and nonlinear processes future pathways are only predictable in very narrow confines (Araujo, Harrison 2002). Thus, past and current
(random) factors determine future decisions and processes in conjunction which makes it unclear in advance in which direction a system will evolve (Arrow 1973).

Furthermore, evolutionary change is context specific; this means that the object of analysis cannot be analysed without taking into account the broader environment in which it is embedded. The environment provides at the same time opportunities and constrains which determine the driving forces of evolutionary change. Finally, evolutionary economics in general accepts the idea that environmental phenomena – such as exogenous shocks – can trigger evolutionary change of economic systems to some extent. However, much more pronounced in this research area is the notion that evolution is largely driven by endogenous process of self-transformation (Witt 2006).

The application of evolutionary concepts in a network context emerged recently on the research agenda. For instance, (Glückler 2007) addresses the question how tie-selection constitutes evolutionary processes in networks. More precisely, he argues that network tie selection processes cause retention and variation within network structure. (Hite 2008) presents an evolutionary multi-dimensional model of network change that explicitly considers micro-level network change processes. (Witt 2006) argues that selection processes are according to Neo-Schumpeterian approaches constitutive for evolutionary economics.

3. Determinants of network evolution

The core of this paper is the question about the determinants for the emergence or dissolution of a tie between two actors. From the perspective of a firm it is the question about the guidelines that determine the decision to cooperate and select a cooperation partner. Collaboration can be understood as a means to cope with the uncertainty of a technology field. 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 the appropriate partners. (Gulati, Gargiulo 1999, p. 1440) make the point that “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”.

Four general factors seem to be relevant for relational tie changes. First, the structural position of actors in a network plays a role, e.g. in the simplest case when friends of friends become friends. Second, the characteristics of actors, e.g. the size of their knowledge base (actor covariates) are determinants for the decision to collaborate. Third, characteristics of pairs of actors (dyadic covariates), e.g. their geographical proximity matter. Finally, there is a residual component which encompasses other influences that cannot be captured in the model.

I applied in this research project a “stochastic actor-based model for network dynamics” (Snijders 2001, Snijders 1996) which allows for statistical inference like analysis based on longitudinal network data. The advantage of this model class it that it is able to capture network dynamics that are driven by a variety of
factors at the same time. Furthermore, the model also allows for testing hypothesis about possible driving factors and estimate the parameters of their magnitude while controlling for other factors. In other words, stochastic actor-based models for network dynamics enable us to shed more light on the process of network evolution and to disentangle the driving factors. Standard regression models can hardly be applied for network data since a central assumption of standard regressions, the independence of observations, is explicitly excluded. The network properties of one actor are not independent of the other actors’ network attributes.

I tested the relevance of the following factors for network evolution: transitivity, absorptive capacity, technological distance, geographical distance and experience with cooperation.

3.1. Transitivity

Transitivity is a structural effect which refers to the positioning of actors in a network. It pronounces a tendency for partners \((j,k)\) of an actor \((i)\) to start a collaboration among them which results in the formation of closed triangles that can supposedly be found in number that exceeds the number of such triadic structures in random networks (e.g. Davis 1970; Holland, Leinhardt 1971). The formation of triads in turn is an indication for the formation of interconnected cliques (Skvoretz, Willer 1991). As firms operate in an environment of bounded rationality and imperfect information, for instance in terms of potential partners, they have to bear 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 about potential partners. 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 \(j\); an effect which leads to closed triangles. Moreover, the formation of triads creates social spaces that prevent actors from opportunistic behaviour, allows for the formation of trust and forges the exchange of tacit knowledge (Uzzi 1997). Positive values for the transitive triad effect signifies that firms which share a common cooperation partner will collaborate with a higher probability than others. 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 et al. 1997). In this regard Reagans and McEvily (2003) demonstrate that strong social cohesion around a relationship reinforces the willingness and motivation to invest time, energy and effort in sharing knowledge with others. Consequently, trust in dense parts of the network facilitates intensive exchange of complex or sensitive knowledge (Zaheer, Bell 2005). Hence, I expect firms which have already a cooperation partner in common to possess a higher propensity to form a cooperation among each other (H1). Transitivity is measured by the number of transitive triplets of actors.

\[
S_{it} = \sum_{j<k} x_{ij} x_{ik} x_{jk}
\]
3.2. Geographical distance

Despite the ampleness and diffusion of modern telecommunication utilities which shrink perceived distances between us and all other person in our social networks, geographical distances may still play a role when it comes to the propensity to cooperate and 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). Figure 1 shows that clustering is a feature of the investigated German automotive firms too.

Figure 1: Geographical positioning of investigated automotive firms

But we often find not only a tendency for clustering with regard to an industry’s location but also in terms of its interaction patterns (e.g. Weterings 2006; Hoekman, Frenken et al. 2009). Shorter distances provide more opportunities to meet which helps to develop trust that is the basis for the willingness to exchange knowledge, in particular the tacit component (Howells 2002). Face-to-face interaction eases 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 physical distance as such which influences network formation. Instead, it is the possibilities and preferences of human beings to communicate (Storper, Venables 2004) and it is the means of transportation which are affected by distances (Marquis 2003). Thus, there is a possible, though indirect, relation between geographical distances and the possibilities and propensities to form fruitful agreements of interaction. Second, locations may play a role in that they provide opportunities, access to specific locally
bound resources and chances for economic development (Sayer 1991; Bathelt, Glückler 2005). From the theoretical arguments it follows that firms which are located in relative spatial proximity compared to other pairs, have a higher propensity to cooperate (H2). In order to form a pairwise distance matrix, geographical distances between all pairs of actors have been retrieved from the web street navigation service Google Maps and logarithmised with the natural logarithm.

$$w_{geoij} = \ln (dist_{ij})$$

3.3. Absorptive capacity

In the understanding of evolutionary economics, firms differ in their ability to make use of external knowledge. This can be explained by the concept of the absorptive capacity of a firm which 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 field it is relatively easy for it to recognise, evaluate, assimilate and apply new knowledge. Studies on learning processes suggest that storing new information in memories is self-reinforcing, i.e. the more there is already stored the easier new information can be acquired (Bower, Hilgard 1981) and contextual knowledge is essential to make full use of the new knowledge (Lindsay, Norman 1977). 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). Hence, we can draw two conclusions: First, it is relatively easy to learn new things in field in which we have developed already some expertise while it is rather difficult in fields which are completely new to us. Second, the characteristics of a 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) bring forward the argument that dynamic absorptive capacity enables the firm to build up the required knowledge to develop other organizational capabilities. Consequently, I expect firms which have higher levels of absorptive capacity to have a higher propensity to collaborate as they have more opportunities to benefit from external knowledge (H3). The absorptive capacity was measured by taking the natural logarithm of the number of patents a firm applied for in the five years prior to the observation point.

$$v_{absorpcal(t)} = NbPatents_{i(t:t-5)}$$

Footnote: For all dyadic covariates $S_{dyadic} = \sum_{ij} (w_{ij} - \bar{w})$
3.4. Technological proximity

In addition, I refer to the notion of cooperation partner similarity (McPherson, Smith-Lovin et al. 2001) in a network context. According to this concept, similar nodes have a higher probability to form a tie between each compared to more heterogeneous network actors. 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 Rotheaermel and Boeker (2008) demonstrate that status similarity increases the rate of tie formations in interorganisational networks. As I follow predominantly a knowledge-based approach, similarity of the technological knowledge base is of primary interest. 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 ought to reflect the similarity of the underlying knowledge bases. This understanding is somewhat similar to the concept of cognitive proximity as it is described, for instance, in Boschma (2005) even though cognitive proximity is more comprehensive.

Knowledge base similarity eases learning and thus fosters the enlargement of a firm’s own knowledge base. 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 organisation 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 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 dissimilar knowledge bases. Accordingly, Nooteboom, Van Haverbeke 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, I applied 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) within a time span 5 years prior to the observation point. The firm vector p is given by the relative share of patents a firms has in the N patent classes. For instance, if N is only two (B60 and B29) and a firm has 40% of its patents in class B60 and 60% in B29 the vector would be (0.4; 0.6). In a second step, differences between vectors representing distances in the technology space are calculated. Thus the technological distance between firms i and j is calculated as
3.5. Experience with cooperation

A last factor I examined is a firm’s experience with cooperation. It supposedly fosters collaborative activities as firms which have been more often involved in cooperation projects signal that they are more attractive for cooperation. The general idea behind this is that from outside it is rather difficult to scan a firms valuable resources, in particular the knowledge, which can be accessed through collaborative R&D projects. Thus, a firm which has been often involved in such projects in the past must obviously be a valuable partner with a good reputation and established routines of collaboration which facilitate the organisation of an effective collaboration process. Alliance or cooperation capabilities are specific not transferable resources which can enhance a firm’s ability to identify partner, initiate collaborations and manage the partnerships successfully (e.g. Makadok 2001). Experienced firms install dedicated collaboration management functions whose task is to coordinate the portfolio of different types of alliances (Kale, Dyer et al. 2002). Developing experience takes time since it also forces a firm to adapt its internal routines (Powell, Koput et al. 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). Furthermore, it demonstrates that a firm made positive and obviously valuable experience with cooperation. The experience of a firm was measured by adding the number of times it participated in subsidised R&D projects with partners from within outside the automotive sample in the years 1998 to 2007.

\[ w_{tec\text{hs}ij} = \sum_{c=1}^{N} (p_i^c - p_j^c)^2 \]

4. Introducing the stochastic actor-based model

The applied “stochastic actor-based model for network dynamics” (Snijders 1996, 2001) allows for network analysis based on longitudinal data. Others models which seek to capture network evolution like Watts, Strogatz (1998) or Barabasi, Albert (1999) are rather limited in their number of accounted driving forces; and are based on the assumption that ties emergence sequentially while they do not model the dissolution of ties.

In the applied model, network ties are not understood as events but as states which presumably persist for some time. For the examined case of publicly funded R&D networks it is a realistic assumption as the projects typically run for at least three years. The current state of the network determines for every point the time its further evolution which means that it is to some extent myopic following 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. But, history can still matter in the model if independent variables are chosen such that they 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 denotation is in line with standard network analysis. Networks are represented by an n x n adjacency matrix $X(t_m) = X_{ij}(t_m)$ for $m = 1, \ldots, M$. $X_{ij}(t)$ takes the values 0 if there is no link at time $t$ between $i$ and $j$ or 1 if there is a link between $i$ and $j$. Furthermore, the diagonal of the matrix takes the value 0; $X_{ii}(t) = 0$ for all $i$ as it makes no sense to have a link from an actor to itself. An additional matrix, the composition change matrix, accounts for changes in the sample. 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.

It is important to understand 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 $\geq 2$. The time parameter $t$ is continuous. For the estimation of parameters it is however assumed that we observe the network at a minimum of two discrete points in time which gives it the character of a panel analysis. This idea can be traced back to earlier publications of Holland, 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 depends on one another. To demonstrate this, imagine the following example: At $t=0$ out of a group of three firms no firm cooperated with one of the other two. At a consecutive point in time $t=1$ 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 to be there out of nothing. 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.

Firms control their ties based on their and all the other firm’s characteristics, on their position in the network and their perception of the structure of the entire network. This incorporated idea is rooted in the concept of structural individualism (Hedström 2005, Udehn 2002). Note, the expression “actor” is used rather than “agent” to stress the fact that the firms in the model are not serving other actor’s interest (Hedström 2005).

The actor which gets the possibility to change a tie is probabilistically chosen; and only one tie in the network can be changed at one point in time (Snijders 2001; Holland, Leinhardt 1977). That is, the change process gets broken down into the smallest possible components, also called mini steps. Also, the actors do not coordinate tie changes in a way that they happen simultaneously; instead, they follow each other tie by
tie with actors reacting to the stepwise changed network structure. This assumption is somewhat
discussable with regard to innovation networks that are based on some kind of coordination or negotiation.

The change process as such consists of two stochastic sub-processes. First, the frequency an actor gets the
opportunity to change a tie (change opportunity process) depends for instance on the position (centrality)
of an actor and on other covariates like experience. 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 meet a high
goodness of fit level. Second, parsimony is a prerequisite, i.e. there should not be any more fine detail in
the model than what can be estimated from the data (Snijders, Van de Bunt et al. 2010).

The parameters of the model are estimated from observed data 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, I modelled the change between two consecutive observation
points but I did not model the first observation.

The first aim is to simulate the decision about the firm which gets the opportunity to change a tie (start or
stop cooperating) or to remain passive and do not change anything. We can assign the same probability to
each actor or make this depended on covariates or network positions. The change as such 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 network of the ego, 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 remaining 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. The higher this value is the higher is also the probability that the actor opts
for this possible network state. Formally the objective function is a linear combination of a variety of
components which are called effects and have, for the particular case, been explained earlier in this paper.

\[
f_i(\beta, x, v, w) = \sum_k \beta_k s_{ki}(x, v, w)
\]

\( f_i(\beta, x) \) is the value of the objective (or evaluation) function for actor \( i \) depending on the state \( x \) of the
network. Functions \( s_{ki}(x) \) are the effects that are based on theoretical considerations and can be tested in
the model. Weights \( \beta_k \) 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. Covariates can be individual attributes (v) or dyadic attributes (w).

5. Data on which the model is based

For the actual empirical research of network evolution, the first challenge is to select the firms the respective author considers to be (potentially) part of the network. This opens the discussion about the boundaries of the network which is a separate topic in the literature about social network analysis (e.g. Laumann, Marsden et al. 1983) and will hence not be discussed in this paper. The aim of this paper was to study 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 probably more contentious. Since the general line of argumentation in this paper is led by a knowledge-based view of the firm, I started to build the sample (which is not to be confused with a probability sample) based on a firm’s patent portfolio instead of for instance applying a standard industry classification like the NACE scheme. A scan of the patent portfolios (OECD June 2010 Regpat database which is a supplemented extraction from Patstat) of the German OEMs and the biggest suppliers has shown that the 3-digit IPC class B60 is the dominant patent class in the industry. Thus, I picked all firms which filed at least one patent application in this class within the observation period 1998 to 2007 and deduced those which were exclusively operating in the market for commercial vehicles or car accessory kits. In other words, I tried to get rid of all firms which were not directly related to the production of passenger cars. I also deduced firms which have not been involved in at least one of the examined research projects. This “calculation” resulted in 153 firms belonging to the network sample.

For the simulation implementation, networks have been observed at six consecutive points in time (2002-2007) resulting in six adjacency matrices reflecting the state of the network at the observation point. It is generally challenging to find sources about interfirm networks, in particular for longitudinal network studies. In this case, the networks have been reconstructed from the database of the German „Förderkatalog“ (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 were eventually picked for the analysis which participated in the observation period 1998-2007 at least once 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, 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 prolific tool of innovation policy makers to
fuel collaborative research for a number of reasons. Firstly, due to the sheer scale of some projects they cannot be stemmed by single firms. Secondly, knowledge transfer from public to private organisations shall be fostered by the participation of universities and other public research facilities such as Max Planck and Fraunhofer Institutes. Most importantly for the here in investigated phenomena, collective learning and knowledge transfer processes are expected to occur (Broekel, Graf 2010). This is why the participants in such research projects need to sign agreements explicitly stipulating that gained knowledge within the project will be freely shared among the participants. They even have to grant each other 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 is in reality more than just a lip service has been empirically demonstrated (Fornahl, Broekel et al. 2011).

In order to reconstruct networks from the project data, at least the following information is needed: name of the project, starting and end date, name of the receiving/executing organisation. All of them are available in the database. In addition, we can 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 used database can be seen as a complementary source to more established sources like patent data or publication data, in particular when it comes to longitudinal network studies (Broekel, Graf 2010). A possible drawback of this data, which is worth to be analysed more in depth in the future, is the political determination, i.e. networks are to some extent designed by political decisions to support certain key technologies that are regarded as particularly relevant for the development and competitiveness of the national economy. This includes also granting schemes that possibly preselect the eligible firms. On the other hand, this kind of data covers research processes at an early stage, something which cannot be achieved with patent data that represent only successful outcomes of the research processes. (Broekel, Graf 2010) argue that in fields of limited R&D outcome appropriability and if externalities are high, there is a strong need for public subsidies in order to create incentives to invest. Thus, technology fields which meet these “criteria” are better covered by subsidy data than by patent data.

6. **Industry context**

I am currently aware of four industry studies that applied the stochastic actor-based network model on their data: Ter Wal (2009) studies network evolution in the German biotechnology industry; Balland (2009) covers the navigation by satellite industry (GNSS); Giuliani (2010) applies it on a Chilean wine cluster; Balland, de Vaan et al. (2011) investigate the computer games industry. These studies cover industries
which have relatively recently emerged as well as an agricultural industry. However, traditional manufacturing industries like the automotive industry have not been investigated yet.

Intensified competition in the global automotive industry and particularly the growing-up of Asian firms forced the German producers to improve their cost structure wherever it was possible. In order to escape this pressure, new strategies needed to be developed and implemented. Innovations have been identified as the key to success since the enable firms to leave a destructive price competition and to create unique selling propositions. This in turn created a new playing field, namely intensified innovation competition resulting in 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 characterised by few 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 Volkswagen, Mercedes etc. During the last decade more and more value creation, and with it relevant know-how, has been shifted from the OEMs to specialised suppliers 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 totally reliable manner. Taken together, this means that the different parts have to be developed within a comprehensive framework resulting in integrated solutions. Collaboration within common research projects can be seen as the answer to this challenge (Staiger, Gleich 2006). Staiger, Gleich (2006) found in interviews evidence for the strategic collaboration approach. Most firms even participated 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 or failure of national and regional innovation systems or clusters which is in essence linked to the respective competiveness, the relational view of the networks has to be taken into consideration. The key advantage of the network compared to a firm is that the network incorporates a greater variety of knowledge which offers numerous possibilities for recombination (Dyer 1996; Dyer, Nobeoka 2000).

7. **Descriptive Network Statistics**

Figure 2 and table 1 show a strong increase in the number established ties between the observation points 3 and 4 and in particular between points 4 and 5. This can at least to some extent be explained by an increased number of subsidised research projects as this policy tools 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 2: Evolution of the automotive R&D network (2002-2007)
In order to receive proper simulation results it is necessary to have a certain amount of change between two consecutive waves which means at the same time that too much of change cannot be handled with the model at hand. 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 1) has been calculated ($M_{11}$ = Number of pertained links; $M_{01}$ = Number of interrupted links; $M_{10}$ = Number of formed links).

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

Based on experience, the value of the Jaccard Index should ideally be higher than 0.3 (Snijders, Van de Bunt et al. 2010). This is the case for all observation periods which makes the data a good basis for simulation.

<table>
<thead>
<tr>
<th>Observation</th>
<th>0→0</th>
<th>0→1</th>
<th>1→0</th>
<th>1→1</th>
<th>Jaccard Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1→2</td>
<td>10846</td>
<td>14</td>
<td>43</td>
<td>123</td>
<td>0.683</td>
</tr>
<tr>
<td>2→3</td>
<td>11174</td>
<td>14</td>
<td>39</td>
<td>98</td>
<td>0.649</td>
</tr>
<tr>
<td>3→4</td>
<td>11149</td>
<td>65</td>
<td>56</td>
<td>55</td>
<td>0.312</td>
</tr>
<tr>
<td>4→5</td>
<td>11085</td>
<td>120</td>
<td>25</td>
<td>95</td>
<td>0.396</td>
</tr>
<tr>
<td>5→6</td>
<td>11050</td>
<td>60</td>
<td>47</td>
<td>168</td>
<td>0.611</td>
</tr>
</tbody>
</table>

Table 1: Link development 2002-2007

The density of the network 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>
<thead>
<tr>
<th>Observation</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td>0.015</td>
<td>0.012</td>
<td>0.010</td>
<td>0.011</td>
<td>0.019</td>
<td>0.020</td>
</tr>
<tr>
<td>Average Degree Centrality</td>
<td>2.258</td>
<td>1.839</td>
<td>1.483</td>
<td>1.611</td>
<td>2.886</td>
<td>3.060</td>
</tr>
<tr>
<td>Number of ties</td>
<td>166</td>
<td>137</td>
<td>112</td>
<td>120</td>
<td>215</td>
<td>228</td>
</tr>
</tbody>
</table>

Table 2: Density measure 2002-2007
8. Simulation 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 was selected. This indicates that the actor $i$ initiates a tie and the potential partner $j$ has to accept the demand 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. Convergence is excellent if the t-value is smaller than 0.1, which I found for all variables of the objective function.

<table>
<thead>
<tr>
<th>Variable</th>
<th>t-value (sd)</th>
<th>Significance</th>
<th>Hypotheses</th>
</tr>
</thead>
<tbody>
<tr>
<td>transitive triads</td>
<td>0.4065 (0.0200)</td>
<td>***</td>
<td>H 1 confirmed</td>
</tr>
<tr>
<td>geodis</td>
<td>-0.1310 (0.0258)</td>
<td>***</td>
<td>H 2 confirmed</td>
</tr>
<tr>
<td>techdis</td>
<td>-0.0002 (0.0002)</td>
<td></td>
<td>H 3 rejected</td>
</tr>
<tr>
<td>exp</td>
<td>0.0123 (0.0019)</td>
<td>***</td>
<td>H 4 confirmed</td>
</tr>
<tr>
<td>absorpca</td>
<td>0.1074 (0.0256)</td>
<td>***</td>
<td>H 5 confirmed</td>
</tr>
</tbody>
</table>

Table 3: Simulation results

Table 3 summarises the resulting variables for the model as it was simulated. First, H1 could be confirmed which indicates a significant endogenous network effect leading to the formation of cohesive triadic subgroups formed by trusted partnerships. This is in line with studies conducted in other industries making it supposedly a general effect which regularly plays its role in innovation network evolution.

Second, the variable for geographic distance is significant and negative. This indicates that ties emerge between firms that are located in relative geographical proximity rather than between more distant firms. The conclusion is that geographical distance is an important factor in the automotive industry despite the fact that it has moved from an explorative phase to a more exploitative phase.

For the technological distance I found a negative parameter value which suggests that there is a tendency for firms with similar knowledge bases to cooperate. However, the parameter is not significant in the tested model. As there are various ways of operationalizing the concept of technological distance (see Benner, Waldfogel 2008)) this factor provides room for further investigation.

A further tested variable was the experience in cooperation. The results confirm the hypotheses suggesting that firms with more experience in cooperation are more open to participate in collaboration projects.
Finally, hypothesis five was confirmed. This demonstrates that 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.

9. Conclusion

The objective of this paper was to outline conceptual considerations of evolutionary economic thinking and the knowledge-based view of the firm in order to pave the ground 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 prevail on the field of creative destruction. This holds in particular for the automotive industry in Germany (but also elsewhere in Europe) that has become challenged by firms from the emerging markets in Asia. New knowledge is the basis for new ideas that can be transformed into products at a later stage. This knowledge can partly be acquired internally. A more promising approach than solely relying on own R&D is, however, to use networks as strategic tools in order to gain access to more sources of knowledge which offer a multitude of possibilities to complement and recombine the own knowledge base.

These networks are evolving structures with dynamic changes in terms or emerging and dissolving ties over time. A core question was: what are drivers and mechanisms that determine the change process? I applied a stochastic actor-based model which simulates network evolution between observation periods and serves to estimate parameters. For the network that has been built from publicly funded R&D projects in the German automotive industry, structural as well as individual and dyadic covariates are relevant drivers: The formation of triadic structures could be observed; spatial proximity between firms increases the propensity to cooperate as well as experience. Firms with high levels of absorptive capacity tend to be more often involved in networks. This indicates that internal R&D has not become obsolete but is a prerequisite to benefit from networks.

The paper led to a number of interesting research questions that can be posed for further research:

- Policy makers have often special groups of actors (SMEs, firms from less developed regions, public research institutes) in mind when they design the programmes for public support. Are the ties in reality formed between those organisations that are expected to form ties?
- Are the observed drivers only valid for firms or, for instance, also for inventors?
- The operationalisation of the potential effects should be subject to further discussion. Like in the case of the technological distance there are sometimes various possibilities which may lead to diverging results.
- Other factors might be relevant but have not been tested such as the cultural distance, the experience in an industry or the complementarity of knowledge bases.
References


DOPFER, K., ed, 2005. The evolutionary foundations of economics. Cambridge Univ Pr.


OECD, June 2010. REGPAT database.


