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Cluster Emergence and Network Evolution: A longitudinal analysis of the inventor network in Sophia-Antipolis

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Abstract:

A widely held view in cluster research is that clusters are characterized by the presence of networks of local collective learning. However, with a growing number of studies indicating this is not necessarily the case, the question arises under which conditions clusters exhibit dense networks of local collective learning. Taking a longitudinal view at the high-tech cluster of Sophia-Antipolis this paper investigates whether and how networks of collective learning among inventors emerged throughout the growth of the cluster from the late 1970s onwards. On the basis of EPO and USPTO patent data we reconstructed co-inventorship networks for the cluster's two main industries. Detecting a network of local collective learning only in Information Technology, in which growth has been increasingly based on spin-offs and start-ups, and not in Life Sciences, we suggest that the extent and nature of the local concentration of firms over time strongly affect the evolution of local collective learning networks.

Key words: cluster evolution, network evolution, collective learning, Sophia-Antipolis

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1. Introduction

The cluster of Sophia-Antipolis originates from the private initiative of Pierre Laffitte to turn a 'greenfield' site just off shore the Côte d'Azur into a high-tech park. Partly due to public support and marketing, high-tech activities started to be co-located there from the 1970s onwards. International high-tech firms, mainly from Information Technology and Life Sciences industries, that wanted to adapt their products to the requirements of the European market, were attracted by favourable locational characteristics like the pleasant climate and the presence of an extensive tourist infrastructure. This implies that the 'cluster' was originally nothing more than pure co-location of high-tech firms, completely lacking a local interaction structure. This has changed through the course of time. It is often argued that Sophia-Antipolis' Information Technology sector is more and more characterized by local knowledge-based interaction among its firms and research institutes, whereas such interaction is less apparent and convincing in Life Sciences (Longhi 1999; Quéré 2007).

This story is very much in line with important findings in the recent literature on clusters. It is more and more agreed upon that it cannot be assumed beforehand that all firms in a cluster are involved in local networks of collective learning (Giuliani 2007). The case of Sophia-Antipolis once more illustrates that geographical proximity is certainly not a sufficient condition for local collective learning to emerge; clusters and networks do not necessarily coincide. An important follow-up question then is under which conditions clusters exhibit a local collective learning milieu. One way of studying this relationship between clusters and networks is a longitudinal analysis. As a cluster emerges, grows and eventually declines, the conditions under which firms and individual inventors in that particular cluster interact change as well. Ter Wal and Boschma (2007) set out from a theoretical perspective how the nature and extent of clustering varies throughout a industry lifecycle and how these processes might affect the evolution of local networks of learning.

This study takes a closer look at the early introductory and growth stages of co-evolution of clusters and networks as described in Ter Wal and Boschma (2007). By means of a longitudinal analysis of the example case of Sophia-Antipolis, this paper aims to demonstrate how local networks of collective learning evolved while the cluster emerged and grew. It shows that the extent to which clusters and networks show overlap might be dependent on the nature and extent of firm clustering in space. In so doing we aim to deviate from the mainstream literature of static cluster studies and respond to the increasing need for studies that examine under which conditions local networks of collective learning emerge.

In order to accomplish these aims, we will proceed as follows. First, based on interviews with key actors at local authorities and research institutes and on secondary sources, Section 2 describes how Sophia-Antipolis emerged and grew from the 1970s onwards. Then, in Section 3, we detect the evolution of co-inventorship networks throughout these years on the basis of USPTO and EPO patent data. We consider co-inventorship networks as a proxy for local networks of collective learning practices. In Section 4 these networks are analyzed with social network analysis techniques, testing propositions on how they evolved in terms of their geographical orientation, connectivity, path length and clustering coefficient. By looking at these four dimensions we claim to demonstrate if and how an integrated network of collective learning practices emerged in the two main sectors of Sophia-Antipolis: Information Technology and Life Sciences. Finally, section 5 concludes.

2. The evolution of the cluster of Sophia-Antipolis

Nowadays it is widely agreed upon that it is very hard to create clusters or innovation systems in an artificial way through planning or regional policy (Martin and Sunley 2003). Cohesive clusters and innovation systems are mostly considered as being the result of 'natural' developments, which at best can be facilitated or further stimulated by policy initiatives. Sophia-Antipolis constitutes a quite unique example of a cluster in that it is to a large extent created artificially. This section aims to describe the emergence and growth of Sophia-Antipolis from a qualitative perspective. It is based on interviews with key actors within the political and academic spheres of Sophia-Antipolis. To be precise, in October 2006 we conducted interviews at the five key public and semi-public authorities that are involved in economic development policy in Sophia-Antipolis[1] and with the representatives of knowledge valorisation of four main research institutes in the field of Information Technology and Life Sciences within Sophia-Antipolis[2].

Emergence

Although Sophia-Antipolis is an artificially created cluster, the starting point was not in the public sphere. The very beginning of Sophia-Antipolis stems from the private initiative of Pierre Laffitte (Member of the Board of the "Ecole Nationale Supérieure des Mines de Paris") in the late 1960s, early 1970s. He envisioned a City of Science, Culture and Wisdom in the South of France where its participants would be attracted by the so-called Sunbelt effect, i.e. the pleasant climate and other comfortable living conditions. He acquired a forested plain between Antibes and Valbonne at the French Côte d'Azur in order to realise his plans. This area can be viewed upon as a 'vacant space' or 'greenfield site', lacking any industrial or university tradition (Longhi 1999). The first buildings arose in 1972.

The initial project ended up soon in severe budgetary problems. The high costs of providing the necessary infrastructure did not outweigh the benefits that accrued from the initiative. However, being interested to diversify the economy of the Côte d'Azur from mere tourism, the local public authorities supported the initiative already in an early stage and soon the project transformed completely from a private initiative into a public one. With this transformation the focus of the project shifted more explicitly towards high-tech activities,

[1] Department of Economic Development at the Regional Council (Conseil Général Alpes-Maritimes), Syndicat SAM, Team Côte d'Azur, Fondation Sophia-Antipolis

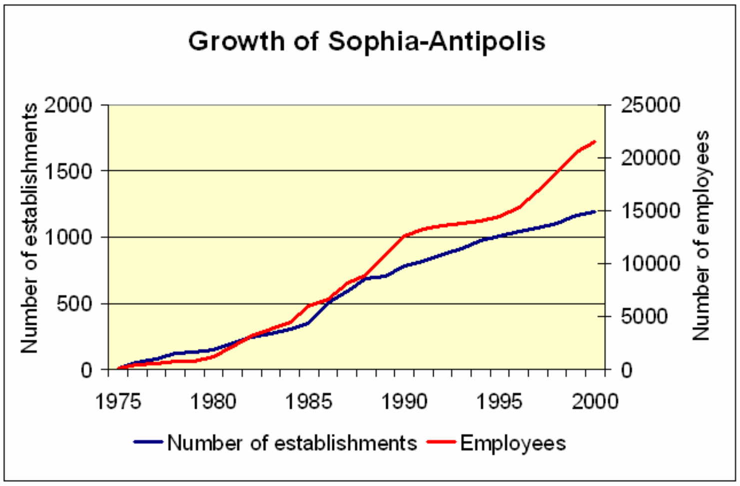
[2] INRIA (The French National Institute for Research in Computer Science and Control), Eurécom (a private research centre in communication systems), Ecole des Mines de Paris (Paris Institute of Technology). Nice Sophia-Antipolis University. INRA (French National Institute for Agricultural Research) refused cooperation.

since this type of activity could easily complement tourism without causing negative externalities (e.g. pollution) to the region's main economic resource (Quéré 2002, 2007).

From the late 1970s, the agglomeration of firms and employment in the park started (see figure 1). This can be considered the first phase of development of the business park of Sophia-Antipolis and consisted mainly of the entry of extra-European firms that wanted to open an R&D facility in which they could adapt their products to the specific requirements of the European market. Although it did not result from an explicit strategy, particularly Information Technology firms – and to a lesser extent firms in the Life Sciences and Energy industries – turned out to be attracted to Sophia-Antipolis (Longhi and Quéré 1997).

Three main reasons can be held responsible for this successful take-off (Quéré 2002). First, there are some structural characteristics of the region that made the Côte d'Azur, in itself a region without any prior industrial background, an attractive region for foreign investment. These characteristics included the pleasant climate and other natural conditions, the presence of an extensive tourist infrastructure, including an international airport, but also conference rooms, hotels etc. The newly established firms could benefit easily from this present physical infrastructure. Second, but not less importantly, the local authorities developed an explicit and active advertising strategy to promote Sophia-Antipolis as a high-tech business park, especially in the United States. A third factor that stimulated the increasing concentration of firms in Sophia-Antipolis was the explicit decentralisation policy the French government exerted during the 1970s in order to promote economic development outside the traditional booming regions (Longhi 1999). In this light the early arrival of France Télécom in the area can be seen as a crucial development. France Télécom provided a modern and efficient fibre-optical network that worked out as an important pull factor for other Information Technology firms that could use this advanced infrastructure base to develop applications readily and efficiently (Lazaric et al 2004).

Figure 1: Emergence of the business park of Sophia-Antipolis



Source: Quéré (2005)

In short, as is often the case in the early emergence of clusters (Arthur 1994; Maskell and Malmberg 2007), the initial concentration of firms in Sophia-Antipolis has shown to depend considerably on chance factors. First of all, the visionary pioneer Pierre Laffitte happened to be located in the region. Moreover, the attraction of international firms' subsidiaries to Sophia-Antipolis on the basis of its pleasant climate is at least remarkable, especially when considering the completely lacking industrial tradition in the region and the wide set of alternative locations across Europe. The subsequent take-off of the growing concentration of firms, however, has been much less dependent on chance factors. The active promotion strategy and the creation of the first agglomeration advantages – for instance related to France Télécom's internet infrastructure – further stimulated the concentration of firms in Sophia-Antipolis. Or as Brenner (2004) puts it, local self-augmenting processes were put in place, that reinforced the initial forces towards spatial clustering.

Intermediate crisis

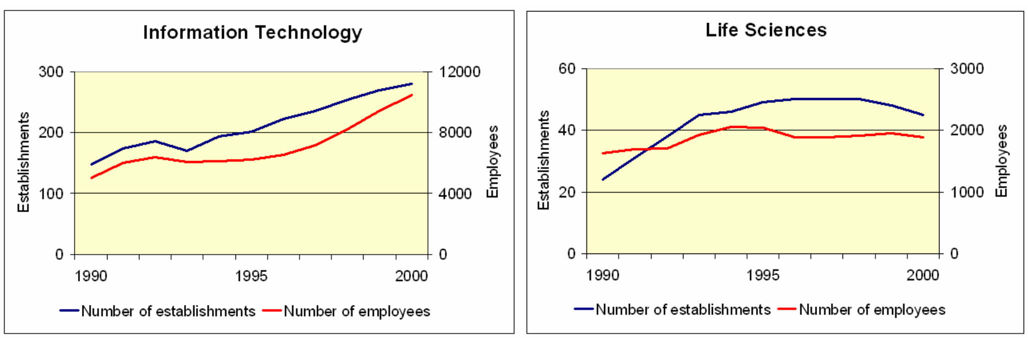
At the end of the 1980s and beginning of the 1990s the growth process in terms of number of firms and employment started to slow down, particularly in Sophia-Antipolis' main sector of Information Technology. The business park of Sophia-Antipolis started to suffer from a number of important shortcomings. First, it lost competitiveness relative to other regions concerning the attraction and keeping of international companies, since those companies changed and expanded their set of location requirements and got a deeper knowledge of the alternatives. Ireland and Scotland, for instance, could provide cheaper qualified labour in comparison to Sophia-Antipolis, while central cities like Paris and London offered a closer proximity to customers and/or financial and administrative services (Quéré 2002). Whereas Sophia-Antipolis was highly competitive in the 'globalisation regime' of the 1980s, the park was in a much less advantaged position in the 1990s. In the 1980s companies were to a large extent vertically integrated and firm location decisions were mainly based on costs and the presence of facilities. In the 1990s, however, these decisions started to be based more on locational features that might stimulate innovation (Lazaric et al. 2004; Longhi 2002), since high-tech firms acknowledged more the importance of knowledge from outside the company for reaching innovation. As a consequence of this shift in locational preferences, the growth of the number of companies in Sophia-Antipolis stagnated and some of the established companies even decided to relocate to other areas (Quéré 2002).

A second, related shortcoming concerns Sophia-Antipolis as a cluster of innovative activity. Beside the fact that through the course of time many companies had been attracted on site that did not focus explicitly on R&D and innovation, innovation in Sophia-Antipolis took place exclusively within the boundaries of the firms. In other words: until the end of the 1980s at least, Sophia-Antipolis was not a cluster in the 'Porter' sense, where innovations accrue through interaction of related firms. By contrast, it was nothing more than a concentration of firms that were co-located on the basis of a similar set of pull factors. Obviously, the local agglomeration process of related firms is a necessary, but insufficient condition for constituting an innovation system (Longhi and Quéré 1997). Considering also, that most of the companies did not have their market locally, Sophia-Antipolis could be viewed upon as a compilation of highly footloose firms (Quéré 2002). In other words: Sophia-Antipolis functioned as a 'satellite platform', as defined by Markusen (1996), where the companies due to their international background had a wide array of international relations beyond the cluster's boundaries, whereas local interactions were almost completely absent (Lazaric et al. 2004; Longhi 1999).

Growth

After the crisis in the early 1990s the Information Technology and Life Sciences industry in Sophia-Antipolis show a strongly divergent pattern of development. In the Information Technology industry it is exactly the 'crisis' of the disappearing international firms that triggered important endogenous developments. The relocating international companies left a pool of highly qualified labour that to a large extent did not move along with the company, but that wanted to stay in the Côte d'Azur region. Many of those people started their own companies. Consequently, the shock of the shrinking presence of multinationals provided a stimulus for stronger locally-based growth of the park that resulted in the emergence of technologically advanced SMEs (Quéré 2007).

Figure 2: Growth in number of establishments and employees in Sophia-Antipolis



Source: Quéré (2005)

This transformation from externally-driven to locally-based growth in the IT industry was further reinforced by the arrival of public and private education and research institutes in Sophia-Antipolis. Most of these institutes, like the University of Nice Sophia-Antipolis, INRIA (National Research Institute on Informatics and Automation) and CNRS (National Centre of Scientific Research), were not present on site already in the early stages of development of the park, but were established in a later stage only. The same holds for the European authority on Telecommunication Standards (ETSI) that has been located in Sophia-Antipolis since 1989. Considering that generally most of the attempts to build a science park start with the location of research institutes in the park, this makes Sophia-Antipolis an atypical, ‘reverse’ science park (Quéré 2007). The research institutes have been attracted in the late 1980s on the basis of an explicit strategy of the national and regional authorities to promote synergies between science and industry. These synergies consist largely of building a highly qualified local labour market, but of PhD students doing traineeships or projects in firms as well.

These new developments mainly concerned the Information Technology industry in Sophia-Antipolis. Three important differences between the Information Technology and Life Sciences sector can be observed. First, there is a large difference in the total amount of concentration of firms between the two industries. As a result of the shift in IT from growth led by foreign multinationals to growth mainly based on local spin-offs and high-tech start-ups, for this industry the crisis turned out to be only a relatively short interruption between the initial emergence of the cluster and the subsequent follow-up phase of extensive growth (see figure 2). The period of transition from externally-driven to locally-based growth took off from the first half of the 1990s onwards and still continues nowadays (for more details, see Lazaric et al. 2004; Quéré 2007). The concentration of Life Sciences firms was not strongly affected by the crisis, but at the same time did not show an increase in the second half of the 1990s like in the Information Technology sector. As figure 2 shows, the growth of the number of firms in the Life Sciences sector has always proceeded at a lower rate than in the Information Technology sector. The increase of the number of Life Sciences firms came to a hold in the 1990s. Nowadays, Information Technology firms constitute about 75% of Sophia-Antipolis’ high-tech companies, whereas Life Sciences firms make roughly 13% (SYMISA 2004). Consequently, from the middle of the 1990s onwards Sophia-Antipolis specialised progressively towards Information Technologies at the relative expense of Life Sciences companies (see figure 2) and Energy and Earth Sciences.

Second, the increasingly locally-based growth in Information Technology made this sector diversify in terms of size. Whereas the park was strongly dominated by large firms in the early stages, the changing nature of the growth in the Information Technologies industry resulted in an increasing share of small- and medium sized enterprises. The Life Sciences sector, however, nowadays is still largely dominated by relatively large subsidiaries of international pharmaceutical companies.

Third, the cognitive distance is smaller between firms in Information Technology than in Life Science. Partly due to the presence of the European Telecom Standardization Institute (ETSI), most of the Information Technology firms work in segments of the same value chain (Krafft 2004). Nowadays, Sophia-Antipolis’ IT sector consists of the three main building blocks infrastructure (equipments, networks and hardware), platforms (interfaces and software) and applications (including services). These three building blocks are more or less equally present in Sophia-Antipolis and are strongly related to each other (Krafft 2004). The interrelatedness of the products and services they develop positively affects the opportunities for collaboration and collective learning. This potential is perceived more and more as well by public and private stakeholders in IT in Sophia-Antipolis. An important private initiative in this respect is made by the Telecom Valley Association that aims to map competences of agents in the park and promotes the emergence of clubs and associations that attempt to link small firms, large firms and research institutes in the field of Information Technology (Lazaric et al. 2004; Longhi 1999). In the Life Science sector however the cognitive distance between agents seems much larger. The activities within the sector range from drugs, biotechnology and cosmetics to medical equipment and fine chemistry. Hence, the specializations among Life Sciences companies in the park differ largely and hence the potential for complementarities might be limited (Longhi 1999).

3. Co-evolution of clusters and networks

The foregoing section demonstrated that the Information Technology and Life Sciences industries within the cluster of Sophia-Antipolis show a divergent evolution path in terms of the emergence and growth of the cluster. Not only has the total growth of the number of firms in Information Technology been bigger, from the first half of the 1990s the growth has also been based increasingly on local spin-offs and high-tech start-ups, whereas the growth of Life Science remained dependent mainly on the growth of multinational enterprises. We argue these differences in the evolution path of spatial clustering have implications for the evolution of local networks of collective learning. When a cluster emerges and grows, the size and composition of its set of firms is subject to change. This has direct implications for the potential for local collective learning and can be considered the basic mechanism behind the coupling of cluster dynamics and network dynamics into a process of co-evolution (Ter Wal and Boschma 2007). More specifically, two main mechanisms link the emergence and growth of a cluster to the evolution of its network of local collective learning.

First, the higher the local concentration of inventors active in a certain technology, the more opportunities for local collective learning emerge. A local concentration of firms doing similar things will facilitate knowing about each other's activities – and hence the potential for collective learning – at low cost (Malmberg and Maskell 2002). Since the total concentration of firms and research institutes is much larger for Information Technology than for Life Sciences, we expected a critical mass of agents for collective learning will only have been reached in Information Technology and not in Life Sciences (Longhi and Quéré 1997; Quéré 2007).

Second, the formation of high-tech start-ups and the emergence of spin-off companies in the Information Technology sector might contribute to the emergence of a local collective learning process. Spin-offs and high-tech start-ups tend to maintain linkages with the incumbent firm. Since spin-offs inherit capabilities from the incumbent firm (Klepper and Sleeper 2005) and – due to myopia (Levinthal and March 1993; Maskell and Malmberg 2007) – tend to do relatively similar things as the incumbent firm – these firms have a potential for collective learning with the incumbent firm and its partners right from the start. Furthermore, both high-tech start-ups and spin-off firms are signs of the presence of a highly qualified and relatively mobile labour market. Mobility of highly qualified personal across firms are important channels of unintended, though valuable forms of collective learning (Almeida and Kogut 1999). The research institutes in Information Technology present on site play a key role in the creation and maintenance of this labour market.

Hence, based on the differences in the clustering process of Information Technology and Life Sciences industries we expect differences in whether and to what extent collective learning practices have emerged in the two main sectors of Sophia-Antipolis. For the Information Technology industry we expect to observe a trend towards the emergence of a local collective learning milieu throughout the evolution of Sophia-Antipolis, though particularly when the growth regime switched from being mainly externally-driven to mainly locally-based in the middle of the 1990s. For the Life Sciences industry we expect not to observe any trend towards the emergence of a local collective learning milieu.

Dimensions of collective learning

We assess the network of collective learning in Sophia-Antipolis by looking at co-inventorship networks. Co-inventorship networks capture two important dimensions of a local network of collective learning. First, a co-inventorship network is a representation of the local structure of intended knowledge exchange between individual actors (Ejermo and Karlsson 2006). The fact that inventors are mentioned on a single patent document is a clear sign of knowledge-intensive team work, irrespective of the fact whether or not the inventors belonged to the same firm or research institute at the time of innovation. Second, a co-inventorship network has a strong social connotation. People who have worked together on the same innovation project (Breschi and Lissoni 2003) or who have worked for the same firm at the same time (Casper 2007) have a social relationship that tends to endure over time, even when they move to another firm or even to another region (Agrawal et al. 2006). These types of interpersonal networks are considered an important channel for the diffusion of technological knowledge (Zander and Kogut 1995; Dahl and Pedersen 2004). Breschi and Lissoni (2003) and Singh (2005) demonstrated that the fact that knowledge spillovers tend to be localized, is in fact due to the localized nature of social networks. The underlying network of co-inventorship relations – interpreted as a social network among engineers – could very well explain the localized pattern of patent citations. A cohesive network of this kind in a cluster – with indirect relationships between inventors in a network – is of utmost importance for knowledge to circulate (Nooteboom and Klein-Woolthuis 2005) and can be considered a clear sign of the existence of local collective learning milieu.

We will look at four different dimensions of such a network of collective learning. Among these we deliberately do not include density. Density is highly sensitive to the size of the network and cannot be compared among networks of different size. Almost as a rule density will decline for growing networks, since the growth of the number of possible links is quadratic when the number of nodes increases linearly. Also path length and clustering coefficient are sensitive to size. In contrast to density, however, these can be analysed longitudinally by comparing the actual values to the values you would expect in random networks of equal size. The four dimensions of collective learning we consider are geographical orientation, connectivity, average path length and clustering coefficient.

First, we look at the geographical orientation of the network of inventors. Since, we include all inventors with whom local inventors have co-invented, our network encompasses also all linkages from local inventors to non-local (national or international) inventors. Bearing in mind the original international character of the business park we expect a strong international orientation in the emergence and early growth stages for both sectors. Due to the change from externally-driven to locally-based growth in Sophia-Antipolis we expect to see an increase in interaction between local inventors for the Information Technology sector only. The propositions are formulated as follows:

Proposition 1a: *In Information Technology the inventor network has become more locally oriented throughout the growth of Sophia-Antipolis.*

Proposition 1b: *In Life Sciences the inventor network has not become more locally oriented throughout the growth of Sophia-Antipolis.*

Here the focus is primarily on the emergence of local collective learning, although we acknowledge that it is extremely important for a cluster to be linked to the outside world as well. The importance of local interaction within a cluster should clearly not be overstated (Waters and Lawton-Smith 2008). An external gaze to world that brings codified knowledge about scientific discovery and technological advancement in the wider industry is of utmost importance for a cluster and its firms to remain competitive (Amin and Cohendet 1999; Asheim and Isaksen 2002).

A second dimension of collective learning is the cohesive nature of the inventor network. An integrated network of inventors allows knowledge to flow not only through direct linkages, but also through indirect linkages (Nooteboom and Klein-Woolthuis 2005). Fleming and Frenken (2007) demonstrated for inventor networks in Silicon Valley and Boston that through the course of time multiple components in the network joined together and formed a giant component. We expect the locally-based growth in Sophia-Antipolis to have stimulated the emergence of high connectivity in the network in Information Technology, whereas we do not expect to observe such a trend in Life Sciences. When looking to the evolution of connectivity in a network, we need to acknowledge that fast growing networks will find relatively more difficulty to retain a high level of connectivity than a constant or slow growing network, due to the fact that the number of potential linkages grows in quadratic terms in a linearly growing network. Since the Information Technology in Sophia-Antipolis is characterized by a much higher number of entrants than the Life Science sector, the tendency towards more connectivity might be partly counteracted by the growth of the network in terms of number of inventors. Casper (2007), however, found in his study of the inventor network in the San Diego biotech cluster that connectivity remained high, notwithstanding the massive growth of the network. Therefore, we formulate our expectations as follows:

Proposition 2a: *In Information Technology connectivity of the inventor network has increased throughout the growth of Sophia-Antipolis.*

Proposition 2b: *In Life Sciences connectivity of the inventor network has not increased throughout the growth of Sophia-Antipolis.*

The third and fourth dimension of a local collective learning milieu relate to the presence of a small world structure (Watts and Strogatz 1998). A small world structure combines two network properties that tend to be beneficial for learning: structural holes and social capital (Verspagen and Duysters 2004; Cowan et al. 2006). Structural holes, that bridge otherwise unconnected or weakly connected parts of a network (Burt 2004), ensure the inflow of novel information into the denser parts and are important to avoid situations of cognitive lock-in (Glückler 2007). Moreover, the presence of structural holes leads to a short average path length between actors in a network, which makes knowledge flow easily through a network. Dense local structures with many redundant ties, on the other hand, are generally interpreted as a sign of social capital (Coleman 1988; Walker et al. 1997). Hence the presence of this type of structures, expressed in a high average clustering coefficient, facilitates trust-based and frequent exchange of high-quality information among the actors involved. A small world network that combines a high clustering coefficient with a short path length then has both advantages of embeddedness and efficiency. Accordingly, Fleming et al. (2007) demonstrated that a regional small world structure positively affects regional innovativeness. We view both short path length and high clustering coefficient as important characteristics of a collective learning milieu. Thus, we expect to observe a trend towards shorter path lengths and increasing clustering coefficients only in Information Technology and not in Life Sciences:

Proposition 3a: *In Information Technology a trend towards decreasing average path length of the inventor network can be observed throughout the growth of Sophia-Antipolis.*

Proposition 3b: *In Life Sciences a trend towards decreasing average path length of the inventor network can be observed throughout the growth of Sophia-Antipolis.*

Proposition 4a: *In Information Technology a trend towards an increasing clustering coefficient of the inventor network can be observed throughout the growth of Sophia-Antipolis.*

Proposition 4b: *In Life Sciences a trend towards an increasing clustering coefficient of the inventor network cannot be observed throughout the growth of Sophia-Antipolis.*

4. Methodology

Patent documents have come to be a rich source of information on knowledge production and innovation activity. Although it can be easily argued that patents do not capture the whole spectrum of innovation activity and therefore patent documents are not the ideal sources of information in that respect, the highly detailed information they contain provides ample opportunities for studying the geography of innovation activity. For instance, patents – that are not equally distributed in space – are widely used in economics as a measure of regional knowledge production (Acs et al. 2002). Moreover information on patent citations is used for tracing knowledge spillovers across firms and to investigate the role of geographical or other forms of proximity in their spatial pattern (Jaffe et al. 1993; Breschi and Lissoni 2003).

A relatively new use of patent data is their application to the reconstruction of cooperation networks back in time (Breschi and Lissoni 2003; Cantner and Graf 2006). In this paper we will use patent data to reconstruct the networks of collective learning in which inventors from Sophia-Antipolis have been involved.

Data

We have detected networks on the basis of two different patent sources. We used patents from the European Patent Office (EPO) for the period from 1978 till 2002 and American (USPTO) patent data from 1975 till 1999 (Hall et al. 2001). The patents have been dated on the basis of the application date – as opposed to the granting date – since this date is closest to the time the innovation was created.

Both for EPO and USPTO patent data all patents were selected on the basis of the inventor address. As long as the spatial unit of analysis is not too small – i.e. not smaller than a labour-market area – taking the inventor address as the selection basis is an appropriate and commonly applied method for allocating patents to the geographical origin in which the innovation has been factually developed. The reason for doing so is that patents developed by a subsidiary of a multi-establishment firm generally tend to be assigned to the headquarters that are possibly located in a different region. For Sophia-Antipolis we defined the surrounding province of Alpes-Maritimes as its labour market area. As figure 3 shows the patent portfolio of Alpes-Maritimes has always been dominated by the Information Technology and Life Sciences sectors, both for EPO and USPTO patents. Since these two sectors are mainly concentrated in Sophia-Antipolis, the dominance of these sectors in the total number of patents from Alpes-Maritimes justifies the choice of this surrounding province as the spatial scale of analysis.

The constructed networks encompass all local actors and the non-local actors they are connected too. Like that, it is possible to compare the extent to which the cooperation takes place purely within the local system with the extent to which the system and its actors are opened up to the external world by means of collaboration with actors outside the local system. Patents have been allocated to the Information Technology, Life Sciences or Miscellaneous categories on the basis of the main technology class mentioned on the patent document. For the EPO patents we have used the OST-INPI/FhG-ISI technology nomenclature as developed by Schmoch et al. (2003) to recode the patent IPC technology classes into sector codes. Which sectors have allocated to the IT and Life Sciences industries is explained in Appendix 1. For the USPTO patents we have made use of the classification as proposed by Hall et al. (2001). The two-digit subcategories that constitute the Information Technology and Life Sciences industries are specified in Appendix 2. Both for EPO and

USPTO patents Information Technology has been broadly defined, including also related fields in Electronics like semiconductors.

Figure 3: Number of patents and inventors for EPO and USPTO data sources

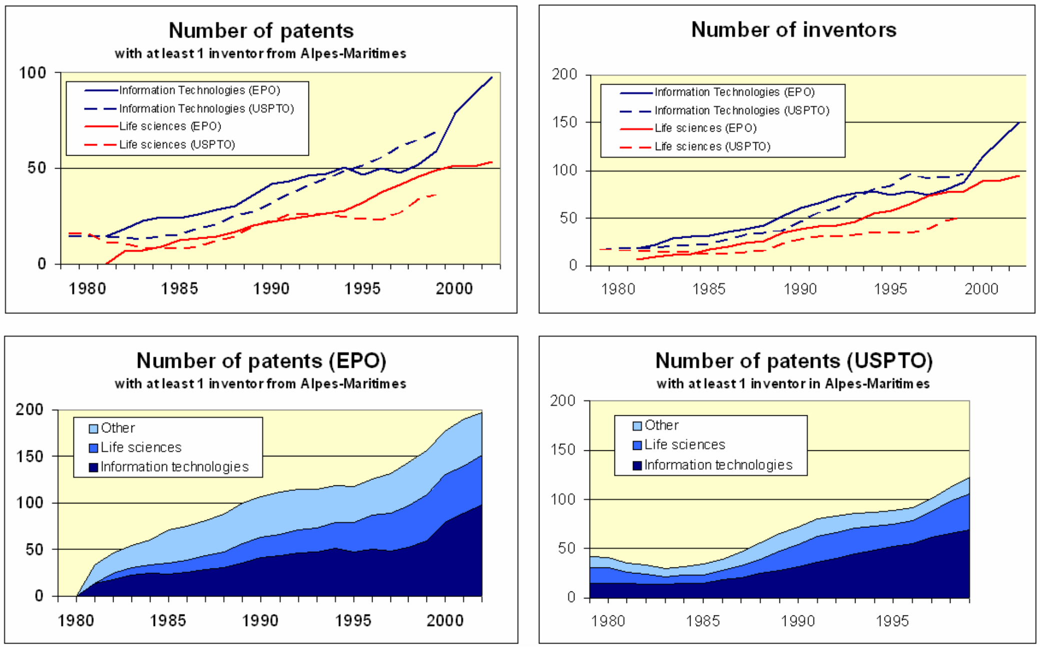


Figure 3 shows the number of patents and inventors in 5-year moving averages for each of the data sources. In line with the general trend towards more patenting, these figures show a nearly constant increase in the number of patents. Strikingly, the crisis in the first half of the 1990s is visible in a decreasing growth rate of the number of patents. After this crisis, in the second half of the 1990s, one can observe a strong increase in this growth rate. The increased share of IT-patents in total number of regional patents confirms this observation.

<u>Network reconstruction</u>

In these networks individual inventors are linked when they have worked together on a patent. Hence, the co-inventorship networks are a one-mode projection of a two-mode (or bipartite) network between patents and inventors. Inventor level networks have been generated in two different ways. The two methods differ from each other in the assumptions they make about how long links between inventors persist. This kind of assumption needs to be made, since no information on the dissolution of links can be distracted from patent data.

In the first procedure, we have built networks using a 5-year moving window procedure. This implies that a network of a particular year contains all co-inventorship linkages of this and the preceding four years. We used the networks that have been generated this way to plot trends in terms of geographical orientation and fragmentation in the network. The second procedure concerns a cumulative network over the complete period of investigation. The assumption here is that social links between inventors persist over time

(Agrawal et al. 2006), although it needs to be acknowledged that people might exit the region, the industry or might simply die. Whereas the networks generated by the five-year moving window procedure could be considered more as an approximation of structure of the existent interpersonal knowledge flows and acts of cooperation in a region (Ejermo and Karlsson 2006), the cumulative inventor network is more an indication of the ever growing underlying social network that potentially functions as a network through which relevant innovation-related knowledge flows (Breschi and Lissoni 2003). Hence, we will use the five-year moving window procedure for the analysis of the cooperative structure of collective learning, whereas we use the cumulative inventor network for the analysis of small world properties.

We acknowledge that patents are not the ideal sources of information for studying innovation activity or cooperation networks (Ter Wal and Boschma forthcoming). They do not provide the complete network of cooperation in which the firms of Sophia-Antipolis have been involved. Cooperation activity that did not lead to a patent is not captured by the methodology. This implies that for instance that more informal collaborations as well as unsuccessful collaborations are neglected. More importantly, Information Technology firms differ in their tendency to protect their innovations by patents. Especially software producers have a relatively low tendency to patent (Bessen and Hunt 2007) and consequently will be underrepresented in the constructed networks. The fact that small firms and research institutes tend to be underrepresented in patents is largely compensated for by looking at the network of inventors as opposed to a network of applicants. Patents in which inventors from smaller firms or research institutes have been involved will often be possessed exclusively by large firms that have either bought the patent or were involved as a cooperation partner. The inventors of small firms or research institutes will nevertheless be put forward on the patent document.

Four dimensions of network evolution

As explained before, the evolution of the cooperation networks in Sophia-Antipolis and the emergence of collective learning practices are assessed along four different dimensions of network structure. Each of these dimensions has been expressed in a separate proposition for both industries.

The first dimension is the geographical orientation of actors – i.e. inventors or applicants – in the network. Both the inventor level and applicant level networks encompass all local actors and all non-local actors that are linked to these local actors. Therefore we distinguish network relationships at three different spatial scales: local-local, local-national and local-international interaction.

The second dimension relates to the connectivity – or inversely the fragmentation – of the networks. As Giuliani (2007) showed it should not be assumed beforehand that knowledge networks in clusters are pervasive. Network fragmentation can be measured in various ways. First, we will use the fragmentation index. This is defined as the proportion of nodes in the network that cannot reach other. This is the case when two nodes belong to different components. Another measure of connectivity is the share of the network's main component or largest components in terms of number of nodes or number of links (see also Cantner and Graf 2006; Casper 2007; Fleming and Frenken 2007). We will apply the fragmentation index and the share of the main component for the 5-year moving window inventor level networks that are the best approximation of the evolution of actual collective learning practices in Sophia-Antipolis.

The third dimension is average path length of the network's Main Component of the cumulative inventor network. Generally an average path length that is similar to the value that could be expected in a random network of the same size is taken as an indicator of small world properties (Watts and Strogatz 1998). Therefore we calculated the Path Length ratio that indicates to what extent the observed path length differs from the value you would expect to observe when the network is random.

The Path Length ratio is the average path length in the actual network over the expected path length in a random network of equal size. The more the PL-ratio exceeds 1.0, the stronger the small world nature of the network (Uzzi and Spiro 2005). The actual path length is calculated as the average of the geodesic distance between all dyads in the network. In order to calculate the expected path length in a random network, we need to take the bipartite (two-mode) nature of our network into account. Instead of using the average degree and the number of nodes in the network for calculating the path length in the random network as you would do in a one-mode network, we take into consideration the number of inventors per patent (μ) and the number of patents per inventor (ν). For a one-mode projection of a two-mode network, like the cumulative inventor network, the Path Length Ratio can be calculated as follows (Newman et al. 2001):

$$PL_{actual} = \frac{1}{n \cdot (n-1)} \cdot \sum_{i,j} d(v_i, v_j)$$

$$PL_{random} = \frac{\ln(n)}{\ln(\mu \cdot \nu)}$$

$$PL_{ratio} = \frac{PL_{actual}}{PL_{random}}$$

$d(v_i, v_j) =$ geodesic distance between node i and j
$n =$ number of nodes in the network
$\mu =$ average number of inventors per patent
$\nu =$ average number of patents per inventor

A high clustering coefficient is fourth dimension of the network of collective learning that is considered. The CC ratio compares the actual clustering coefficient to the expected clustering coefficient of a random network of the same size. The further this ratio goes from 1.0, the more the network is of a small world nature (Uzzi and Spiro 2005). Again, the bipartite nature of the inventor network has implications for the way in which the actual and expected values of the clustering coefficient are calculated. Since all inventors that have worked together on a patent form a fully connected clique, the clustering coefficient is intrinsically much higher than in a one-mode network. Hence, calculating the average clustering coefficient, defined as the extent to which the alters of a node are connected among them, results in very high values. An alternative way of calculating the actual clustering coefficient is taking the number of closed triangles (completely connected triads) over the number of 'potential' triangles (a set of three nodes connected by at least two links). Similar to the expected random path length, the random clustering coefficient takes the average number of inventors per patent (μ) and the average number of patents per inventor (ν) into account. It is assumed that both μ and ν follow a Poisson-distribution. The formulas for calculating the actual and random clustering coefficient and the CC ratio are as follows (Newman et al. 2001):

$$CC_{actual} = \frac{3 \cdot \text{number of triangles on the graph}}{\text{number of connected triplets of nodes}} = \frac{\text{number of triangles with at least 3 legs}}{\text{number of triangles with at least 2 legs}}$$

$$CC_{random} = \frac{M\nu^3}{N\nu^2(\mu^2+\mu)} = \frac{1}{\mu+1}$$

$$CC_{ratio} = \frac{CC_{actual}}{CC_{random}}$$

$M =$ number of patents
$N =$ number of inventors
$\mu =$ average number of inventors per patent
$\nu =$ average number of patents per inventor

5. Results

In section 2 we formulated propositions for the four different dimensions of collective learning: geographical orientation, connectivity, average path length and clustering coefficient. In synthesis, we expected to observe a trend towards more local-local interaction, stronger connectivity, shorter path lengths and higher clustering coefficient for Sophia-Antipolis' Information Technology sector. We expected not to observe these trends of the emergence of local collective learning milieu in Life Sciences.

<u>Geographical orientation</u>

As expected, marked differences can be observed in the geographical orientation of the Information Technology and Life Sciences inventor networks (see figure 4). In the IT industry the number of links is increasing very strongly. The increase takes place at similar rates for all spatial scales, at a relatively constant rate over time. Hence, local interactive learning is increasing, though certainly not at the expense of interaction at higher spatial scales. Hence, although local collective learning has increased, Sophia-Antipolis' Information Technologies industry is still characterized by a strong connection to the outside world, with the extent of local-international interaction strongly increasing from the middle of the 1990s onwards. Hence, we only find moderate support for proposition 1a.

The Life Sciences industry shows a different picture. Most striking is the relative limited total number of links and its moderate growth rate over time. Even when compensating for the lower total number of patents, the total amount of inventor interaction is extensively lower than in Information Technology (figure 5). Similar to Information Technology we observe a trend towards more international interaction from the middle of the 1990s. In contrast to this industry, the increase in nationally and internationally oriented interaction reduces the share of local interaction, particularly in the EPO-based network. Therefore we find strong support for proposition 1b, since no trend towards more local interaction can be observed.

Figure 4: Evolution of geographical orientation of actors in Sophia-Antipolis in terms of number of links per geographical scale [3] *(left: absolute; right: relative)*

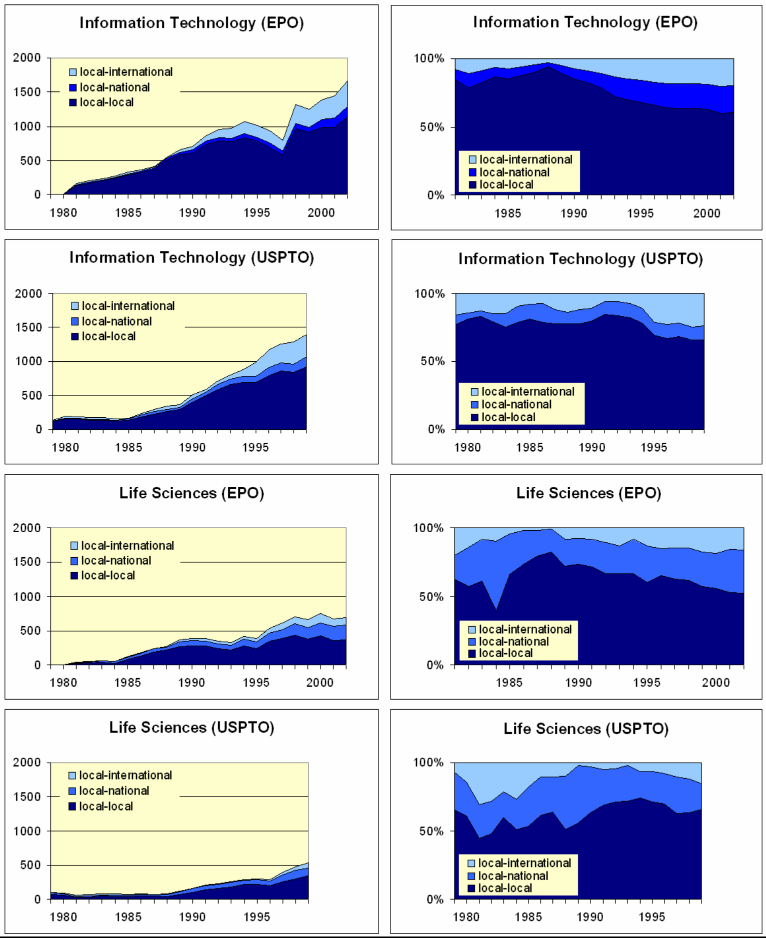
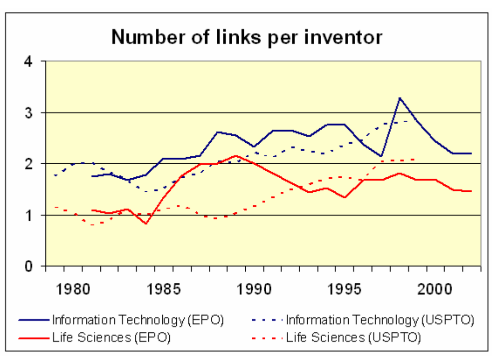


Figure 5: Number of links per inventor

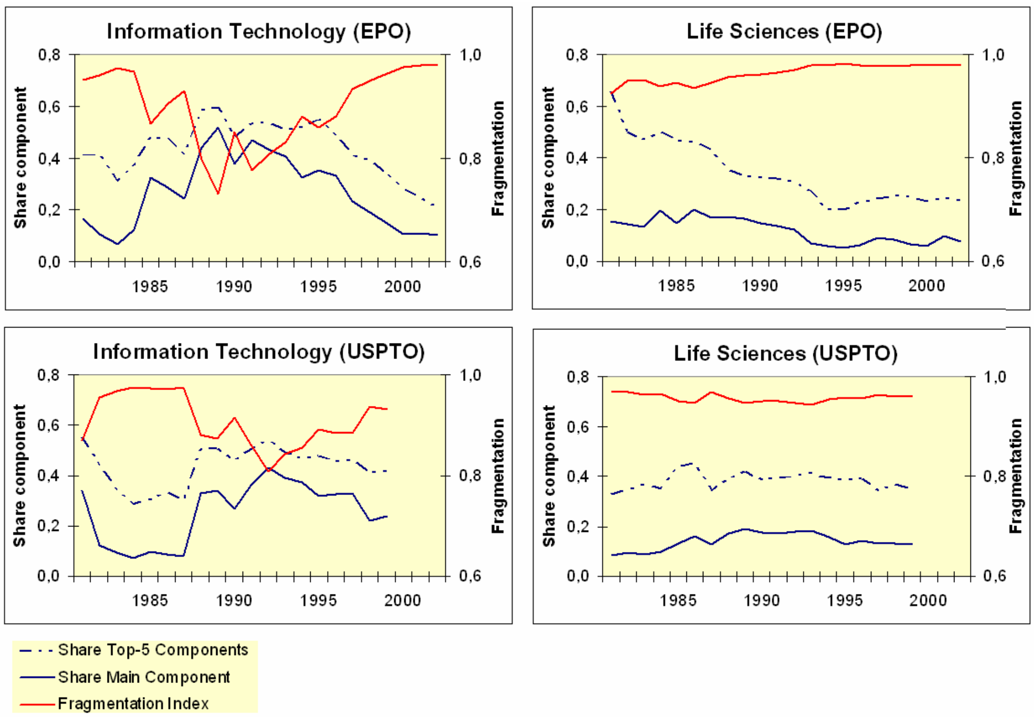


[3] For the inventor level network the count of number of linkages concerns the total number of linkages of 5-year moving window networks of co-inventorship. For the applicant level networks the total count refers to 3-year moving networks of co-patenting and multiple-applicant inventorship.

Connectivity

Connectivity has been plotted in two main ways. First, the fragmentation index measures the proportion of nodes that cannot reach each other. The second measure is the share of the Main Component and the Top-5 components in the total number of nodes in the network.

Figure 6: Evolution of connectivity of the Sophia-Antipolis inventors' network

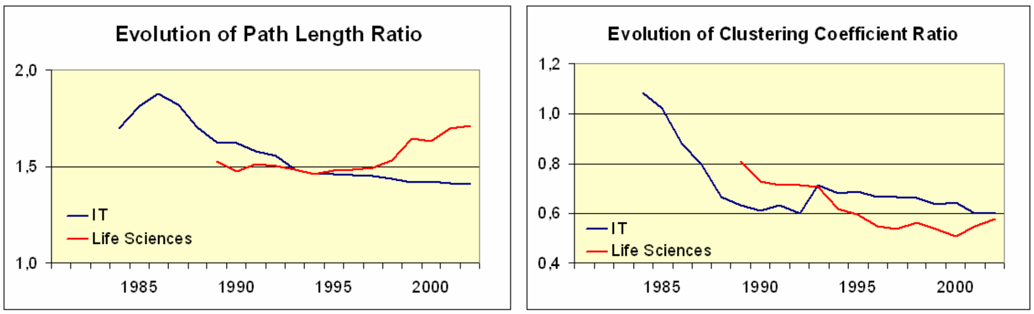


The fragmentation index is high for both industries. For Information Technologies we observe an increased connectivity – i.e. a declining fragmentation index and an increase share of the Main Component – at the turn of the 1980s and 1990s (figure 6). A closer look to the patents of this period reveals that the dominance of large firms (like Texas Instruments and IBM) in the total numbers was relatively high in these years. Through the course of the 1990s we see a strong decrease in connectivity. This decrease is related to the growth of the network in terms of inventors (and the exponential growth of the number of dyads), which makes it more difficult to retain high levels of connectivity. However, unlike the network of the San Diego Biotech cluster studied by Casper (2007), the connectivity of the IT inventor network in Sophia-Antipolis cannot keep pace with its strong growth in these years. Hence, we do not find support for hypothesis 2a. The inventor network in Life Science shows very constant levels of connectivity through time, both in the EPO- and USPTO-based networks. Although the inventor network in Life Science grows slightly over time, and hence it is difficult to prevent a decline in connectivity, a trend towards increasing connectivity definitely cannot be observed. Hence, we support proposition 2b.

Path Length

We expected to observe a trend towards shorter average path length (as compared to the value of a random network of equal size) and towards a higher clustering coefficient (as compared to a random network with equal number of patents per inventor and inventors per patent). Figure 7 shows the Path Length Ratio and Clustering Coefficient Ratio for main components of the EPO inventor networks in both industries. The Ratios are reported as soon as the Main Component's size exceeds 30.

Figure 7: Evolution of PL- and CC-ratio in Sophia-Antipolis inventors' network



EPO patent data – 5-year moving window procedure – Lines are plotted for the Main Components, starting from MCs of more than 30 nodes

The more the PL-ratio approximates 1.0, the easier knowledge flows through the network and the more the network evolves towards a small world structure. In Information Technology there is a clear trend towards shorter path lengths. Hence, the core of inventors in Information Technology gets a more coherent and efficient structure of interaction over time, with a sufficient level of structural holes. In Life Science the opposite trend can be observed: the PL-ratio moves away from 1.0 over time. No trend towards a coherent structure of core inventors can be observed. Thus we find strong support for propositions 3a and 3b.

Clustering coefficient

The CC-ratio shows a different picture. The observed clustering coefficients – for both industries – are much lower than could have expected in random bipartite networks of the same size. This implies that *within-team clustering* is high – due to the two-mode nature of the network in which all inventors on a patent form a clique in the network – whereas *between-team clustering* is lower than could have been expected in a random network (Uzzi et al. 2007). Hence, there is no trend towards a small world structure in terms of clustering coefficients. Therefore, eventually we do not find support for proposition 4a and full support for proposition 4b.

In synthesis, we observe marked differences between the inventor networks in Information Technology and Life Sciences in Sophia-Antipolis. Whereas a local collective learning milieu has evidently always been non-existent in Life Science, we observe a slight trend towards the emergence of a local collective learning milieu in Information Technology.

Particularly, the sheer increase in local-local inventor interaction and the decrease in path length ratio are apparent. These findings are in line with Krafft (2004), who observed that the cyclical downturn the Information Technology industry experienced at the turn of the century did not affect the firm population in Sophia-Antipolis. Whereas at the national level of France a clear shake-out pattern of Information Technology companies can be observed, the number of Information Technology companies in Sophia-Antipolis continued to grow, although at a slightly lower pace. This development could be a sign of well-functioning local knowledge dynamics that positively affect the performance and survival of the firms involved (Krafft 2004).

6. Conclusion

Starting from the observation in earlier research (e.g. Giuliani 2007) that clusters do not necessarily exhibit a cohesive local network of collective learning, this paper addresses the question under which conditions these networks emerge within clusters. By doing a longitudinal case study of the cluster of Sophia-Antipolis, we aim to shed light on the question how differences in the evolution path of spatial clustering can have implications for the evolution of local networks of collective learning. In order to do so, we carried out a longitudinal case study of the cluster of Sophia-Antipolis at the French Côte-d'Azur in which we reconstructed the co-evolution of spatial clustering and networks of collective learning.

Sophia-Antipolis is one of the archetypes of successful European high-tech clusters that to a large extent have been created artificially. Through the course of time the cluster has progressively specialized towards Information Technology and, to a lesser extent, Life Sciences. Whereas the growth of firms in the Information Technologies industry has become stronger based on local spin-offs and high-tech start-ups from the early 1990s, the Life Sciences Sector in Sophia-Antipolis does not grow any longer and is still dominated by relatively large subsidiaries of international firms. Due to the fact that nowadays IT firms are more numerous and comprise more spin-off and high-tech start-up firms than Life Sciences firms, we expected a local collective learning milieu has only emerged in Information Technology.

On the basis of USPTO and EPO patent data we reconstructed co-inventor networks from Sophia-Antipolis' emergence in the late 1970s till 2002 for both Information Technology and Life Sciences. In Information Technology a slight trend towards the emergence of collective learning could be observed. Local-local inventor interaction increased massively over time, though not at the expense of interaction at higher spatial scales. Furthermore the inventor network got more coherent with the average path length – as compared to the path length in a random network of equal size – decreasing over time. However, the connectivity of the network declined over time due to the high number of entrants in the network and the clustering coefficient of the network has always been lower than in a random network of equal size. As expected, in Life Science no trend towards the emergence of a local collective learning milieu could be observed. The inventor network has always been very outward oriented, highly fragmented, with long path lengths and low clustering coefficients.

These outcomes have two important implications. First, the outcomes of this study suggest that the extent to and the way in which firms get concentrated locally highly affect the structure of the local inventor network in a cluster. The local concentration of Life Sciences firms did not lead to detectable forms of local collective learning within this industry. In Information Technology, on the other hand, local collective learning is increasingly taking place. The bigger total concentration of firms and the locally-based nature of its growth recently have apparently been necessary conditions for local collective learning to emerge. Hence, the study once more demonstrates that geographical proximity is not a sufficient condition for local collective learning to take place.

Second, this study demonstrates the emergence of a local collective learning milieu is a very incremental and long-lasting process, which in the case of Sophia-Antipolis has taken about 20 years. It has only been since the growth regime changed from the being the result of newly arriving foreign multinationals to a growth mainly based on local spin-offs and high-tech start-ups in the early 1990s that collective learning practices have emerged. And even then it is evident that the potential for local collective learning still is far from being exhausted.

References

Acs, Z.J., L. Anselin and A. Varga (2002), Patents and Innovation Counts as Measures of Regional Production of New Knowledge. *Research Policy* **31** (7): 1069-1085.

Agrawal, A., I. Cockburn and J. McHale (2006), Gone but Not Forgotten: Knowledge Flows, Labour Mobility and Enduring Social Relationships. *Journal of Economic Geography* **6**: 571-591.

Almeida, P. and B. Kogut (1999), Localization of Knowledge and the Mobility of Engineers in Regional Networks. *Management Science* **45** (7): 905-917.

Amin, A. and P. Cohendet (1999), Learning and Adaptation in Decentralised Business Networks. *Environment and Planning D-Society & Space* **17** (1): 87-104.

Arthur, W.B. (1994), Increasing Returns and Path Dependence in the Economy. Ann Arbor: University of Michigan Press.

Asheim, B.T. and A. Isaksen (2002), Regional Innovation Systems: The Integration of Local 'Sticky' and Global 'Ubiquitous' Knowledge. *Journal of Technology Transfer* **27**: 77-86.

Bessen, J. and R.M. Hunt (2007), An Empirical Look at Software Patents. *Journal of Economics and Management Strategy* **16** (1): 157-189.

Brenner, T. (2004), Local Industrial Clusters: Existence, Emergence and Evolution. London/New York: Routledge.

Breschi, S. and F. Lissoni (2003), Mobility and Social Networks: Local Knowledge Spillovers Revisited: CESPRI, Working Paper no. 142.

Burt, R.S. (2004), Structural Holes and Good Ideas. *American Journal of Sociology* **110** (2): 349-399.

Cantner, U. and H. Graf (2006), The Network of Innovators in Jena: An Application of Social Network Analysis. *Research Policy* **35** (4): 463-480.

Casper, S. (2007), How Do Technology Clusters Emerge and Become Sustainable? Social Network Formation and Inter-Firm Mobility within the San Diego Biotechnology Cluster. *Research Policy* **36** (4): 438-455.

Coleman, J.S. (1988), Social Capital in the Creation of Human Capital. *American Journal of Sociology* **94**: 95-120.

Cowan, R., N. Jonard and J.B. Zimmermann (2006), Evolving Networks of Inventors. *Journal of Evolutionary Economics* **16** (1-2): 155-174.

Dahl, M.S. and C.Ø.R. Pedersen (2004), Knowledge Flows through Informal Contacts in Industrial Clusters: Myth or Reality? *Research Policy* **33** (10): 1673-1686.

Ejermo, O. and C. Karlsson (2006), Interregional Inventor Networks as Studied by Patent Coinventorships. *Research Policy* **35** (3): 412-430.

Fleming, L. and K. Frenken (2007), The Evolution of Inventor Networks in the Silicon Valley and Boston Regions. *Advances in Complex Systems* **10** (1): 53-71.

Fleming, L., C. King III and A.I. Juda (2007), Small Worlds and Regional Innovation. *Organization Science* **18** (6): 938-954.

Giuliani, E. (2007), The Structure of Knowledge Networks. Uneven and Selective, Not Pervasive and Collective. . In: Applied Evolutionary Economics and Economic Geography, edited by K. Frenken. Cheltenham/Northampton: Edward Elgar.

Glückler, J. (2007), Economic Geography and the Evolution of Networks. *Journal of Economic Geography* **7** (5): 619-634.

Hall, B.H., A.B. Jaffe and M. Trajtenberg (2001), The Nber Patent Citations Data File: Lessons, Insights and Methodological Tools: NBER Working Paper 8498.

Jaffe, A.B., M. Trajtenberg and R. Henderson (1993), Geographic Localisation of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics* **108**: 577-598.

Klepper, S. and S. Sleeper (2005), Entry by Spinoffs. *Management Science* **51** (8): 1291-1306.

Krafft, J. (2004), Entry, Exit and Knowledge: Evidence from a Cluster in the Info-Communications Industry. *Research Policy* **33**: 1687-1706.

Lazaric, N., C. Longhi and C. Thomas (2004), From Geographical to Organized Proximity: The Case of the Telecom Valley in Sophia-Antipolis: Paper presented on the 4th Congress on Proximity Economics, June 17-18, Marseille.

Levinthal, D.A. and J.G. March (1993), The Myopia of Learning. *Strategic Management Journal* **14**: 95-112.

Longhi, C. (1999), Networks, Collective Learning and Technology Development in Innovative High Technology Regions: The Case of Sophia-Antipolis. *Regional Studies* **33** (4): 333-342.

Longhi, C. (2002), From Exogenous to Endogenous Local Development: The Cases of the Toulouse and the Sophia-Antipolis Technopoles. In: Complexity and Industrial Clusters: Dynamics and Models in Theory and Practice., edited by Q. Curzio and M. Fortis. Heidelberg: Physica-Verlag.

Longhi, C. and M. Quéré (1997), The Sophia-Antipolis Project or the Uncertain Creation of an Innovative Milieu. In: The Dynamics of Innovative Regions., edited by R. Ratti, A. Bramanti and R. Gordon. Aldershot: Ashgate.

Malmberg, A. and P. Maskell (2002), The Elusive Concept of Localization Economies: Towards a Knowledge-Based Theory of Spatial Clustering. *Environment and Planning A* **34** (3): 429-449.

Markusen, A. (1996), Sticky Places in Slippery Space: A Typology of Industrial Districts. *Economic Geography* **72** (3): 293-313.

Martin, R. and P. Sunley (2003), Deconstructing Clusters: Chaotic Concept or Policy Panacea? *Journal of Economic Geography* **3** (1): 5-35.

Maskell, P. and A. Malmberg (2007), Myopia, Knowledge Development and Cluster Evolution. *Journal of Economic Geography* **7** (5): 603-618.

Newman, M.E.J., S.H. Strogatz and D.J. Watts (2001), Random Graphs with Arbitrary Degree Distributions and Their Applications. *Physical Review E* **6402** (2): -.

Nooteboom, B. and R. Klein-Woolthuis (2005), Cluster Dynamics. In: Learning from Clusters: A Critical Assessment from an Economic-Geographical Perspective, edited by R. A. Boschma and R. C. Kloosterman. Dordrecht: Springer Verlag.

Quéré, M. (2002), Territoire Et Gouvernance Locale: Le Cas De Sophia-Antipolis. *Géographie, Economie et Société* **4**: 335-346.

Quéré, M. (2005), Le Développement Technopolitain En France: Quels Enseignements Pour L'attractivité Des Territoires? *Revue de l'OFCE* **94**: 71-96.

Quéré, M. (2007), Sophia-Antipolis as a 'Reverse' Science Park: From Exogenous to Endogenous Development. In: Applied Evolutionary Economics and Economic Geography, edited by K. Frenken. Cheltenham/Northampton: Edward Elgar.

Schmoch, U., F. Laville, P. Patel and R. Frietsch (2003), Linking Technology Areas to Industrial Sectors: Final Report to the Ec Commission. Karlsruhe/Paris/Brighton: DG Research.

Singh, J. (2005), Collaborative Networks as Determinants of Knowledge Diffusion Patterns. *Management Science* **51** (5): 756-770.

SYMISA (2004), Liste Des Entreprises Sophia-Antipolis 2004-2005.

Ter Wal, A.L.J. and R.A. Boschma (2007), Co-Evolution of Firms, Industries and Networks in Space. In: Regional Studies: Papers in Evolutionary Economic Geography 07.07, Utrecht University, Utrecht.

Ter Wal, A.L.J. and R.A. Boschma (forthcoming), Applying Social Network Analysis in Economic Geography: Framing Some Key Analytic Issues. *Annals of Regional Science*.

Uzzi, B., L.A.N. Amaral and F. Reed-Tsochas (2007), Small-World Networks and Management Science Research: A Review. *European Management Review* **4**: 77-91.

Uzzi, B. and J. Spiro (2005), Collaboration and Creativity: The Small World Problem. *American Journal of Sociology* **111** (2): 447-504.

Verspagen, B. and G. Duysters (2004), The Small Worlds of Strategic Technology Alliances. *Technovation* **24** (7): 563-571.

Walker, G., B. Kogut and W.J. Shan (1997), Social Capital, Structural Holes and the Formation of an Industry Network. *Organization Science* **8** (2): 109-125.

Waters, R. and H. Lawton-Smith (2008), Social Networks in High-Technology Local Economies: The Cases of Oxfordshire and Cambridgeshire. *European Urban and Regional Studies* **15** (1): 21-37.

Watts, D.J. and S.H. Strogatz (1998), Collective Dynamics of 'Small-World' Networks. *Nature* **393** (6684): 440-442.

Zander, U. and B. Kogut (1995), Knowledge and the Speed of the Transfer and Imitation of Organizational Capabilities - an Empirical-Test. *Organization Science* **6** (1): 76-92.

Appendix 1: allocation of EPO patents to industries

In order to allocate EPO patents to Information Technology, Life Sciences or Miscellaneous, we used the Concordance Table as developed by Schmoch et al. (2003). The following technological fields have been assigned to Information Technology: 12 Audiovisual Technology, 13 Telecommunications, 14 Information Technology, 15 Semiconductors, 22 Analysis, measurement and control technology.
The following technological fields have been assigned to Life Sciences: 23 Instruments – Medical Technology, 31 Organic fine chemistry, 32 Macromolecular chemistry and polymers, 33 Life Sciences, cosmetics, 34 Biotechnology, 35 Agriculture and food chemistry, 36 Chemical industry, petrol industry and basic materials chemistry.

Appendix 2: allocation of USPTO patents to industries

In order to allocate USPTO patents to Information Technology, Life Sciences or Miscellaneous, we used the Sub-Categories as used by Hall et al. (2001). The following sub-categories have been assigned to Information Technology: 2 Computer and Communications (including Communications, Hardware and Software, Computer Peripherals and Information Storage) and 4Electrical and Electronic (including Electrical Devices, Measuring and Testing, Power Systems and Semiconductor Devices).
The following sub-categories have been assigned to Life Sciences: 1 Chemical (including Agriculture, Food, Textiles; Coating; Gas; Organic Compounds; Resins) and 3 Drugs and Chemical (including Drugs; Surgery and Medical Instruments; Biotechnology).