The Spatial Dynamics of the Inventor Network in German Biotechnology: Geographical Proximity Versus Triadic Closure

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Abstract:

This paper analyses the spatial dynamics of the inventor network in German biotechnology between 1970 and 1995, aiming to introduce a spatial dimension into the dynamic analysis of innovation networks. After a long-lasting phase of knowledge exploration biotechnology experienced a transition towards increasing knowledge exploitation in the late 1980s. We argue that this transition impacts on the dynamics of the inventor network. On the basis of a patent-based reconstruction of the inventor network and a stochastic estimation model of network evolution, this paper shows that geographical proximity between inventors is mostly relevant in a situation of knowledge exploration, when knowledge is predominantly tacit. By contrast, triadic closure gains relevance in a situation of knowledge exploitation, with higher levels of knowledge codification and the associated risk of unintended and costly knowledge leakages. Accordingly, triadic closure is becoming a more important driver of network dynamics over time.

1. Introduction

Nowadays, biotechnology is a very popular object of study in a variety of disciplines. Economists and management scientists are interested in the way in which innovations come to existence predominantly through joint efforts of firms in the field (e.g. Powell et al. 1996; Owen-Smith and Powell 2004; Gay and Dousset 2005; Roijakkers and Hagedoorn 2006). Most firms rely on collaborative action with other firms and scientific actors for developing innovations due to the costly, time-intensive and science-based nature of innovation search activity and its unpredictable ex-ante outcomes. This makes biotechnology an ideal case for studying innovation networks and its dynamics over time.

The biotechnology sector also attracted close attention of geographers and regional economists (Prevezer 1997; Zeller 2001; Lemarié et al. 2001). In many countries all over the world biotechnology firms tend to be spatially concentrated in a limited number of regions. To give just two examples: in the biotechnology industry in the United Kingdom firms are agglomerated mainly in the Cambridge area; in the United States biotech can mostly be found in California and around Boston. This makes biotechnology an ideal case for studying spatial clustering.

The observation that most high-tech industries, including biotechnology, show a marked and uneven spatial configuration does hardly receive any attention from network researchers. The emerging literature on the dynamics of innovation networks (e.g. Gulati 1995; Ahuja 2000; Orsenigo et al. 2001; Powell et al. 2005), tends to neglect the potential role of geographical proximity in network formation. This paper aims to introduce a spatial component in the dynamic analysis of innovation networks. We argue that the importance of geographical proximity for network formation will change as a technology experiences a shift from exploration to exploitation. On the contrary, we expect the mechanism of triadic closure – leading to the formation of cliques in the network – to increase when knowledge exploitation becomes increasingly important.

Thus far, we are unaware of any systematic research that has tested the effects of triadic closure and geographical proximity on the spatial evolution of innovation networks. Taking biotechnology in Germany between 1970 and 1995 as an example of a spatially agglomerated high-tech industry, we aim to find out to what extent geographical proximity, on the one hand, and triadic closure, on the other hand, act as driving forces in the network's dynamics. We reconstruct the spatial dynamics of the inventor network on the basis of USPTO patent data. Subsequently, on the basis of simulation-based stochastic estimation models (Snijders 2001) we test empirically whether these mechanisms have played a significant role and whether their effect on network dynamics changes over time.

The next section briefly introduces the specific context of the biotechnology industry as a science-based and knowledge-intensive industry that recently has experienced a shift from a long-lasting phase of knowledge exploration into increasing knowledge exploitation. Section 3, then, reviews the existing literature on geographical proximity and network dynamics. It formulates hypotheses on the role of geographical proximity and triadic closure in

the dynamics of the inventor network in German biotechnology. Subsequently, Section 4 describes how the spatial dynamics of the innovation network are reconstructed on the basis of USPTO patent data. The empirical analysis on the role of geographical proximity and triadic closure is then performed in two steps. First, Section 5 conducts univariate analyses that empirically demonstrate the individual roles of geographical proximity and triadic closure. Second, in Section 6 stochastic simulation modelling is applied in order to estimate parameters for various forces of network change in a multivariate analysis. Section 7 concludes.

2. Exploration and exploitation in biotechnology

Biotechnology can be considered an archetypical science-based industry (Pavitt 1984; Tamada et al. 2006). Today's commercial applications in the field – ranging from medical drugs and food-processing to chemical substances – heavily rely on relatively recent scientific advancements in molecular and cellular biology (Powell et al. 1996). The origins of the field of biotechnology as we know it today date back to the discovery of the double helix structure of DNA in the 1950s and the subsequent discoveries of recombinant DNA and monoclonal antibody technology in the 1970s. In the 1980s scientists booked considerable progress in the development of genetic engineering (Liebeskind et al. 1996).

These new scientific discoveries had an enormous technological potential in various industries, though particularly in the pharmaceutical industry. Until the 1960s the knowledge base of the pharmaceutical industry had been dominated by organic chemistry (Gilsing and Nooteboom 2006) and drug development and food processing were largely based on random screening and trial and error practices (Gambardella 1995). In Germany large pharmaceutical companies like BASF, Bayer and Hoechst prospered in this period (Lehrer 2005). The revolutionary discoveries in biotechnology had a strong competence-destroying effect on the pharmaceutical industry, enabling a more rational approach to the development of new chemical substances and drug design (Powell et al. 1996). In the words of Nooteboom and Gilsing (2006): the pharmaceutical industry moved from knowledge exploitation on the basis of organic chemistry into a phase of knowledge exploration on the basis of molecular biology and genetic engineering.

Initially, in the late 1970s and 1980s small biotech firms, generally referred to as Dedicated Biotech Firms (DBFs), played a dominant role in the development of the biotechnology industry (Audretsch 2001; Powell et al. 2005). These small firms were largely university spin-offs and stood in close connection to academic research laboratories (Zucker et al. 1998; Lehrer 2005). The small firms specialized in biotechnology research and the development of applications in products and techniques with potential commercial value. However, they lacked the resources for extensive clinical tests and complex regulatory approval procedures (Gilsing and Nooteboom 2006). From the mid-1980s onwards large established pharmaceutical firms started to take their role here in giving financial support to DBFs, developing new technologies into safe and effective products and bringing them to the

market (Audretsch 2001). This makes the emergence of biotechnology an *'unusual case of competence destruction'* (Powell et al. 1996, p. 124); those large pharmaceutical companies from the era of organic chemistry that successfully adapted to the 'biotechnology revolution' could retain dominant positions in the industry (Gilsing and Nooteboom 2006). Although in Germany large companies like BASF and Boehringer Mannheim entered the field of biotechnology rather late, large investments in research and development secured they could catch up and could maintain leading positions next to newly emerging DBFs (Krauss and Stahlecker 2001).

It is the distinct division of labour between established pharmaceutical firms, DBFs and universities that gives the biotechnology field its collaborative nature (McKelvey 1997). As Powell et al. (1996, p. 118) note: *"Sources of innovation do not reside exclusively inside firms; instead, they are commonly found in the interstices between firms, universities, research laboratories, suppliers and customers"*. Here, DBFs act as intermediaries between scientists and established firms (Liebeskind et al. 1996). In addition, Roijakkers and Hagedoorn (2006) found that in strategic alliance networks small biotechnology firms form the bridge between established pharmaceutical companies that otherwise would be unconnected.

The increased role of large pharmaceutical companies spurred a transition from exploration to exploitation in the biotechnology industry. After extensive clinical testing and long approval procedures the first biotechnology products reached the market in the late 1980s and early 1990s (Audretsch 2001). The transition from exploration to exploitation in biotechnology can be described on the basis of two main changes in its technological regime (Malerba and Orsenigo 1997).

First, there has been a shift from a predominantly generic knowledge base to a more specialized knowledge base. Initially, the biotechnology industry was characterized by a high level of technological uncertainty, typical for the exploration stage of an emerging technology (March 1991). The uncertainty made it difficult to judge the commercial value of new scientific developments and to develop industrial applications (Liebeskind et al. 1996). Along these lines, Nesta and Saviotti (2005) find that in the 1980s knowledge diversity was driving innovation in biotechnology, whereas knowledge integration was a more important determinant of innovative activity in the 1990s. Knowledge integration – expressed as a measure of the coherence of the technologies a firm holds – has become an increasingly important determinant of the market value of biotech firms from the early 1990s onwards. They argue that this development signals a starting exploitation stage in the technology that follows a long-lasting phase of knowledge exploration (Nesta and Saviotti 2006). Similarly, Audretsch (2001) notes that from the late 1980s large experienced pharmaceutical firms replace their broad learning strategies of the exploration phase to a more focused approach targeting specific technologies and applications.

A second and related development has been a shift from a very tacit knowledge base to a more codified one. This development is illustrated by what is often referred to as the second biotechnology revolution (Gambardella 1995). From the late 1980s onwards the

combination of new genetic engineering techniques and existing insights from molecular biology were increasingly used *"as a research tool to enhance the speed and efficiency of the discovery process of new drugs"* (Gilsing and Nooteboom 2006, p. 8). In this light, Rothaermel and Thursby (2007) note that the knowledge involved in these new methods – such as automatic gene sequencing – became increasingly codified in commercially available documents and instrumentation. This increased codification of the technology's knowledge base implies a decreased ability to control knowledge flows and, hence, a greater risk of unintended knowledge spillovers and imitation by competing firms (Gilsing and Nooteboom 2006; García-Muiña et al. 2009). This increased risk is reflected in intense competition for patentable know-how. As Liebeskind et al. (1996, p. 429) note, strict property right regimes make that *"only firms that are the first to discover a process or product can reap any financial rewards from it".*

3. The spatial dynamics of an innovation network

The previous section has demonstrated that biotechnology has gradually shifted from a long-lasting exploration stage from the early 1970s onwards into an exploitation stage around the edge of the 1980s and 1990s. We argue that this change, expressed in a more specialized and more codified knowledge base, has implications for the spatial dynamics of the industry's inventor network.

We distinguish network structural effects and attribute-related effects (Snijders 2001). Structural effects in network dynamics only depend on the prior structure of the network. Actors decide to create or dissolve links on the basis of the existing structure of the network and the position of the actors within it. In undirected networks such endogenous drivers of network dynamics include, for instance, preferential attachment and triadic closure. In this study we focus on triadic closure[1]. This can be defined as the tendency of new links to be formed between the direct network neighbours of a node, resulting in closed triangles in the network (Davis 1970).

Attribute-related effects, by contrast, depend on the network actors' characteristics. Social comparison theory in sociology argues that actors base their choices with whom to connect on the characteristics of alters in comparison to theirs (Festinger 1954). We claim that the German biotechnology inventor network will not only evolve through endogenous forces that are purely dependent on prior network structures, but that the geographical attributes of the nodes play a role in this dynamic process as well. Hence, the analysis of network dynamics also includes exogenous mechanisms of network change, which in the context of this study are inextricably linked to the underlying geographical structure of the technological field. This section provides our theoretical expectations concerning the

[1] Various studies indicate that preferential attachment also applies to innovation networks at the inter-firm level (e.g. Gay and Dousset 2005; Powell et al. 2005). However, we argue that preferential attachment does not apply to innovation networks at the individual level. There is a strong upper limit to the number of direct collaborations an inventor can or wants to engage in. This is supported by the data. The patent-based inventor network in German biotech exhibits scale-free properties at no point in time. For those cases in which newcomers connect to incumbent inventors there is no statistically significant association between the incumbent inventor's degree and the number of attracted new links from newcomers.

changing role of geographical proximity and triadic closure in the dynamics of the German biotechnology inventor network.

3.1 Geographical proximity

Economic geography and regional science have an established tradition of studying spatial clustering and the role of geographical proximity for innovation. Various studies point towards the positive effect of a firm's location in a cluster on its innovative performance (e.g. Baptista and Swann 1998). Particularly high-tech industries show a strong tendency to cluster in space (Audretsch and Feldman 1996). Concerning biotechnology Lemarié et al. (2001) observe that the creation of new biotech firms in France is strongly localized. Similarly, Zeller (2001) notes that the pattern of biotech firms in Germany is highly unequal and concentrated in a limited number of regions only.

The theoretical foundation of the cluster concept was laid by the economist Alfred Marshall at the end of the 19th century. He identified three major advantages firms can reap through their location in a cluster with similar firms. First, firms have access to a localized pool of specialized labour. Second, the firms benefit from the presence of specialized suppliers that are attracted by the concentration of their client firms. Third, the firms take advantage of knowledge externalities; they have access to knowledge that exclusively circulates within the boundaries of the cluster. This latter advantage is of particular relevance to high-tech industries, where timely access to knowledge on recent technological developments and scientific progress is a key competitive advantage.

Various case studies of industrial districts, innovative milieus and regional innovation systems have highlighted the importance of local collective learning practices and local knowledge exchange between firms for the competitiveness of clusters and its constituent firms (e.g. Asheim 1996). Consequently, networks have come to play a key role in the explanation of the strength of clusters. Traditionally, firms in clusters were argued to have full and unique access to the knowledge that resides in these local knowledge networks. More recently, however, the mapping of local networks in clusters through the application of social network analysis techniques has provided the insight that networks are neither homogeneously spread across clusters (Giuliani 2007), nor are confined to the clusters' boundaries (Morrison 2008; Boschma and Ter Wal 2007). Following this earlier work at the interface between clusters and networks, we conceive clusters and networks as separate entities. The presence of an extensive and cohesive network of knowledge exchange within clusters – encompassing all local firms – cannot be assumed beforehand. Not only do some firms in clusters act isolated from local networks, some firms outside clusters are in fact connected to these networks through non-local linkages. Hence, geographical proximity is neither a sufficient, nor a necessary condition for links in innovation networks to exist (Rallet and Torre 1999; Boschma 2005). As a consequence, the pattern of spatial clustering in an industry and the innovation network in which its actors interact are two separate entities that do not necessarily show overlap, let alone completely coincide.

This is not to say that geographical proximity does not affect the formation of innovation networks in any way. Network relations are more easily established and maintained at short distance than at large distance. Hence, one expects network relationships to be more common over short distances (Maggioni et al. 2007; Hoekman et al. 2009). In other words, geographical proximity is a dyadic – or pair wise – node attribute that might affect the evolution of the network. Therefore, we formulate the first hypothesis as follows:

Hypothesis 1a: Geographical proximity between inventors positively affects the probability they get connected in the innovation network.

The extent to which geographical proximity matters for network formation will be dependent on the nature of the knowledge base. Audretsch and Feldman (1996) argue that in the exploratory stages of a new technology, when knowledge tends to be highly tacit, firms and individuals benefit most from geographical proximity. Tacit knowledge, strongly embedded in human capital, is most easily exchanged through repeated face-to-face interaction or the mobility of people, which both in turn are easier and more frequent at short geographical distances (Zander and Kogut 1995; Moodysson and Jonsson 2007; Torre 2008). When an industry grows and matures, knowledge gets more codified and is, hence, more easily transferable over larger distances (Cowan et al. 2004). This is why Audretsch and Feldman (1996) expect geographical proximity among firms will become less important to the performance of firms in later – exploitative – stages of the industry lifecycle. According to this line of reasoning we expect the distance over which inventors collaborate in German biotechnology to increase over time. To be more precise, we expect the importance of geographical proximity as a driver of network dynamics to decline, as biotechnology moves from exploration to exploitation. Therefore, hypothesis 1b is stated as follows:

Hypothesis 1b: The effect of geographical proximity as a driver of network dynamics declines over time, as biotechnology experiences a shift from knowledge exploration to increasing knowledge exploitation.

3.2 Triadic closure

A structural force in network dynamics is triadic closure. Closure describes the tendency that partners of partners become partners among themselves, resulting in the formation of closed triads in the network (Davis 1970). At the dyad level this implies that prior indirect ties – at geodesic distance two – turn into direct ties. The fundament of the mechanism is the *tertius iungens* or the 'third who joins', *"connecting people in one's social network by either introducing disconnected individuals or facilitating new coordination between connected individuals"* (Obstfeld 2005, p. 102).

A tendency towards closure produces dense cliques of strongly interconnected actors in the network (Skvoretz 1991). In sociological research the presence of cliques is generally

interpreted as a sign of social capital (Coleman 1988; Kilduff and Tsai 2003). Closed social structures tend to promote greater trust among individuals (Uzzi 1997). Groups of strongly interconnected actors – with a large number of redundant ties – generally show a high level of mutual trust (Walker et al. 1997; Buskens 2002). 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 facilitate intensive exchange of complex or sensitive knowledge (Zaheer and Bell 2005). Therefore, we expect that two inventors that have a common partner have a higher probability to get connected than those that do not have a common partner:

Hypothesis 2a: Having a collaboration partner in common positively affects the probability two inventors get connected in the innovation network.

In contrast to closed triangles, open structures like structural holes are generally associated to higher levels of creativity (Fleming, Mingo et al. 2007). In case the link that closes a triad is missing, there is a structural hole in the network (Burt 2004). Defined as such, a tendency towards the formation of structural holes is the inverse effect of triadic closure. The node that acts as the bridge between the other two nodes has an information-rich position with access to a variety of information, stemming from two distinct sources that do not communicate with each other. Various network studies show that structural holes have a positive influence on innovation (e.g. Ahuja 2000; Zaheer and Bell 2005), but the overall evidence whether it is structural holes or closure that matters for creativity and innovation is far from clear-cut. In a study on inventor-level collaboration Fleming, Mingo et al. (2007) find that structural holes are indeed positively associated to creativity and innovation. However, they also find that cohesive structures tend to promote innovation in case one of the collaboration partners bring broad experience into the collaboration, has recently worked for multiple organizations, or works with external colleagues. In that way, the input of diverse knowledge into the collaboration that is generally associated to structural holes is captured by differences in the experience of the inventors, whereas the increased levels of trust associated to closure are maintained.

Shifting the level of analysis to the industry, we argue that the importance of triadic closure increases when a technological field shifts from exploration to exploitation. At this transition, the necessity of trust for collaboration increases. The increased level of codification that typically accompanies knowledge exploitation has serious implications in terms of the appropriability of knowledge. The risk of involuntary knowledge spillovers increase with the level of codification (Saviotti 1998). Such unintended knowledge spillovers come at a high cost in high-tech fields like biotechnology, where it matters to be the first to bring new industrial applications to the market and strict patent regimes ensure the first-mover to reap the benefit associated to them (Liebeskind et al. 1996). However, notwithstanding the fact that

patents legally protect the innovation, they do by no means cancel out the risk of involuntary knowledge spillovers. In actual fact, the codification of the new knowledge embodied in the innovation by means of a detailed description on the patent facilitates the use of that knowledge by others, albeit in a slightly modified form.

In situations of high risk and high cost of opportunistic behaviour, organizations have a clear preference to form embedded ties, which may result in network closure (Gargiulo and Benassi 2000). Closed network structures act as a *"repository of information on the availability, competencies and reliability of prospective partners"* (Gulati and Gargiulo 1999, p. 1440) and, as such, reduce search costs and the risk of opportunistic behaviour. In the context of US venture capital networks Sorenson and Stuart (2008) find that, when higher risks are at stake, actors will be inclined to form network relationships with socially proximate individuals. Beckman et al. (2004) argue that in a situation of strong market uncertainty at the (early) exploitation stage, for instance concerning consumer preferences, the need for trust is high. Consistent with this line of reasoning, Vanhaverbeke et al. (forthcoming) find that the presence of redundant network relationships has a positive effect on knowledge exploitation, and not on the exploration of new technological knowledge. Consequently, we expect network closure to become increasingly important in the German biotechnology innovation network:

Hypothesis 2b: The effect of triadic closure as a driver of network dynamics increases over time, as biotechnology experiences a shift from knowledge exploration to increasing knowledge exploitation.

4. Data

The empirical analysis is based on patent data. Patent data are increasingly used in scientific research as relational data (Breschi and Lissoni 2004). We used patent data to reconstruct innovation networks in retrospection. Biotech firms have always exhibited a strong tendency to protect their innovations through patents (Blind et al. 2006). Strict property right regimes are in place to ensure innovators to reap the financial benefits that are connected to their costly discoveries (Liebeskind et al. 1996). This makes patent data a reliable source of longitudinal data on innovation for this sector. We use American patent data from the US Patent and Trademark Office (USPTO). Since the US is the largest market for industrial applications in biotechnology (Powell et al. 1996) and many German biotechnology firms have R&D facilities in the US (Krauss and Stahlecker 2001), it is common practice for German biotech firms to apply for patents at USPTO.

The source of the patent data is the publicly available NBER Patent Citations Data File (Hall et al. 2001). These data contain all USPTO patents with granting dates ranging from 1963 till 1999. We use the application date for dating patents, since this date is closest to the time of innovation. All patents with application year 1996 or later have been excluded from the dataset; not all patents applied for in these years were granted before 1999. Due to this time lag the patent dataset does not provide a full picture of patent activity for these years. We did

not add patent data from other sources in order to avoid compatibility problems across data sources.

The dataset contains information at three different levels: characteristics of the patent itself, of the patent holder (the assignee or applicant) and of the people that have been involved into its realization (the inventors). Since the inventor level database starts from 1974, the information on inventors for the years 1963-1974 has been added manually from the USPTO website's Patent Full-Text Database. All patent data have been checked thoroughly on obvious typing errors in the inventors' names. This is crucial for reconstructing the networks in the network software package UCINET (Borgatti et al. 2002), in which the linking algorithm is based on unique inventor names.

We selected all patents in subcategory 33 (biotechnology, as defined by Hall et al. 2001), which encompasses the USPTO-defined patent classes 435 (molecular biology and microbiology) and 800 (multicellular living organisms and parts thereof). From this subset of patents we retrieved all patent data with at least one inventor resident in Germany. In the dataset each of the inventors on a patent was listed separately, making the 'patent-inventor-combination' (PIC) the unit of analysis. Foreign inventors that co-occurred with German inventors on a patent were excluded from the database. Since the information on their co-invention linkages to other foreign inventors is lacking, we disregard co-invention linkages to foreigners and limit the spatial scale of analysis to German-based inventors. For most of the observation period foreign inventors still play a marginal role. Their share in the total number of inventors in the database increases from under 5% until 1975, through roughly 10% in the 1980s to more than 25% from 1993 onwards.

The German biotech patent data file obtained this way, covering the application years from 1961 to 1995, has 4498 records. It contains 1620 distinct patents, involving 2103 unique German inventors. Boehringer Mannheim, Hoechst and Bayer are the main patent assignees in the German biotech patent database. Figure 1 shows that the number of patents and the number of inventors is increasing rapidly over time. With the number of inventors per patent and the patents per inventor being fairly constant, the growth of the network is mainly the result of the increasing number of patents over time.

FIGURE 1 ABOUT HERE

In these networks two inventors are linked if they have worked on the same patent. For assessing collaborative innovation activities this co-invention level is the most detailed and pure level of collaborative innovation available through patent data. Patent data allow for creating networks at the applicant level, at which links are defined by inventors that occur at patents of different applicants (Ter Wal and Boschma 2009). However, considering the problems with the applicant's location, as stated previously, an inventor-level network analysis is more appropriate for studying the spatial structure of the network.

Certainly, in such a network at the level of individuals, inventors that co-occur on a patent are likely to work for the same company. However, for various reasons it is far from automatic that all inventors mentioned on a patent work for the patent's applicant. First, Giuri et al. (2007) demonstrated on the basis of a large-scale survey among European inventors that on average more than 20% of all patents involved some form of collaboration with an external organization, mostly not mentioned on the patent; about 15% of the surveyed patents included external co-inventors. Second, quite often inventors appear on patents of more than one applicant. In a survey among European biotechnology firms Laforgia and Lissoni (2006) found out that about 20% of these cases of 'multiple-applicant-inventorship' are due to labour mobility. The remaining 80% are largely due to mergers and acquisitions or inventors that also occur on the patents of universities and public research institutes. In addition, many patents are sold on the market for technology. Particularly small firms, including DBFs, often decide not to make the substantial investment to commercially exploit the patent and to sell the patent to larger firms (Giuri et al. 2007).

For the reconstruction of the co-invention networks we have applied a five-year moving window procedure. Each yearly network observation contains all co-invention links for that year and the preceding four years. Hence, in line with other studies on co-invention networks (e.g. Fleming, King III et al. 2007) we assume that co-invention linkages exist during five years. It is reasonable to assume that knowledge flows between collaborating inventors persist for some time, even after the collaboration has finished.

We take the place of residence of the patent's inventors to determine the location of innovation in biotechnology. We deliberately disregard the location of the patent applicant; large companies tend to assign the patent to the headquarters, even in case the patent might have been developed in one of the company's subsidiaries outside the headquarters' region. Notwithstanding the possibility that some inventors might live in another region than where they work, inventor location is generally agreed to be a more reliable approximation of where the innovation was developed (Acs et al. 2002; Ejermo and Karlsson 2006). The distance between two inventors is expressed in distance "as the crow flies" between their places of residence, calculated on the basis of city geographical coordinates.

5. Descriptive analysis

On the basis of USPTO patent data we reconstructed the spatial dynamics of the German biotechnology co-inventor network. This section provides some descriptive analyses that shed light on the role of geographical proximity and triadic closure in the dynamics of the German biotechnology inventor network.

5.1 Geographical proximity

In order to describe the role of geographical proximity in the dynamics of the biotech innovation network, we need to know the pattern of spatial clustering of inventors in the field. Nowadays the German biotechnology industry is highly concentrated in a number of regions.

The cluster of biotechnology firms in and around Munich is generally considered to be one of the main and most successful cores of the industry in Europe (Zeller 2001).

On the basis of the location of German inventors on biotechnology patents we have mapped the evolution of spatial clustering in the industry between 1970 and 1995. The pattern of spatial concentration in German biotechnology is expressed in the number of inventors per spatial unit per year, where we take German districts (NUTS3; N=439) and German regions (NUTS2; N=22; the administrative unit between districts and federal states) as spatial units. Figure 2 shows the evolution of spatial concentration in the industry.

FIGURE 2 ABOUT HERE

Through the course of time five main clusters of biotechnology inventors have emerged (see Figure 2c): the Rhineland area with Wuppertal, Cologne and Düsseldorf as its main centres; the Rhine-Neckar triangle around Heidelberg, Darmstadt and Mannheim; Munich and the area around the Starnberger See; the capital city of Berlin and the small university city of Marburg. This pattern of concentration is consistent with earlier studies on spatial concentration of German biotechnology (Zeller 2001; Krauss and Stahlecker 2001). We notice that all five clusters were already present in the 1970s, when biotechnology was not even known as such, and that the pattern of spatial concentration in these five clusters has been very stable over time.

For each year we calculated a Herfindahl index at both spatial scales to capture trends towards spatial concentration or deconcentration (Figure 2b). From the early 1970s the core of the Rhineland and Rhine-Neckar clusters spreads to neighbouring districts, which causes a drop in the Herfindahl index at the NUTS3-level (districts). Slight variations are observable in the relative dominance of clusters over time. In 1985, for instance, the Ruhr cluster becomes more dominant at the expense of Munich; after that these roles swap definitively with Main-Taunus and particularly Munich coming to dominate the field increasingly. Only from the 1990s onwards the spatial pattern of the German biotechnology industry becomes slightly more dispersed. From this period onwards cities such as Freiburg, Tübingen and Bielefeld emerge as secondary centres of biotechnology. As a consequence, the Herfindahl index at the high spatial scale NUTS2 (Figure 2c) shows a decreasing trend from the early 1990s.

FIGURE 3 ABOUT HERE

The left graph in Figure 3 indicates the changing geographical distance of collaboration over time, expressed in kilometres. The right graph in Figure 3 shows the ratio of the observed distance and the expected distance if German inventors would link randomly, given the spatial distribution of inventors at that point in time. Both graphs show a continuous increase of the average geographical distance between collaborating inventors. A Bonferroni test was carried

out to test the statistical significance of this trend. Generally, the observed average distance differs significantly from the distance observed four to seven years earlier. Hence, thus far, our univariate analyses seem to confirm our hypotheses 1a and 1b, showing an increasing trend in the distance over which inventor collaborate.

5.2 Triadic closure

The descriptive statistics thus far points towards an important, though decreasing role of geographical proximity in network evolution. This section tests the role of the network structural effects of triadic closure in the network dynamics of the German biotechnology inventor network. For this purpose, we distinguish incumbent inventors from network entrants for the networks at each point in time. Incumbent inventors are defined as those inventors that were also part of the preceding (non-overlapping) network observation point five years earlier. The categories being mutually exclusive, entrants are all other inventors at a certain network observation.

If triadic closure plays a role in network evolution, we expect a high number of potential triangles at *t-5* to be closed at time *t.* Every pair of nodes that is connected by a path of length 2 (through one intermediary) is a potential triangle. The tendency for triadic closure is expressed as the ratio of the observed number of closed triangles over the number of random expected closed triangles. The latter is obtained by calculating the share of new possible links that close a triangle among all possible new linkages in the network. Then, if new links are formed randomly, this share would be equal for actual new ties, and hence, the random expected number of closed triangles is expressed as the product of the share of potential new ties that close a triangle and the actual number of new ties among incumbent inventors that were formed between *t* and *t-5*.

FIGURE 4 ABOUT HERE

Figure 4 demonstrates the role of triadic closure in the dynamics of the network. At any point in time the number of observed triangles among incumbent inventors in the network is higher than the number of random expected ones, providing support for hypothesis 2a. The extent to which this is the case – i.e. the tendency for triadic closure – differs across time. The ratio of triadic closure fluctuates around a value of 8. Apart from the period between 1985 and 1990 we can observe a slightly increasing tendency for triadic closure. Hence, on the basis of this univariate test we do not find convincing support for hypothesis 2b that the role of triadic closure increases over time. In order to test the role of triadic closure in response to geographical proximity, we conduct a multivariate test by means of a stochastic estimation model of network evolution in SIENA.

6. A stochastic model of network evolution

6.1 Methodology

The univariate analyses in the previous section has brought (moderate) support for the decreasing role of geographical proximity and the increasing role of triadic closure in the spatial dynamics of the German biotechnology co-invention network. In order to test how these mechanisms jointly drive the dynamics of the network, we apply a stochastic network simulation procedure. We use the program SIENA (Simulation Investigation for Empirical Network Analysis), as developed by Snijders et al. (2001; 2007). This program has been specifically designed for the statistical analysis of dynamic networks. It simulates network evolution in between subsequent network observations and estimates parameters for selected mechanisms of network dynamics. In this way the program detects the forces that have driven the evolution of a network from one state into the next.

As in the univariate analyses, each network observation covers the co-invention links for a five-year interval, covering the period between 1970 and 1995. Accordingly, we also use a five-year time lag for the subsequent network observations between which the dynamics are simulated. In that way, subsequent network observations do not show overlap in terms of the patents on which they are based.

The analyses are limited to the networks among incumbent inventors. Considering the complete time span between 1970 and 1995, we define incumbent inventors as those inventors that occur multiple times and over different years. Inventors enter and exit the network only once; this implies that inventors with a time lag of more than 5 years between subsequent occurrences appear as network isolates in intermediate network observations. The selection on incumbent inventors is made in order to decrease the volatility of inventors entering and exiting again within a short timeframe, which might endanger a stable simulation and estimation procedure in SIENA. It implies that two different network datasets are used for each year between 1975 and 1990: one with those inventors that were active in the preceding period and one with those that will remain active in the subsequent period. For each network observation a square binary matrix indicates the existing linkages between inventors. A geographical distance matrix specifies the distance between the inventors for each observation year, rescaled to integer values between 0 and 255.

Since the sequence of events that have made the network evolve between two observations is unknown, the SIENA program simulates how the network has evolved from one state into the next. This simulation process takes place on the basis of Monte Carlo repetition, the default number of repeated simulations of the network evolution process being 1000. In the simulation of the network evolution process ties can be created or dissolved and node attributes can change. Each of these changes can take place multiple times. Hence, the possibility that links are created and again dissolved in between two observation points is left open. For undirected networks there are various algorithms that define the decision rules of a single simulation run. For our model we selected the ‘unilateral initiative and reciprocal

confirmation' algorithm, in which a new link is created or dissolved when one actor takes the initiative and the other actor confirms. To our view, this algorithm is closest to reality, more so than in a 'forcing model' for instance in which a link change that is proposed by one actor is automatically accepted by the other.

A Methods of Moments estimation procedure is used to estimate parameter values for the selected network evolution mechanisms. Each parameter is associated to a target statistic, which describes the visible outcome of the effect. The target statistic of the closure effect, for instance, is the observed number of closed triads. SIENA iteratively searches the parameter values that lead to a minimal deviation between the generated and observed values for these target statistics. This estimation is a stochastic process, since the repeated network simulation runs are not fully identical. Repeated estimations might lead to slightly different outcomes. Therefore the simulation process has to be rerun at least twice in order to check whether stable outcomes have been obtained. The extent to which model estimation converges to stable outcomes is specified for each parameter by a convergence t-statistic. Values under 0.100 generally indicate good convergence (Snijders et al. 2007). We only report estimation models for which this condition has been met for all parameters.

6.2 Analysis

The descriptive analysis of the inventor network in German biotechnology suggests that geographical proximity has played a role in the evolution of the network. Particularly in the exploration stage of the industry inventors seem to be inclined to collaborate with local partners. Through the course of time non-local collaboration activity has clearly increased. Triadic closure has played a significant role in network dynamics throughout the whole observation period, though a convincing trend of its increasing role could not be detected.

The stochastic estimation procedure in SIENA investigates the joint effect of triadic closure and geographical proximity in network evolution. Table 1 shows the outcomes of the stochastic estimation model in SIENA for the non-overlapping network observations, starting from 1975. Figure 5 graphically depicts the parameter estimates for the triadic closure and geographical distance also for the intermediate, overlapping network observations. The dotted lines indicate the lower and upper bound of the 95% confidence interval. For the observation 1970-1975 the stability in the network – expressed in the number of links retained – was too low for the estimation to converge. The upper part of Table 1 shows that for the remaining network observations the number of links retained account for more than half of all links at time *t*. All reported models are based on repeated estimations and convergence is good ($t < |0.1|$) for all models. Robustness of the results has been tested; estimation models on the basis of the "Forcing model" algorithm have yielded very similar results to those reported.

TABLE 1 AND FIGURE 5 ABOUT HERE

Four parameters have been estimated. The first two parameters are generally included in any estimation model (Snijders et al. 2007). The rate of change parameter accounts for the number of links that are created or dissolved. The rate of change was highest between 1975 and 1985 and considerably drops in the subsequent time periods.

The second parameter is degree. This parameter accounts for the observed density in the model and is generally considered to be the 'baseline' parameter that indicates the general tendency of nodes in the network to increase or decrease the number of direct links (Snijders et al. 2007). It can be interpreted as the 'cost' or 'benefit' of having additional linkages, irrespective of other mechanisms that make nodes decide to create or dissolve linkages. For the German biotechnology inventor network the parameter is consistently negative and significant, which implies that inventors find it 'costly' to increase the number of collaboration partners.

The third parameter concerns the importance of geographical distance as a mechanism of network dynamics. The parameter is negative and significant for nearly all network simulations, apart from the observations from 1985-1990 until 1988-1993. This confirms the first hypotheses concerning the importance of geographical proximity and its decreasing impact over time.

The fourth parameter is the network structural effect of triadic closure. In line with hypothesis 2a the parameter is positive and significant for all observations. As Figure 5 shows, the size of the effect is increasing over time. This is in line with our theoretical expectations and supports hypothesis 2b that triadic closure would become increasingly important as a driver of network dynamics in the exploitation stage of biotechnology with high levels of knowledge codification and high cost of opportunistic behaviour. Apparently, as the industry grows inventors decide to collaborate not necessarily with local partners. Instead, they increasingly select new partners they come to know through their current partners, paying less attention to whether they are geographical proximate or close.

7. Conclusion

This study has analyzed the spatial dynamics of the co-inventor network in German biotechnology over time. On the basis of stochastic estimation modelling we detect a clear shift in emphasis of how inventors select a collaboration partner. Whereas they initially tend to collaborate with geographically proximate partners, they increasingly direct their partner selection towards the principle of the *tertius iungens* (Obstfeld 2005). That is to say, inventors increasingly utilized the network's resources by forming collaboration linkages to partners of their partners. In the early, explorative stage of the technology field the network was organized mainly along geographical lines. During the further, more exploitative stage inventors increasingly exploited the network's endogenous resources by turning indirect linkages into direct ones. In other words, over time geographical proximity becomes less prominent as a driver of network dynamics, whereas triadic closure gains importance in that regard.

These outcomes are in line with our theoretical expectations. We hold the changing nature of the technology's knowledge base responsible for this shift. After a long-lasting phase of knowledge exploration in the 1970s and 1980s, this technology experienced a transition towards knowledge exploitation in the 1990s in the form of a growing number of commercial applications (Audretsch 2001; Nesta and Saviotti 2006). We argue that this transition has implications for the spatial dynamics of the inventor network in the industry. The transition from exploration to exploitation entailed a shift from generic to specific knowledge and from tacit to increasingly codified knowledge (March 1991; Malerba and Orsenigo 1997) that change the conditions under which the formation of collaborative links among inventors takes place (Gilsing and Nooteboom 2006).

Geographical proximity between inventors is mostly relevant in a situation of knowledge exploration, when knowledge is predominantly tacit. Tacit knowledge, strongly embedded in human capital, is most easily exchanged through repeated face-to-face interaction or the mobility of people, which both in turn are easier and more frequent at short geographical distances (Zander and Kogut 1995; Torre 2008). By contrast, triadic closure gains relevance in a situation of knowledge exploitation, with higher levels of knowledge codification and the associated risk of unintended and costly knowledge leakages (Gargiulo and Benassi 2000). The closed triads that closure produces act as vehicles of trust that enable the exchange of sensitive knowledge (Uzzi 1997; Buskens 2002; Zaheer and Bell 2005). Hence, these closed network configurations are more relevant at knowledge exploitation than at knowledge exploration.

These results bring two main contributions to the literature on network dynamics. First, the dynamics of an industry network have an undeniable spatial component. However, the way geography impacts the evolution of networks is not constant through the course of time. Therefore, we hold the view that research at the interface of geographical clustering and innovation networks should not take the role of geographical proximity in network formation for granted. Future research is necessary to verify whether a shift from geography-dependent drivers of network dynamics to endogenous network drivers is also observable in other science-based or knowledge-intensive industries.

Second, the study points toward the strong relevance of the type of knowledge involved in collaboration for the way network dynamics unfold. In essence, under certain conditions regarding the nature of knowledge the role of geographical proximity in network change seems to be almost ruled out. Therefore we take the stance that studies on the dynamics of innovation networks cannot disregard the nature of the knowledge involved. We encourage future research that further scrutinizes the relation between knowledge dynamics and network dynamics, going beyond the raw distinction between tacit and codified knowledge we have stuck to in this paper.

Future research could complement this study in several ways. An important direction for future work would be to broaden the range of endogenous and attribute-related drivers of network dynamics. Sociology offers a much wider array of endogenous network effects than

triadic closure alone that have potential theoretical relevance for the dynamics of innovation networks. In that regard, one could think of betweenness effects that express actors' preference to position themselves between unconnected others (Burt 2004; Snijders et al. 2007). At the time of writing, this effect was not yet available in SIENA for the analysis of undirected networks. Another endogenous network effect could be the tendency to form direct linkages with actors at geodesic distance higher than two. Such tendency could be interpreted as an expression of social proximity. In terms of attribute-related effects, one could think of other forms of proximity. For instance, the inclination of inventors to collaborate with cognitively similar or dissimilar peers could be captured as an attribute-related parameter, provided good data on individuals' competences and knowledge bases is available.

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Figures and Tables

Figure 1: Number of patents, inventors and co-invention links
Figures based on a 5-year moving window procedure

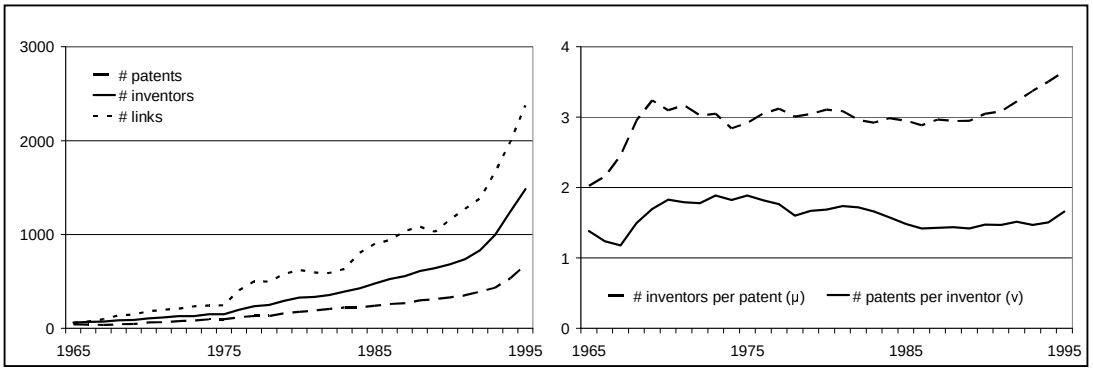

Figure 2: Evolution of spatial clustering of inventors in German biotechnology (1970-1995)

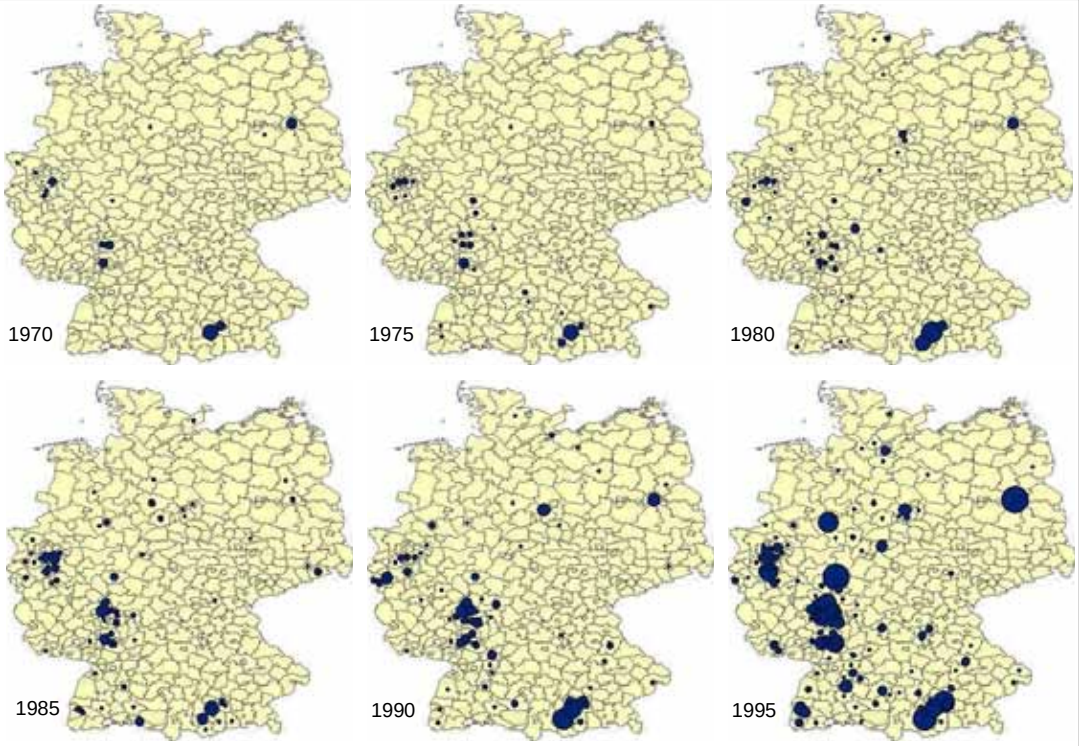

Figure 2a: Number of inventors per district (NUTS3) per year

1 inventor
10 inventors
100 inventors

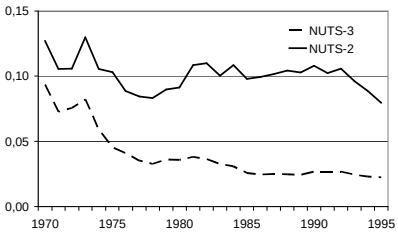

Figure 2b: Evolution of Herfindahl index at NUTS3- and NUTS2-level

Figure 2c: The five main concentrations of German biotechnology inventors
The points indicate districts with at least 40 inventors (1970-95)

Figure 3: Geographical proximity (1970-1995)

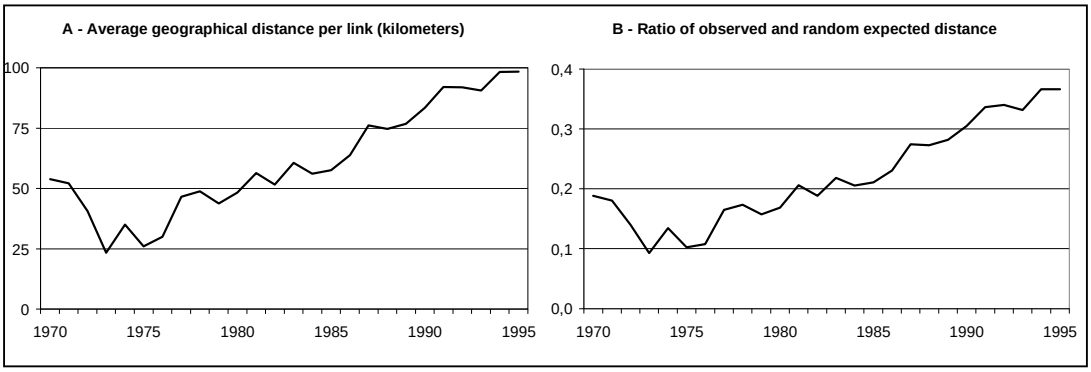

Figure 4: Triadic closure (1970-1995)

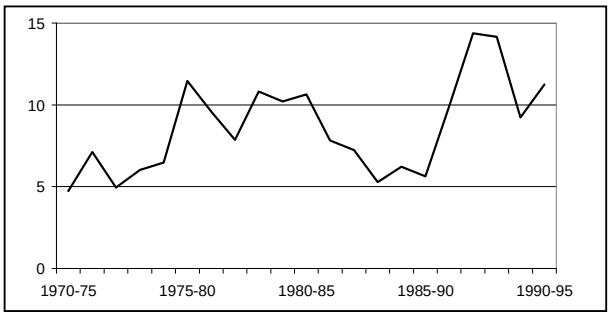

Figure 5: Parameters for network closure and geographical distance over time in stochastic network estimation modelling in SIENA

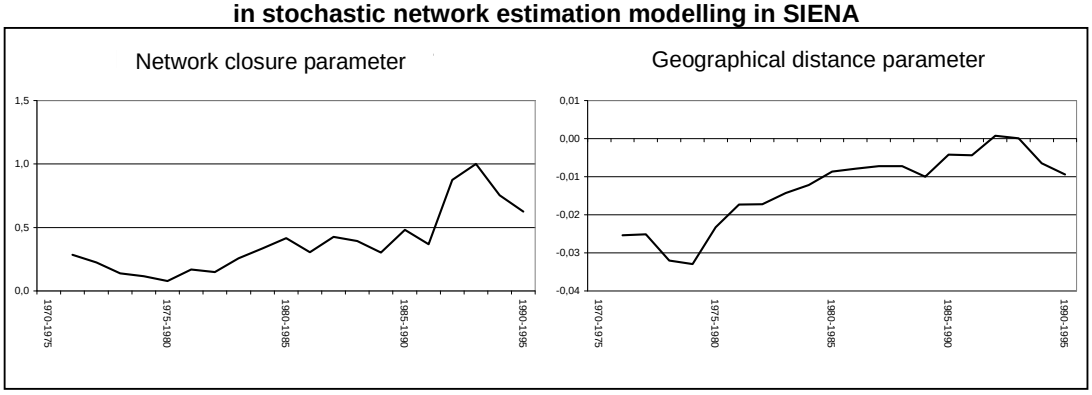

Table 1: Determinants of network evolution: a stochastic estimation model in SIENA

*** Parameter is significant at 0.01 level

	1975-1980	1980-1985	1985-1990	1990-1995
Network change				
Number of nodes	49	96	122	214
Links created	17	64	45	87
Links dissolved	47	76	77	109
Links retained	50	78	111	178
Links *t - t+1*	97 → 67	154 → 142	188 → 156	287 → 265
Parameter estimates				
Rate of change	1.4676 *** (0.1866)	1.5069 *** (0.1174)	1.0932 *** (0.0937)	0.9571 *** (0.0629)
Degree	-2.2926 *** (0.0992)	-1.8339 *** (0.0638)	-1.7881 *** (0.0718)	-2.0348 *** (0.0512)
Geographical distance	-0.0233 *** (0.0031)	-0.0087 *** (0.0021)	-0.0042 (0.0034)	-0.0094 *** (0.0022)
Triadic closure	0.0785 *** (0.0236)	0.4152 *** (0.0376)	0.4812 *** (0.0423)	0.6259 *** (0.0546)
Model				
Number of iterations	1651	1647	1823	1660
Convergence t	0.042	0.037	0.060	0.021
Correlation triadic closure and geographical distance	-0.463	-0.410	-0.340	-0.441