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Abstract:

Economic geography has developed a stronghold analysing how geography impacts innovation. Yet, despite increased interest in networks, a critical assessment of the role of geography in the evolution of networks is still lacking. This paper juxtaposes geographical proximity with the network of prior ties as alternative mechanisms for tie formation. Analysing the evolution of inventor networks in German biotechnology, the paper theoretically argues and empirically demonstrates that – as the technological regime of an industry changes over time – inventors increasingly rely on network resources by forming links to partners of partners, whilst the direct impact of geographical proximity on tie formation decreases.

Keywords: network evolution, geographical proximity, triadic closure, inventor networks

JEL codes: D85, L14, L65, R11

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1. Introduction

From the literature on knowledge spillovers it is known that flows of information decay in quality and quantity with increasing distance (Breschi and Lissoni, 2001). Information about the availability, suitability and reliability of potential partners increases in quality and quantity with geographical proximity, since the channels through which that type of information flows (e.g. social networks and labour mobility) are biased to be local. As a consequence, the geographical proximity between two inventors positively affects the probability that they get acquainted and will subsequently engage in collaboration. However, this study proposes the network of prior ties as an alternative mechanism of tie formation. High-quality information about potential partners resides in the network of prior collaboration ties (Gulati, 1995). Consequently, inventors are strongly inclined to connect to partners of partners. As a result, networks exhibit a tendency towards 'triadic closure', i.e. the tendency that partners of partners become directly connected, closing a triad (a set of three nodes) in the network. Fundamentally, triadic closure operates as a non-geographical mechanism: only to the extent that prior ties are localized, will the effect of triadic closure coincide with geographical proximity, promoting the formation of local ties. An open triad involving inventors in locations far apart is as equally likely to 'close' as a triad contained in a single geographical space, as both are based on information flowing through the network of prior ties. Thus, in contrast to mere geographical proximity, triadic closure is a channel of information flow – and hence a mechanism of tie formation – that is not subject to decay with distance.

This paper presents geographical proximity and triadic closure as two alternative mechanisms in the evolution of collaboration networks at the level of individual inventors. That is, it explicitly aims to introduce a spatial component in the dynamic analysis of inventor networks. Economic geography has developed a stronghold analysing how geography impacts innovation (e.g. Feldman, 1994; Boschma, 2005; Breschi and Lissoni, 2009). Yet, despite increased interest in networks, a critical assessment of geography's role in the evolution of innovation networks is still lacking (see also Ter Wal and Boschma, 2009). At the same time, recent research on network dynamics outside economic geography tends to disregard the role of geography (e.g. Gulati, 1995; Ahuja, 2000; Orsenigo et al., 2001).

This study examines the changing role of geographical proximity in the evolution of networks by contrasting it with the network-endogenous effect of triadic closure. The paper argues – and empirically substantiates – that the role of both mechanisms is subject to change over time as the technological regime of an industry (Malerba and Orsenigo, 1997) is subject to change. More precisely, it is proposed that geographical proximity is most important for successful collaboration when knowledge is predominantly 'basic' and 'tacit' in the earliest stages of an emerging industry, and gradually loses relevance in later stages where knowledge gets increasingly targeted at the development of specific commercial applications. Conversely, it is argued that triadic closure gains importance as a mechanism of network evolution as an industry becomes more established. The closed triads produced by triadic closure act as vehicles of trust, which become more relevant in later stages of industrial evolution. The increasingly less generic nature of knowledge raises concerns about involuntary knowledge spillovers, which are particularly damaging considering the growing focus on the development of commercial applications. Trust during collaboration, and the closed network configurations through which it is maintained, gain prominence in networks over the course of the industry's evolution.

Taking biotechnology in Germany between 1970 and 1995 as an example of an emerging, spatially agglomerated industry, this paper empirically tests the role of geographical proximity and triadic closure as driving forces in network dynamics. The spatial dynamics of the inventor network are reconstructed on the basis of USPTO patent data. Using simulation-based stochastic estimation models (Snijders, 2001) it is empirically tested whether these mechanisms have played a significant role and whether their effect on network dynamics has changed over time. Different to more conventional, descriptive methods of network dynamics, this multivariate method disentangles the effect of 'competing' mechanisms of network change[1]. By analysing repeated simulations of how the network change unfolds between subsequent network observations, stochastic estimation models confront parameter estimates for competing mechanisms of tie formation such as geographical proximity and triadic closure.

[1] Triadic closure and geographical proximity produce overlapping patterns of tie formation to the extent that the network of prior ties – on which triadic closure is based – is localized. Multivariate methods are necessary to disentangle the effects of mere geographical proximity or triadic closure on the creation of local (and non-local) ties.

Unveiling some of the basic principles that underpin the evolution of collaborative innovation networks, this paper connects to an emerging body of research on network dynamics that exists outside economic geography (e.g. Gulati, 1995; Ahuja, 2000; Powell et al., 2005; Orsenigo et al., 2001). Although these studies have certainly increased our understanding of the evolution of networks, they tend to disregard the role of geography in the evolution of networks. Despite the increased interest in networks, economic geography has left this space vacant thus far. In particular, I am unaware of any existing systematic research that has juxtaposed geographical and network-endogenous drivers of network evolution. This paper contributes to the literature on network dynamics by testing the role of these mechanisms empirically. There may be a shifting balance between collaborating with someone 'because he/she is nearby' or 'because you come to know him/her through prior collaboration partners'. A better appreciation of the principles of network formation in collaborative innovation – and the extent to which those principles are geographically determined – yields novel insights into the process of collaborative innovation. As such, a dynamic view on the conditions under which either geographical or non-geographical principles dominate tie formation in innovation networks, contributes to strengthening existing theories on the inherently collaborative nature of innovation, including the literatures on the geography of innovation (Audretsch and Feldman, 1996b) and networks of learning (Powell et al., 1996).

The next section briefly introduces the specific context of the biotechnology industry, describing how its technological regime has changed over time. The third section, 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. The fourth section describes how the spatial dynamics of the inventor network are reconstructed with 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 analysis that empirically demonstrates the individual roles of geographical proximity and triadic closure in tie formation. 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 then provides the discussion and conclusion.

2. The changing technological regime in biotechnology

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 to develop innovations, because of 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 inventor networks and its dynamics over time.

The biotechnology sector also attracted close attention from 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 UK biotechnology industry, firms are agglomerated mainly in the Cambridge area; in the United States, these can mostly be found in California and around Boston. This makes biotechnology an ideal case for studying spatial clustering. This paper argues that the dynamics of inventor networks – and the role of geography therein – are dependent on changes in the industry's technological regime. To this end, this section conducts an extensive literature review to understand how the technological regime in biotechnology evolved. Furthermore, the trends are illustrated empirically with measures of generality and appropriability on the basis of worldwide patent data in biotechnology (Trajtenberg et al., 1997; see also Nicholas, 2009)[2].

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 – rely heavily on relatively recent scientific advancements in molecular and cellular biology (Powell et al., 1996). The origins of modern biotechnology date from the discovery of the double helix structure of DNA in the 1950s, and the subsequent discoveries of recombinant DNA and

[2] Although the analysis of the inventor network focuses on biotechnology in Germany, the trends in the changing technological regime of the industry are illustrated on the basis of worldwide patents to circumvent problems arising from the low numbers of observations, particularly in the early years of German biotech.

monoclonal antibody technology in the 1970s. In the 1980s scientists made considerable progress in the development of genetic engineering (Liebeskind et al., 1996). These new discoveries had enormous technological potential across industries, though particularly in the pharmaceutical industry. Until the 1960s the knowledge base of the pharmaceutical industry was 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.

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 mostly university spin-offs and were closely connected to academic research laboratories (Zucker et al., 1998; Lehrer, 2005). The small firms specialized in biotechnology research and the development of 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 enhance their role by 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: 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 ensured that they could catch up and maintain leading positions alongside 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: 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 would otherwise be unconnected. The increased role of large pharmaceutical companies has spurred substantial changes in the technological regime of the industry (Malerba and Orsenigo, 1997).

First, there has been a shift from a predominantly generic knowledge base to a more specialized knowledge base. This development is illustrated by what is often referred to as the second biotechnology revolution (Gambardella, 1995)[3]. Initially, the biotechnology industry was characterized by a high level of technological uncertainty, typical for the exploration stage of an emerging technology (March, 1991). In the emergence of the biotechnology industry, progress was made in the development of basic knowledge without clear direction of where and how the new set of technology would be applied (Liebeskind et al., 1996). This changed from the 1980s onwards, when 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: 8). To this end, the knowledge involved in these new methods – such as automatic gene sequencing – became increasingly codified in commercially available documents and instrumentation (Rothaermel and Thursby, 2007) and the knowledge embodied in biotech inventions got a more specialized character. Along these lines, Nesta and Saviotti (2005) find that in the 1980s it was knowledge diversity rather than

[3] It is acknowledged that the 'biotech revolution' might in fact not be as revolutionary as is often thought. Like most other emerging technology fields biotechnology follows a pattern of continuous incremental technological change (Hopkins et al., 2007).

knowledge integration that drove innovation in biotechnology, whereas knowledge integration was a more important determinant of innovative activity in the 1990s. Similarly, Audretsch (2001) and Hopkins et al. (2007) note that from the late 1980s onwards large experienced pharmaceutical firms replaced their broad learning strategies during the exploration phase, with a focused approach, targeting specific technologies and applications[4]. In addition, the experimentation process itself became increasingly industrialized over the 1980s and 1990s (Hopkins et al., 2007: 569). The trend from basic, generic knowledge towards increasingly specialized knowledge is further supported when looking at trends in worldwide patented inventions since the 1970s. The generality of an invention is expressed as the extent to which the follow-up technological advances (as captured by the patents that cite the focal invention) are spread across different technological fields, rather than being concentrated in just a few of them (Trajtenberg et al., 1997: 27). As Figure 1 shows, the generality of biotech inventions decreased substantially from the 1980s onwards.

FIGURES 1 AND 2 ABOUT HERE

A second and related development of the knowledge base in the biotechnology industry is a shift towards increasing appropriability, defined as the ability to reap financial benefits from an invention (Teece, 1986). In the early stage of the biotech industry, high levels of technological uncertainty made it difficult to judge the commercial value of new scientific developments and to develop industrial applications from which firms could derive value (Liebeskind et al., 1996). The ability to capture value from their inventions substantially augmented with the increasingly applied and specialized character of patented biotech inventions, stimulating DBFs to focus more explicitly on certain technologies and spurring large pharmaceutical companies to target the development of industrial applications associated to these technologies (Audretsch, 2001; Nesta and Saviotti, 2006). At the same time, the increased codification of

[4] 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 technology's knowledge base that accompanied this trend (see also Saviotti, 1998) implied 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: 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"*. Trends signalling increased efforts to derive financial benefit from their patented biotech inventions are also apparent in patent-based measures of appropriability at the aggregate industry level (Trajtenberg et al., 1997). As Figure 2 shows, appropriability[5] – measured as the extent to which citing patents are held by the same organization as the focal patent – increases dramatically after 1985, providing further support for the conjecture that appropriability increased over the development of the biotechnology industry.

3. Hypotheses

The previous section has demonstrated that the technological regime in biotechnology changed through the course of time, shifting towards a more specialized knowledge base, more strongly focused on value appropriation. The central argument in the paper is that the changing technological regime has implications for the spatial dynamics of the inventor network. Two alternative mechanisms through which information about potential partners is available – and that hence underlie the formation of networks – are juxtaposed: geographical proximity and triadic closure. Geographical proximity is an attribute-related mechanism of network evolution dependent on characteristics (i.e. the location) of inventors. Triadic closure, by contrast, is an endogenous network effect, where the formation of ties is dependent on the prior structure of the network (Snijders, 2001). This section sets the theoretical expectations concerning the changing role of geographical proximity and triadic closure, in the dynamics of the German biotechnology inventor network.

[5] The logic behind taking self-citations as an approximation for appropriability is that self-citations to a focal patent signal an organization's subsequent developments of the focal patent and hence, the importance the organization holding the focal patent attaches to it in terms of (potential) financial value (Trajtenberg et al., 1997).

3.1 Geographical proximity

Economic geography and regional science have an established tradition of studying the importance of geographical proximity for innovation and the formation of networks. In this stream of research the concepts of geographical clusters and knowledge spillovers are strongly intertwined. When Alfred Marshall laid the foundations of the cluster concept by the end of the 19th century, he identified access to local knowledge externalities as one of the main benefits firms derive from their location in a cluster. Consequently, 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). High-tech industries, in particular, show a strong tendency to cluster (Audretsch and Feldman, 1996a). For those industries, knowledge externalities are of particular relevance, as timely access to knowledge on recent technological developments and scientific progress is a key competitive advantage.

Through analysis of knowledge flows as evidenced by patent citations, the literature on knowledge spillovers (Jaffe et al., 1993; Breschi and Lissoni, 2001) has shown that the quality and quantity of information flows are subject to decay with distance. Whilst initial research on localized knowledge spillovers leaves the mechanisms through which knowledge is transmitted unexplored, later research has explicitly searched for explanations for the localized character of knowledge transfer between individuals or organizations. Under the surface of direct observation various channels, other than direct collaboration, serve as a conduit for knowledge flows in a local system (Owen-Smith and Powell, 2004; Ibrahim et al., 2009). In particular, Singh (2005) and Breschi and Lissoni (2009) show empirically that the localized nature of knowledge spillovers is largely due to knowledge transmission in strongly localized social networks and localized flows of mobile labour. Often, by sharing a common educational background and work experience, entrepreneurs and technicians in a local area form communities exhibiting strong personal relationships across organizational boundaries (Grabher and Ibert, 2006). Particularly when communities are located in specialized geographical clusters, these social networks among inventors are strongly localized, providing at least a partial explanation for localized knowledge spillovers (Dahl and Pedersen, 2004; Suire and Vicente, 2009). Mobility of labour constitutes another

important means of knowledge transfer across firms (Song et al., 2003). Since mobile labour is strongly inclined to stay in its home region, this mechanism of knowledge transfer also contributes to the localization of knowledge flows (Almeida and Kogut, 1999).

As mechanisms of knowledge transfer between agents are strongly localized, agents are more likely to know about each other in close geographical proximity than if they were located further apart. Therefore, information about the availability, suitability and reliability of potential partners is subject to decay with distance. In consequence, the geographical proximity between two inventors positively affects the probability that they will engage in collaboration. This intuitive relationship between geographical proximity and network formation has been proved to exist in a variety of research contexts (e.g. Bell and Zaheer, 2007; Maggioni et al., 2007), but cannot be assumed to be generally applicable (Gordon and McCann, 2005). Particularly, the extent to which geographical proximity matters for network formation will depend on the nature of the knowledge.

The importance of geographical proximity in the formation of collaborative relations among inventors depends on the level of 'basicness' of the knowledge involved. Zucker et al. (1998) demonstrate that the initial development of technology by both DBFs and large pharmaceutical companies is strongly supported by the co-presence of academic scientists who are actively contributing to the basic science underlying the technology. Such company-scientist links are particularly prone to be localized when they are formed around 'star scientists' who are most likely associated to important scientific discoveries (Audretsch and Stephan, 1996). This suggest that local component of collaborative innovation is particularly important when basic, early-stage tacit knowledge of scientists has not yet diffused to the broader community and is not yet available in readily accessible codified form. Along the same lines, Gittelman (2007) observed in a study of research collaboration in biotechnology that local partnerships are more likely to lead to patented outcomes, whereas distant collaborations instead result in scientific impact. Strongly codified knowledge for the production of scientific knowledge is more easily communicated at distance than knowledge geared towards the development of innovations. Even though a patent itself is a

codified piece of knowledge, the tacit knowledge that was needed to develop it is more easily transferred and co-produced at geographical proximity.

Tacit knowledge, strongly embedded in human capital and a crucial building block of generating basic knowledge, is most easily exchanged through repeated face-to-face interaction or the mobility of people, which are easier and more frequent at short geographical distances (Zander and Kogut, 1995; Gertler, 2003; Faulconbridge, 2006; Torre, 2008). The knowledge base of an industry is predominantly basic and tacit in young emerging industries. Along those lines, Audretsch and Feldman (1996a) argue that in the early stages of a new technology, when knowledge tends to be highly tacit, firms and individuals benefit most from geographical proximity. When an industry grows and matures, knowledge gets more codified and is more easily transferable over larger distances (Cowan et al., 2004). As described in the previous section, the development from tacit to increasingly codified knowledge – that accompanied the trend from a generic to more specialized knowledge base – could also be observed in biotechnology. Accordingly, I expect the importance of geographical proximity in the formation of networks to decline over time, and the distance over which inventors collaborate in German biotechnology to increase over time. In other words: it is expected that the influence of geographical proximity on tie formation declines in response to changes in the technological regime in biotechnology. Therefore Hypothesis 1 is formulated as follows:

Hypothesis 1: The role of geographical proximity in tie formation declines over time, as the technological regime in biotechnology experiences a shift from tacit to increasingly codified knowledge.

3.2 Triadic closure

Triadic closure is the tendency for new links to be formed between the direct network neighbours of a node, resulting in closed triads in the network (Davis, 1970). That is, two direct partners *j* and *k* of a node *i* get directly connected, producing a completely connected triangle among nodes *i, j,* and *k* in the network.

At the dyad level this implies that a prior indirect tie between *j* and *k* via *i* – at geodesic distance two – turns into a direct tie. Triadic closure is a network structural effect of network dynamics: the formation or dissolution of ties only depends on the prior structure of the network and is not affected in any way by characteristics of the nodes involved.

A tendency towards closure produces dense cliques of strongly interconnected actors in the network (Skvoretz, 1991). The fundamental 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: 102). Closed network structures act as a *"repository of information on the availability, competencies, and reliability of prospective partners"* (Gulati and Gargiulo, 1999: 1440) and, as such, reduce search costs. Thus, having a partner in common provides detailed information about the availability, suitability and reliability of that common partner, making the closing link more likely to be formed. As such, it acts as an alternative, more precise channel of such information to geographical proximity.

The closed structures triadic closure produces foster the development of trust in the relation. In sociological research the presence of cliques is generally interpreted as a sign of social capital (Coleman, 1988; Kilduff and Tsai, 2003). Typical properties of closed and cohesive network structures are reciprocal, repeated and frequent interactions between the actors, with the possibility to cross-check information obtained from direct ties through indirect routes in the network. Each of these properties stimulates the creation of trust in the collaboration. Moreover, closed network structures promote similarity among nodes in a network. As elaborated by social comparison theory in the 1950s (Festinger, 1954), actors in a network tend to be linked to nodes that are similar, either because they connect to others who are similar or because they become similar to those they are connected with (McPherson et al., 2001). The similarity among actors also fosters mutual respect and agreement among them.

Consequently, closed social structures produced by triadic closure 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. As a result, trust in dense parts of the network facilitates intensive exchange of complex or sensitive knowledge (Zaheer and Bell, 2005).

In situations of high risk and high cost to opportunistic behaviour, actors have a clear preference to form ties embedded in dense structures, which may result in network closure (Gargiulo and Benassi, 2000). Several studies empirically demonstrate the preference of organizations and individuals to form ties embedded in cohesive network structures. In the context of US venture capital networks Sorenson and Stuart (2008) found that, at higher risks, actors will be inclined to form network relationships with socially proximate individuals. Beckman et al. (2004) argued that in a situation of strong market uncertainty at the (early) exploitation stage the need for trust is high.

In sum, two inventors that have a common partner have a higher probability to become connected than those without a common partner. However, the importance of trust in collaboration – and hence the effect of triadic closure in network formation – is expected not to be constant over time. Rather, triadic closure becomes more important as the technological regime in biotechnology evolves. The increasing importance of triadic closure is particularly associated to the increase in appropriability, as trust through triadic closure becomes of utmost importance in growing industries where commercial applications are developed and, at the same time, knowledge codification increases the risk of involuntary knowledge spillovers. The increasing level of codification that characterizes the biotechnology industry in later stages of development has serious implications for the risk of involuntary knowledge spillovers, which increase with the level of codification (Saviotti, 1998). Such unintended knowledge spillovers are costly 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). Notwithstanding the fact that patents legally protect the innovation, they by no means overcome 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. Consequently, the necessity of trust for collaboration increases over time when the technological regime in biotechnology shows a trend towards increasing appropriability. Therefore, network closure is expected to become increasingly important in the German biotechnology inventor network over time:

Hypothesis 2: The role of triadic closure in tie formation increases over time, as the technological regime in biotechnology experiences a shift from tacit to increasingly codified knowledge.

4. Data and Method

The empirical analysis is based on patent data. Patent data is increasingly used in scientific research as relational data (Breschi and Lissoni, 2004). This study uses patent data to reconstruct inventor networks in retrospection. Biotech firms have always exhibited a strong tendency to protect their innovations through patents (Blind et al., 2006). This makes patent data a reliable source of longitudinal data on innovation for this sector. The study is based on 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). This data contains all USPTO patents with granting dates ranging from 1963 till 1999. The application date is used for dating patents, since this is closest to the time of invention. All patents with application year 1996 or later have been excluded from the dataset, as 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. No patent data were added 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 has been checked thoroughly for obvious typing errors in inventors' names. This is crucial for reconstructing the networks in the software package UCINET (Borgatti et al., 2002), in which the linking algorithm is based on unique inventor names.

All patents in subcategory 33 (biotechnology, as defined by Hall et al. 2001) were selected, encompassing the USPTO-defined patent classes 435 (molecular biology and microbiology) and 800 (multicellular living organisms and parts thereof). From this subset of patents all patent data was retrieved 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 links to other foreign inventors is lacking, the study disregards foreign inventors and limits the spatial scale of analysis to German-based inventors. For much of the observation period, foreign inventors still play a marginal role. Their share in the total number of inventors in the database increased from under 5 percent until 1975, to roughly 10 percent in the 1980s, and to more than 25 percent from 1993 onwards. More importantly, they do not often reoccur on more than one patent, and as such, are unlikely to influence the formation of ties through triadic closure.

The German biotech patent data file obtained this way, covering the application years from 1961 to 1995, has 4498 records (patent-inventor combinations). 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. Data from 1970 onwards was analysed. Although it is acknowledged that 1970 is an early start for analysing biotechnology, particularly outside the US, it is fair to say that the early patents cover discoveries lying at the roots of biotechnology, as the inventors involved in those early patents recur on later patents that can be more convincingly labelled as biotechnology.

In co-inventorship networks as studied here, two individual inventors are linked if they have worked on the same patent. For assessing collaborative innovation activities this level is the most detailed and pure level of collaborative innovation available through patent data. Patent data allows for creating networks at the applicant level, where links are defined by inventors that occur on patents from different applicants. Considering the fact that patents developed by subsidiaries are often assigned to the company's headquarters, however, an inventor-level network analysis is more appropriate for studying the spatial structure of the network. Certainly, in such a network at the individual level, inventors that co-occur on a patent are likely to work for the same company. However, for various reasons it cannot be automatically assumed 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 of European inventors that on average more than 20 percent of all patents involved some form of collaboration with an external organization, usually not mentioned on the patent; about 15 percent 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 percent of these cases of 'multiple-applicant-inventorship' are due to labour mobility. The remaining 80 percent are largely the result of 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 but to sell the patent to larger firms (Giuri et al., 2007). In a recent paper, Paruchuri (2010) showed that the centrality of inventors in co-invention networks spanning organizational boundaries is – up to a certain threshold level - positively related with their impact on the firm's innovation activities.

A five-year moving window procedure was a applied to reconstruct the inventor networks. Each yearly network observation contains all co-invention links for that year and the preceding four years. In line with other studies on inventor networks (Fleming et al., 2007), it is assumed that co-invention links 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. The place of residence of the patent's

inventors is used to determine the location of innovation in biotechnology, deliberately disregarding the location of the patent applicant (see also Nicholas, 2009). 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.

Figure 3 shows that the number of patents and the number of inventors increases rapidly over time. With the number of inventors per patent and the number of patents per inventor being fairly constant, the growth of the network is mainly the result of the increasing number of patents over time. This is important to notice; since any group of inventors mentioned on a patent forms a fully connected clique in the network, a strong change in either of the two would directly affect the formation of closed triads and hence the estimation of triadic closure.

FIGURES 3 AND 4 ABOUT HERE

5. Descriptive analysis

USPTO patent data were used to reconstruct the spatial dynamics of the German biotechnology inventor network. This section provides some descriptive analyses to shed light on the role of geographical proximity and triadic closure in the dynamics of the German biotechnology inventor network.

5.1 Geographical proximity

To describe the role of geographical proximity in the dynamics of the biotech inventor network, one needs 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 most successful in Europe (Zeller, 2001). On the basis of the location of German inventors on biotechnology patents this study 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 German districts (NUTS3; N=439) and German regions (NUTS2; N=22; the administrative unit between districts and federal states) are the spatial units. Figure 4 shows the evolution of spatial concentration in the industry.

Through the course of time five main clusters of biotechnology inventors have emerged (see Figure 4c): 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). One may 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 since been remarkably stable.

For each year the Herfindahl index was calculated at both spatial scales to capture trends towards spatial concentration or deconcentration (Figure 4b). 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 observed 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 the Rhine-Neckar triangle and Munich now dominating the field. Only from the 1990s onwards did the spatial pattern of the German biotechnology industry become slightly more dispersed. From this period onwards cities such as Freiburg, Tübingen and Bielefeld emerged as secondary centres of biotechnology. As a consequence, the Herfindahl index at the high spatial scale NUTS2 (Figure 4c) shows a decreasing trend from the early 1990s.

The left graph in Figure 5 indicates the changing geographical distance of collaboration over time, expressed in kilometres. The right graph in Figure 5 shows the ratio of the observed distance and the

random expected distance (if German inventors linked randomly, given the spatial distribution of inventors at that point in time). Both graphs show a continuous increase in 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, the descriptive analysis supports the first hypothesis, showing an increasing trend in the distance over which inventors collaborate.

FIGURES 5 AND 6 ABOUT HERE

5.2 Triadic closure

The descriptive statistics thus far point towards an important, though decreasing role of geographical proximity in network dynamics. This section tests the role of the network structural effect of triadic closure in the network dynamics of the German biotechnology inventor network. For this purpose, incumbent inventors are distinguished 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, it is expected that a high number of potential triangles at *t-5* will be closed at time *t.* Every pair of nodes that are connected by a path of length 2 (through one intermediary) form a potential triangle. The tendency for triadic closure is expressed as the ratio of the observed number of closed triads over the number of random expected closed triads. The latter is obtained by calculating the share of new possible links that close a triangle among all possible new links 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 triads 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 6 demonstrates the role of triadic closure in the dynamics of the network. As may be expected, 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. However, 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, one can observe a slightly increasing tendency for triadic closure. On the basis of this univariate test no convincing support is found for hypothesis 2 that the role of triadic closure increases over time. A multivariate test by means of a stochastic estimation model of network evolution in SIENA is used to test the role of triadic closure in conjunction with geographical proximity.

6. A stochastic model of network evolution

6.1 Methodology

The descriptive 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 inventor network. In order to test how these mechanisms jointly drive the dynamics of the network, the study applies a stochastic network simulation procedure, using the program SIENA (Simulation Investigation for Empirical Network Analysis), developed by Snijders et al. (2001; 2007). This program has been specifically designed for the statistical analysis of dynamic networks[6]. It simulates network evolution between subsequent network observations, and estimates parameters for selected mechanisms of network dynamics. Through this procedure the program detects the forces that have driven the evolution of a network from one state into the next.

[6] It is acknowledged that the main power of stochastic estimation models in SIENA lies in the modelling of the co-evolution of network structure and actor attributes, in which the effects of social selection (attributes influence network) and social influence (network influences attributes) can be disentangled. However, the technique is equally valuable and appropriate for gaining insight into the principles of network dynamics without co-evolution.

As in the descriptive analyses above, each network observation covers the co-invention links for a five-year interval, covering the period 1970 - 1995. Accordingly, a five-year time lag is used 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 analysis is limited to the networks among incumbent inventors. Incumbent inventors are defined as those occurring multiple times and in 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 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 inventors who were active in the preceding period and one with those who will remain active in the subsequent period. For each network observation a square binary matrix indicates the existing links 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 between two observation points is left open. For undirected networks there are various algorithms that define the decision rules of a single simulation run. The model is based on 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. This algorithm is closest to reality, more so than the '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). Only estimation models for which this condition has been met for all parameters are reported.

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 early 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.

TABLE 1 AND FIGURE 7 ABOUT HERE

The stochastic estimation procedure in SIENA investigates the joint effect of geographical proximity and triadic closure 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 7 graphically depicts the parameter estimates for triadic closure and geographical distance also for the intermediate, overlapping network observations. The dotted lines indicate the lower and upper bound of the 95 percent 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.

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 drops considerably in the subsequent time periods. The second parameter is degree. This parameter accounts for the observed density in the network 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 they have (Snijders et al., 2007). It can be interpreted as the 'cost' or 'benefit' of having additional links, irrespective of other mechanisms, that make nodes decide to create or dissolve links. For the German biotechnology inventor network the parameter is consistently negative and significant, implying 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. This parameter is negative and significant for nearly all network simulations, apart from the observations from 1985-1990 until 1988-1993. Over time, the parameter values move closer to zero, confirming the first hypothesis on the importance of geographical proximity and its decreasing impact over time.

The fourth parameter is the network structural effect of triadic closure. The parameter is positive and significant for all observations. As Figure 7 shows, the effect increases over time. This is in line with the theoretical expectations and supports hypothesis 2, that triadic closure would become increasingly important as a driver of network dynamics over time as the biotechnology industry is characterized by increasing levels of knowledge codification and higher costs 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 distant.

7. Discussion and conclusion

The paper has juxtaposed geographical proximity and triadic closure – i.e. the formation of closed triads – as two alternative mechanisms in the evolution of networks. Taking collaboration networks of inventors in German biotechnology as an example, it has empirically demonstrated that the role of both mechanisms shifts over time as the technological regime of the industry changes. More precisely, 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 for tie formation in the early stage of the industry, when its knowledge base is largely 'basic' and 'generic' as opposed to specialized and applied. By contrast, triadic closure gains relevance once the industry becomes more established, with a growing focus on the development of specific applications, higher levels of knowledge specialization and codification and the associated risk of unintended and costly knowledge leakages.

These results imply that the nature of how collaborative innovation comes about changes over time. Whilst inventors 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 collaborative links to the partners of their partners. In the early stage of the biotechnology industry, the evolution of the network was organized along geographical lines; during the later growth stage of the industry, inventors increasingly exploited the network's endogenous resources by turning indirect links into direct ones. In other words, over time, geographical proximity becomes less prominent as a driver of network dynamics, whereas triadic closure gains importance. Through this shift the impact of geography on network formation becomes indirect; triadic closure promotes the formation of local ties only to the extent that

prior ties are localized, but equally spurs the formation of non-local ties when inventor involved in a triad are geographically dispersed.

These outcomes are in line with the theoretical expectations. The changing nature of the technological regime in biotechnology is held responsible for this shift. These changes entailed a shift from generic to specific knowledge, from tacit to increasingly codified knowledge and an increased focus on the development of commercial applications (March, 1991; Malerba and Orsenigo, 1997; Audretsch, 2001; Nesta and Saviotti, 2006). Geographical proximity between inventors is mostly relevant in the early stages of a new technological field, when knowledge is predominantly tacit and basic. Tacit knowledge, strongly embedded in human capital, is most easily exchanged through repeated face-to-face interaction or the mobility of people, which are easier and more frequent at short geographical distances (Zander and Kogut, 1995; Torre, 2008). By contrast, triadic closure gains relevance when a field is more established, 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 in the later stages of the evolution of the biotechnology field.

By unveiling the basic principles underpinning the evolution of collaborative innovation networks, these results provide support for existing theoretical principles related to the collaborative nature of innovation, as described in the literatures on the geography of innovation (Audretsch and Feldman, 1996b) and networks of learning (Powell et al., 1996). More specifically, these results bring three main contributions to the growing literature on network dynamics.

First, this paper contributes to the growing literature on network dynamics through its distinctive geographical angle. This study critically assesses and empirically substantiates the variable spatial component in the evolution of networks rather than assuming it is constant or negligible. The way geography impacts on the evolution of networks is shown to be inconstant over time. Therefore, research at the interface of geographical clustering and inventor 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 studies on the dynamics of inventor networks should not disregard the nature of the knowledge involved. Given our detailed knowledge about the relation between knowledge characteristics and geographical proximity from a static perspective (Gittelman, 2007; Zander and Kogut, 1995), one would encourage future research that further scrutinizes the relationship between knowledge and networks from a dynamic perspective. Content-based network analysis techniques could be an interesting way forward. Such network analysis does not only analyse the pattern of interaction among agents, but also treats the knowledge they have in common as a network of ideas or a network of knowledge itself (Criscuolo et al., 2007).

Third, this study has shown the value of stochastic modelling techniques in coming to grips with the forces and mechanisms that underlie the evolution of networks. It is acknowledged that the method might be rather unconventional and is not without limitations. For instance, the size of the networks that can currently be analysed in the program is limited, particularly when repeated network observations are analysed at once. More importantly, a considerable level of stability among subsequent network observations is required for the model to converge towards stable outcomes. In order to meet this requirement this study has focused on the core of inventor networks consisting of incumbent inventors that repeatedly occur on patents and has excluded all inventors that occur only once. It is acknowledged that this might affect the findings, although the multivariate results of the model are largely consistent with the descriptive analysis.

Notwithstanding these limitations, stochastic estimation models of network evolution are well-suited to detect forces of network evolution empirically, leaving vast potential for future research. It is still

largely unknown what drives the dynamics of knowledge networks and how network dynamics differ across industries. Since this paper has only provided a 'stylized model' contrasting two main mechanisms of network dynamics, 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 inventor 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). 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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Figure 1*: Evolution of level of 'basicness' in biotechnology

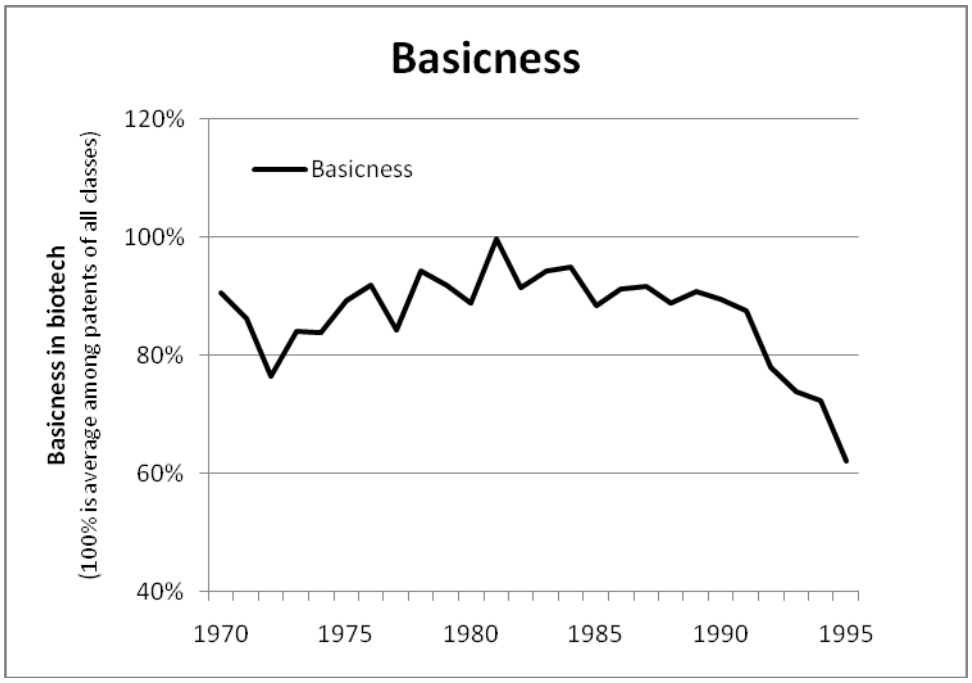
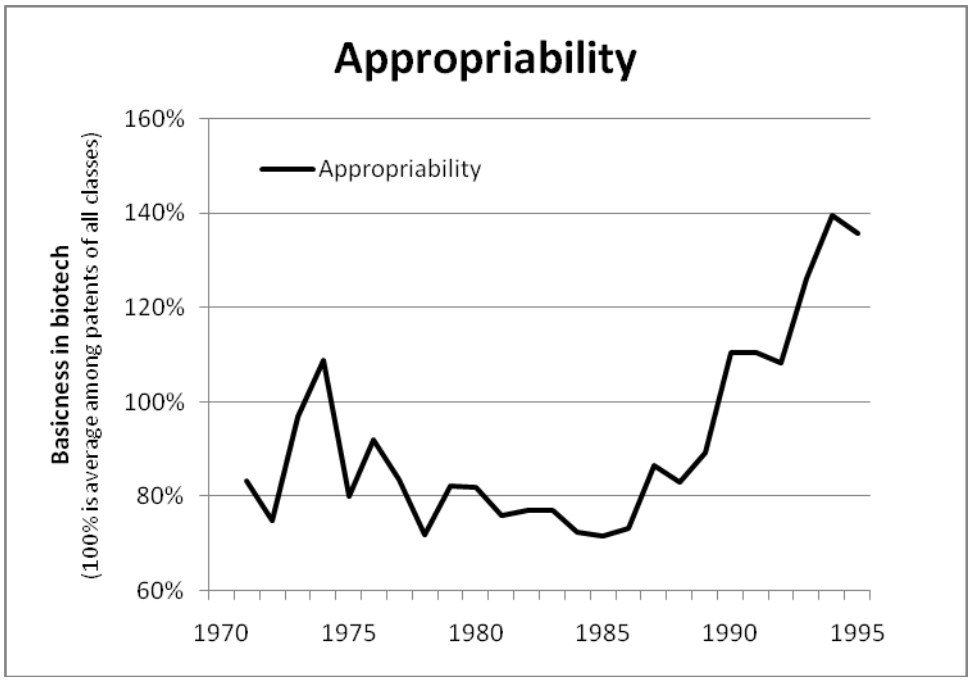


Figure 2*: Evolution of 'appropriability' in biotechnology



Figures 1 and 2 depict the average measures of 'generality' and 'appropriability' as proposed by Trajtenberg et al. (1997) for worldwide USPTO patents in biotechnology. The measure is indexed (where 100% is set to the average among all patents in all classes in a certain year) to offset non-sector-specific trends in patenting and to circumvent problems related to yearly variations in number of citations and the time lag between a patent and its citations.

Figure 3: Number of patents, inventors, and co-invention links over time

Figures are based on a 5-year moving window procedure

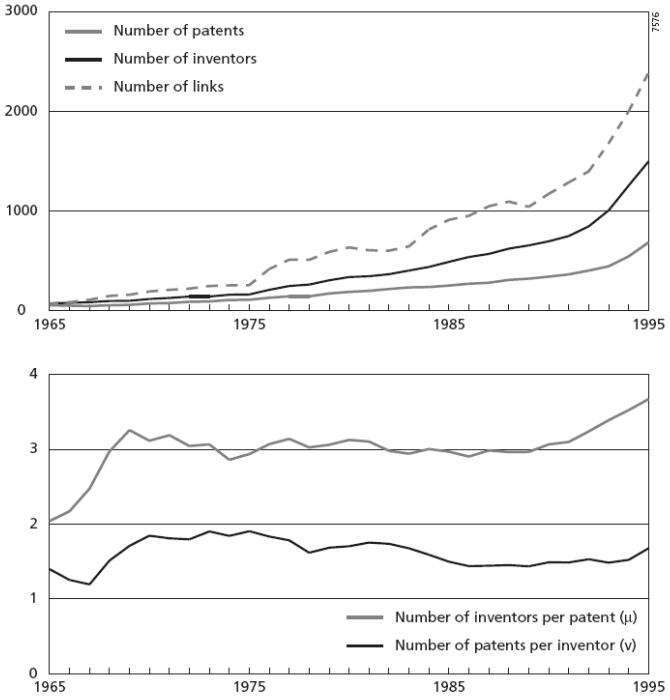


Figure 4: Evolution of spatial clustering of inventors in German biotechnology

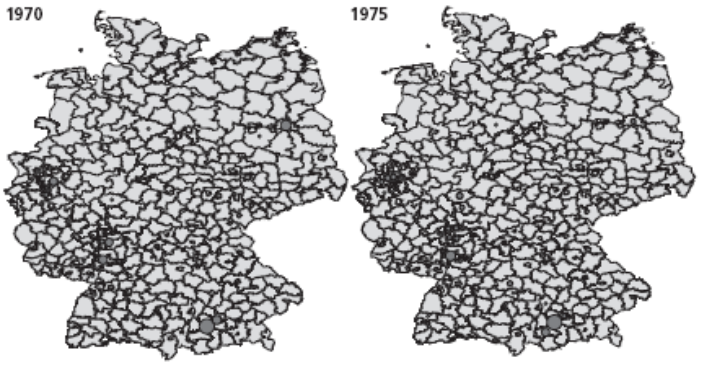
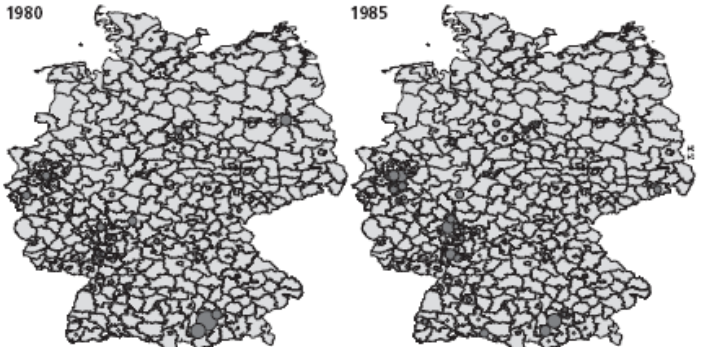
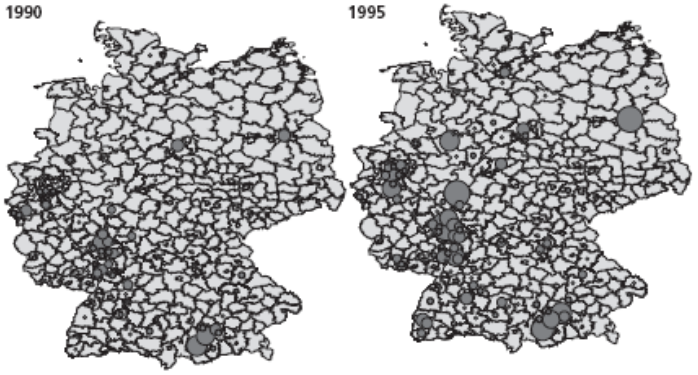


Figure 4a: Number of inventors over time





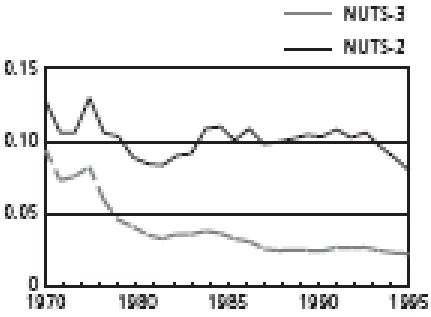


Figure 4b: Evolution of Herfindahl index at NUTS-2 and NUTS-3 level

Figure 4c: Five main concentrations of German biotechnology inventors. The points indicate districts with at least 40 distinct inventors from 1970-1995.

Figure 5: Geographical proximity (1970-1995)

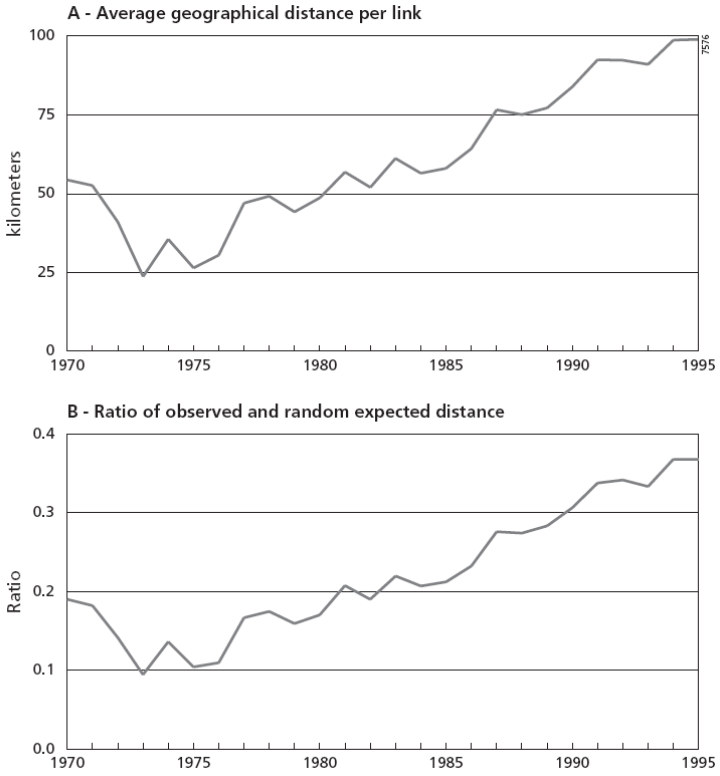


Figure 6: Triadic closure (1970-1995)

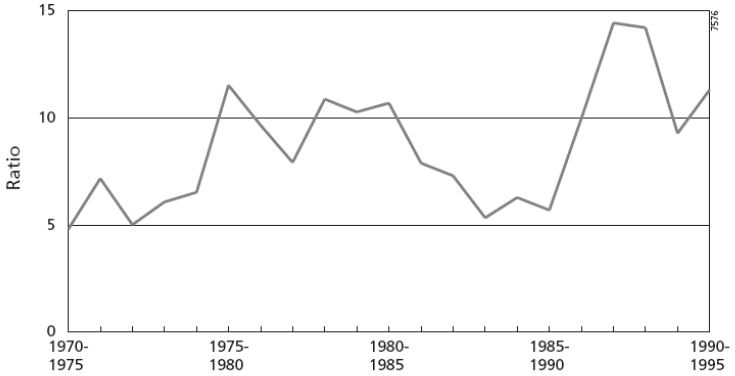


Table 1: Determinants of network evolution: a stochastic estimation model in SIENA

*** 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 ***	1.5069 ***	1.0932 ***	0.9571 ***
	(0.1866)	(0.1174)	(0.0937)	(0.0629)
Degree	-2.2926 ***	-1.8339 ***	-1.7881 ***	-2.0348 ***
	(0.0992)	(0.0638)	(0.0718)	(0.0512)
Geographical distance	-0.0233 ***	-0.0087 ***	-0.0042	-0.0094 ***
	(0.0031)	(0.0021)	(0.0034)	(0.0022)
Triadic closure	0.0785 ***	0.4152 ***	0.4812 ***	0.6259 ***
	(0.0236)	(0.0376)	(0.0423)	(0.0546)
Model				
Number of iterations	1651	1647	1823	1660
Convergence t	0.042	0.037	0.060	0.021
Correlation triadic closure	-0.463	-0.410	-0.340	-0.441
and geographical distance				

Figure 7: Parameters for triadic closure and geographical distance over time in stochastic estimation model in SIENA