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Inventor networks in emerging key technologies: Information technology vs. semiconductors

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by

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Inventor networks in emerging key technologies: information technology vs. semiconductors

Holger Graf*

July 15, 2009

Abstract

We analyze the development of the German knowledge base measured by co-classifications of patents by German inventors and relate this technological development to changes in the structure of the underlying inventor networks. Our central hypothesis states that technologies which become more central to the knowledge base are also characterized by a higher connectedness of the inventor network. We exemplify our theoretical considerations in a comparative study of two patenting fields – information technology and semiconductors. It turns out that information technology shows the highest increases in patents but shows no of a key technology. Contrary, semiconductors develops towards a key technology, despite a moderate increase in the number of patents. The dynamic analysis of inventor networks in both fields shows an increasing connectedness and the emergence of a large component in semiconductors but not in information technology, which is in line with our expectations.

Keywords: Knowledge relatedness; Innovator networks; Interdisciplinary research; Patents; Key Technology

JEL Classification: O31; Z13

1 Introduction

In a recent study [Wuchty et al. \(2007\)](#) show that research across all fields is increasingly performed in teams. Between 1975 and 2000, average team size in patenting has risen from 1.7 to 2.3 inventors per patent and the tendency towards increased team size can be observed in all patenting subfields ([Wuchty et al., 2007](#)). While some authors suggest that this is due to the increasing capital intensity of research in laboratory sciences ([de Solla Price, 1963](#)), or an

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increasing division of labor between specialized scholars (Jones, 2005), Wuchty et al. (2007) argue that this is unlikely to explain similar increases in fields with low capital intensity such as the social sciences, or in fields where the growth of the knowledge stock has been comparably slow. Guimerà et al. (2005) propose a model of network formation in which increasing specialization leads to the emergence of a large connected community of actors. In a longitudinal study on network formation of all patenting inventors in the U.S. from 1975 to 2002, Fleming and Frenken (2007) observe a sudden rise of a giant component in Silicon Valley but not in the Boston region. This result is explained by differences in the rate of labor mobility between the two regions.

We suggest another mechanism that could be responsible for differences in team building and component size distribution based on the nature of the technology and economic incentives for team building. We view innovation as a directed search process, where the direction of innovation is guided by technological and economic opportunities. Its path-dependent nature manifests itself in technological trajectories which are guided by paradigms that are only disrupted in few instances (Dosi, 1982). Technological opportunities decline over the course of an industry life cycle as the variety of technological solutions decreases in the paradigmatic stage (Malerba and Orsenigo, 1997). However, technologies are not to be seen in isolation. While opportunities in terms of variety might decrease over time within a specific field, new opportunities can emerge through combinations of previously unrelated fields, i.e. through a changing *source*, or through an increasing *pervasiveness* when the technology is applied to new markets (Malerba and Orsenigo, 1997). For example, the early publications that tackled economic problems in applying social network analysis opened the door for many economists who follow this approach. Such interdisciplinary tendencies can be observed in many scientific or technological fields, however, in most cases scientists and engineers are not educated in such an interdisciplinary way. As such, teams of authors of publications or patents become more prevalent than individual authors, especially in fields that connect to other fields. On the basis of these considerations, we develop our central hypothesis which states that technologies which become more central to the knowledge base are also characterized by a higher connectedness of the inventor network.

We exemplify our theoretical considerations in a comparative study of two patenting fields – information technology (IT) and semiconductors – which are quite similar in many respects, but differ in one important characteristic. In a first step, we map the technological knowledge base (i.e. a network of technologies), to identify key technologies which we assume to be characterized by a high betweenness centrality. To observe changes within the structure of the knowledge base, we build such networks for seven consecutive years and calcu-

late growth rates of network positions. It turns out that IT shows the highest increases in patents and in degree centrality, while betweenness centrality grows only slowly. Contrary, semiconductors shows the highest growth in betweenness centrality while patents and degree centrality only show a moderate increase. To put it clearly, over the period of observation, semiconductors developed by far more into the direction of a key technology than did IT.

In the second step, we construct inventor networks where inventors are related by common team membership. The dynamic analysis of the networks shows an increasing connectedness and the emergence of a large component in semiconductors but not in information technology, which is in line with our expectations.

The remainder of the paper is structured as follows. In section 2, we present a short review of the literature that constitutes the building blocks of our argument. The analysis of the German knowledge base and the identification of interesting objects of analysis is conducted in section 3. In section 4, we study the structural characteristics and changes that occurred in the IT and semiconductor inventor networks. Our results are summarized in the concluding section 5.

2 Theoretical building blocks

2.1 Cumulativeness and changing technological opportunities

In his highly influential article on *the nature of the innovative process*, Dosi (1988, pp. 222–223) presents five stylized facts about innovation, that are shared by most, if not all, scholars of innovation. (i) *uncertainty*, which is not simply the lack of all relevant information about the occurrence of known events but also the existence of techno-economic problems whose solution procedures are unknown and the inability to predict precisely the consequences of one's actions; (ii) *increasing reliance* of major new technological opportunities on advances in scientific knowledge; (iii) *increasing complexity* of research and development activities which causes such activities to be more formally organized rather than carried out by individual innovators; (iv) *increasing role of experimentation* in the form of learning-by-doing and learning-by-using; and (v) the *cumulative character* of innovative activity.

Here, we will concentrate on two of these facts, namely on the cumulative character of innovative activity and on the sources of technological opportunities. The path-dependent nature of innovation processes manifests itself in trajectories which are guided by technological paradigms (Dosi, 1982). Along

these trajectories, knowledge is accumulated by generating knowledge built on previous findings, just as Isaac Newton already noted in 1676 “If I have seen further it is only by standing on the shoulders of giants.”¹ An increasing knowledge stock will then have consequences for later scholars as they will have to learn more and more about their field before being capable of developing something new. This might lead to either a longer time before researchers can produce new knowledge or it might lead to specialization which demands team building to tackle complex scientific problems.

While the direction of the search process for new ideas is surely dependent on past achievements, it is also guided by actual and perceived opportunities. Opportunities in terms of deepening a technological field are often subject to decreasing returns. At a point where advances can only be made at very high effort and cost, actors will generate new opportunities through combinations of previously unrelated fields, i.e. through a changing *source*, or through an increasing *pervasiveness* when the technology is applied to new markets (Malerba and Orsenigo, 1997). In one sector, plenty of opportunities might arise from advances in the sciences, in others, changes in the demand structure might call for new solutions. Pavitt (1984) showed how sectors differ in terms of their sources of new opportunities. But these patterns are far from static, many industries follow a life cycle in which not only the market structure and demand conditions change but also opportunities for generating novelty. The literature on the industry life cycle provides us with many examples how innovation shifts from product innovation (generating variety) to process innovation in large scale manufacturing, such as automobiles, penicilin, TV, or tyres (Klepper, 1996; Buenstorf and Klepper, 2009). Interestingly, there are also counterexamples like the laser industry (Buenstorf, 2007), where such a development (at least so far) did not take place. One explanation here is the ongoing formation of submarkets by specialized producers (Klepper and Thompson, 2006), which might be considered as a form of increasing pervasiveness.

In both cases, changing source or increasing pervasiveness, a technological field is subject to changes in its relatedness to other fields or in its relative position within knowledge space. A technology that holds a central position in knowledge space is to be considered a key technology that functions as a source of novelty not only in terms of its own development but for many other fields as well.

¹The metaphor of a dwarf standing on the shoulder of a giant is actually attributed to Bernard of Chartres and dates back to the twelfth century, see http://en.wikipedia.org/wiki/Standing_on_the_shoulders_of_giants, May 28, 2009

2.2 Knowledge Relatedness

The issue of measuring relatedness between different fields is far from new and various approaches have been taken to broaden our understanding. [Scherer \(1982\)](#) or [Pavitt \(1984\)](#) use information on knowledge flows to measure relatedness between industries and show how knowledge produced in one sector influences progress in others. Patents have been used by [Jaffe \(1989\)](#) to show that the productivity of R&D varies systematically across clusters of technologically related firms, and that this variation is related to the notion of “technological opportunity.” [Teece et al. \(1994\)](#) introduce the theoretical concept of technological coherence and derive implications for firms’ diversifying strategies that are confirmed by [Breschi et al. \(2003\)](#), who show that firms diversify only into related fields of their existing technology portfolio. Accordingly, [Nesta and Saviotti \(2005\)](#) show that firms with a coherent knowledge base are more successful in innovation. In a related study, [Nesta and Saviotti \(2006\)](#) show the importance of knowledge integration for firms’ stock market value in biotechnology.

This bulk of research suggests that knowledge flows or spillovers tend to occur more intensely between related fields, but this literature does not address the issue of the dynamics of knowledge relatedness and how it might be shaped by actors’ decisions to direct their search towards new opportunities. Before we are going to tackle this problem, let us move into some empirical regularities regarding the organization of innovation on a more micro-level, i.e. in network studies of innovation.

2.3 Knowledge spillovers through interpersonal relationships

A number of studies, which build on the work of [Jaffe et al. \(1993\)](#), trace knowledge flows through people. [Johnson and Mareva \(2002\)](#) perform their exercise on biotechnology patents in the US but in addition calculate measures on interpersonal networks. Their findings suggest a negative effect of distance on knowledge flows which decreases over time while the connectedness of actors is of growing importance. Using a sample of highly cited, semiconductor-related patents, [Almeida and Kogut \(1999\)](#) also replicate the study by [Jaffe et al. \(1993\)](#). Focussing on mobility patterns of engineers, they find individual patent holders to be highly localized only in Silicon Valley. [Breschi and Lissoni](#), using Italian patent data ([2003](#)), and US patent data ([2009](#)), additionally control for the mobility of inventors across companies and space, as well as for the network ties established by this mobility, referred to as social proximity. In their interpretation, geographical proximity is not a sufficient condition for the flow of knowledge, as localization effects vanish for citing and cited patents that are not

linked by network relationships. They conclude that the observations of localized knowledge spillovers are due to social proximity, which is higher between co-located firms or other organizations. These findings are supported by [Singh \(2003, 2005\)](#), who performs similar studies using US patent data.

The research by Zucker, Darby and co-authors also highlights the importance of contacts between people in the transfer of knowledge. In biotechnology, [Zucker et al. \(1998b\)](#) find localized effects through the connections of star scientists to local firms, which they cannot demonstrate to be spillovers. In another paper, the authors claim that these effects are largely mediated by market mechanisms like contractual cooperations or scientists who start their own firm ([Zucker et al., 1998a](#)). Interpersonal networks are considered an important channel for the diffusion of knowledge and information in various other studies (e.g. [Zander and Kogut, 1995](#); [Sorenson, 2003](#)). [Sorenson \(2004\)](#) show that the importance of these transmission channels depends on the complexity of the underlying knowledge base, and in particular, that knowledge complexity limits the rate at which knowledge diffuses across geographic boundaries.

Within these networks of collective invention and innovation, knowledge exchange can only be effective if several conditions are met. First, a certain degree of technological proximity or technological relatedness between the actors is required in the sense that technical problems can be solved commonly ([Mowery et al., 1998](#); [Cantner and Graf, 2004, 2006](#)). Secondly, the knowledge bases of the (potential) cooperation partners should be different and show a certain degree of complementarity. Third, even when the two former conditions are met, actors have to have some abilities or absorptive capacities to understand the technological knowledge of others ([Cohen and Levinthal, 1989](#)). Fourth, geographical proximity as well as social proximity are often helpful to find the appropriate cooperation partner, especially when thinking of informal exchange or the transfer of so-called tacit knowledge ([Breschi and Lissoni, 2003](#); [Boschma, 2005](#); [Boschma and ter Wal, 2007](#)). Last but not least, in a dynamic context, factors such as success, trust, and learning to cooperate become relevant for the repeated and continued exchange of knowledge between actors.

2.4 Inventor networks: Increasing team size and the formation of large components

Having discussed why actors want to access other competencies and to engage in exchanging knowledge and capabilities, necessarily leads to the question on the structures of the resulting relationships and their development over time. Over the second half of the 20th century the generation of knowledge seems to have been subject to a major shift towards an increasing dominance of team-

work (Wuchty et al., 2007). This development can be observed across all fields of research. In the sciences average team size almost doubled between 1955 and 2000 and in while in 1956 17.5% of all papers were written by teams this figure increased to 51.5% in 2000. In patenting average team size increased from 1.7 to 2.3 inventors per patent between 1975 and 2000, and this tendency towards increased team size is observed across all patenting subfields (Wuchty et al., 2007). While some authors suggest that this is due to the increasing capital intensity of research in laboratory sciences (de Solla Price, 1963), this can not explain why this sharp increase in teamwork is also observed in the social sciences or economics. Another explanation is an increasing division of labor between specialized scholars (Jones, 2005). However, Wuchty et al. (2007) argue that this is unlikely to explain similar increases in fields where the growth of the knowledge stock has been comparably slow. Others argue that the costs of communication have decreased, making collaboration between researchers from different places in the world more attractive.

The way teams are formed and how this extends to the formation of networks have attracted considerable research. Guimerà et al. (2005) investigate how the mechanisms by which creative teams self-assemble and determine the structure of these collaboration networks. They propose a model for the self-assembly of creative teams that has its basis in three parameters: team size, the fraction of newcomers in new productions, and the tendency of incumbents to repeat previous collaborations. In their model, increasing specialization leads to the emergence of a large connected community of actors. In a longitudinal study on network formation of all patenting inventors in the US from 1975 to 2002, Fleming and Frenken (2007) observe a sudden rise of a giant component in Silicon Valley but not in the Boston region. Their result is explained by differences in the rate of labor mobility between the two regions.

2.5 Hypotheses

Based on the previous discussion, we suggest a mechanism that could be responsible for differences in team building and component size distribution between different technologies. To summarize, we view innovation as a directed search process, where the direction of innovation is guided by technological and economic opportunities. Technological opportunities decline over the course of an industry life cycle as the variety of technological solutions decreases in the paradigmatic stage (Malerba and Orsenigo, 1997). However, technologies are not to be seen in isolation. While opportunities in terms of variety might decrease over time within a specific field, new opportunities can emerge through combinations of previously unrelated fields, i.e. through a changing *source*, or

through an increasing *pervasiveness* when the technology is applied to new markets (Malerba and Orsenigo, 1997).

The direction of the search process should influence the position of a technology within the knowledge base. In cases where opportunities are to be found in knowledge deepening activities, we should expect to observe a relatively stable position within the knowledge base. If opportunities arise from widening activities through combinations of previously unrelated fields, the technology is expected to move towards the center of the knowledge base and develop characteristics of a key technology.

Such interdisciplinary tendencies can be observed in many scientific or technological fields. However, in most cases scientists and engineers are not educated in such an interdisciplinary way. As such, teams of authors of publications or patents become more prevalent than individual authors, especially in fields that connect to other fields. Our argument is not different from the explanation of Jones (2005), but adds a deeper understanding of the reason why we observe an increasing formation of interdisciplinary teams and why this process differs between fields of research. On the basis of these considerations, we develop our central hypothesis which states that technologies which become more central to the knowledge base are also characterized by a higher connectedness of the inventor network.

This connectedness might be measured in two ways. On the individual level, we should observe an increasing degree centrality in technologies that develop towards a key technology. Regarding the structural properties of the network, we would expect the formation of a large component in such a technology.

With these hypotheses, the question of causality remains obscured, though. In principle, the causality could run in both directions. Whenever actors perceive new opportunities in form of connections of their own field of expertise to other areas, they might react to these new opportunities through the formation of interdisciplinary teams. But where do these new opportunities originate? It might well be that through processes of search and experimentation, successful interdisciplinary teams open up these new opportunities.

3 Mapping the technological knowledge base

Our theorizing in the previous sections leads to our research design that has to be performed in two steps. In a first step, we construct the knowledge base of Germany to identify technologies that show significant developments in terms of patenting or in terms of their position within the knowledge base. In a second step, these *interesting cases* are then analyzed in terms of their inventor networks in section 4.

In our setting the knowledge base is to be understood as a network of interrelated parts of knowledge, where two fields of knowledge are related if new knowledge (in our case a patent but this exercise could be performed with academic papers as well) touches both of these fields. The more often two fields are connected, the closer they are assumed to be in technology space (Nesta and Saviotti, 2005, 2006).

We use applications at the German patent office to construct the knowledge base for each year from 1995 to 2001 and use the publishing date to avoid truncation. On each patent, several IPC classes are named and they cover the technological areas for which the patent is relevant. These classes are either provided by the applicant or by patent examiners during the process of review and specify the relevant technological fields. As patents, which share common technological classes, are assumed to be more closely related than other patents, the frequency of co-occurrence is assumed to be proportional to the intensity of the linkage (Saviotti, 2004). We use this information to link the n technologies in our network in the following way: if a patent is in class i and in class j , there is one link between nodes i and j . The more co-occurrences of two technologies, J_{ij} are observed, the stronger these two are assumed to be related. Notice that resulting relations between technological classes are not directed as they would be if citation data were used.

We follow the notation of Nesta and Saviotti (2006) with Ω as the resulting $n \times n$ matrix of co-occurrences, which can be thought of absolute technological relations:

$$\Omega = \begin{pmatrix} J_{11} & \cdots & J_{1j} & \cdots & J_{1n} \\ \vdots & \ddots & & & \vdots \\ J_{i1} & & J_{ij} & & J_{in} \\ \vdots & & & \ddots & \vdots \\ J_{n1} & \cdots & J_{nj} & \cdots & J_{nn} \end{pmatrix}. \quad (1)$$

However, technological classes in which many patents are assigned, have a higher chance of co-occurrence. Therefore, we construct a measure of relatedness based on the matrix Ω as in Nesta and Saviotti (2006). For the calculation of the expected number of co-occurrences, we assume a random process of patents being assigned to technologies i and j that follows a hypergeometric distribution with a mean of μ_{ij} and a variance of σ_{ij}^2 calculated as follows:

$$\mu_{ij} = \frac{O_i O_j}{K}, \quad (2)$$

$$\sigma_{ij}^2 = \mu_{ij} \left(\frac{K - O_i}{K} \right) \left(\frac{K - O_j}{K - 1} \right), \quad (3)$$

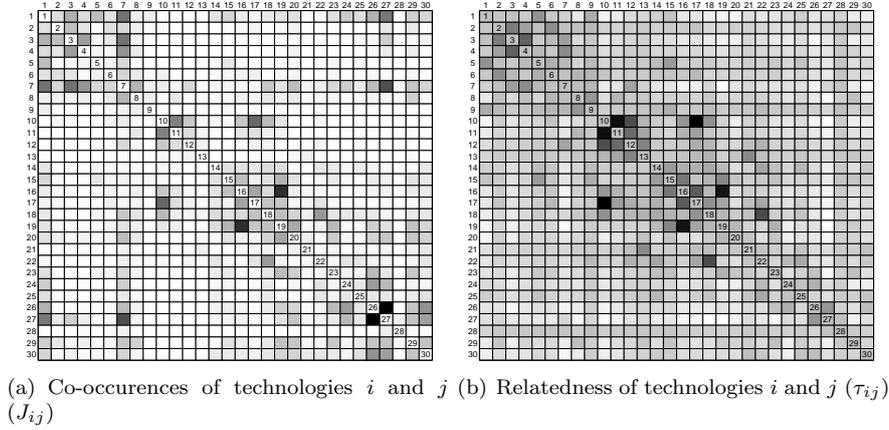


Figure 1: Knowledge base of Germany 1995 – 2001

where K is the total number of patents, O_i of which are assigned to technology i and O_j in technology j . Relatedness is then defined as

$$\tau_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}}, \quad (4)$$

which is positive for technologies that co-occur more often than expected ($J_{ij} > \mu_{ij}$) and negative if $J_{ij} < \mu_{ij}$.

For the technological aggregation of IPC classes, we classify patents according to a technology-oriented classification that distinguishes 5 sectors and 30 technologies based on the International Patent classification (IPC). This classification has been elaborated jointly by the ‘Fraunhofer-Institut für Systemtechnik und Innovationsforschung’ (FhG-ISI), the ‘Observatoire de Sciences et des Techniques’ (OST), and the ‘Science and Technology Research Policy Unit of the University of Sussex’ (SPRU) and is provided in table 2.

We visualize the German knowledge base for the whole period (1995 to 2001) in figure 1 in the form of a levelplot. Figure 1(a) displays the network of co-occurrences, while in figure 1(b) the relatedness between technologies τ_{ij} determines the coloring of cells.

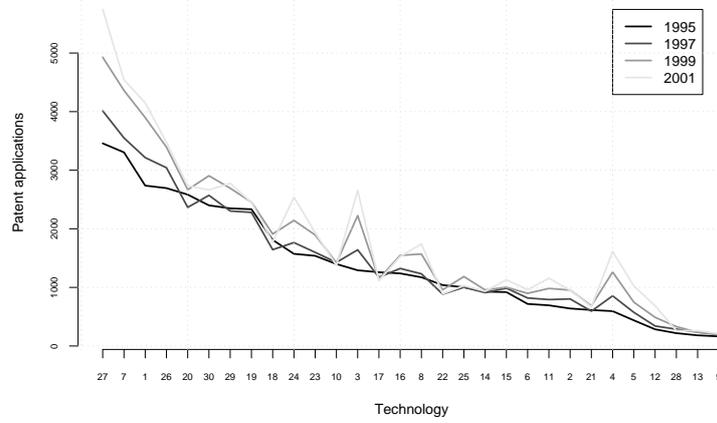
Strong connections can be observed between technologies 1 to 7 which covers five technologies within the sector of electrical engineering together with optics and analysis, measurement and control technology. Another group of connected technologies is in technologies within large scale chemistry and process engineering (14 to 19). What can also be read from this plot are the generic features of analysis, measurement and control technology (7) and electrical machinery (1), which show high levels of connection to many different fields. Especially strong linkages exist between 16 (Macromolecular chemistry, polymers) and 19

(Materials processing, textiles, paper) and between 26 (Mechanical elements) and 27 (Transport).

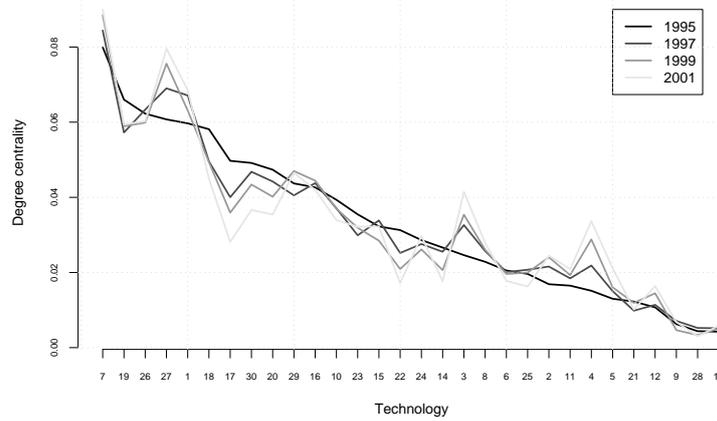
While the general structure of both figures is the same, it is noteworthy that in figure 1(b), high patenting fields such as transport (27) or analysis, measurement and control technology (7) are not as much related to other fields as if the absolute number were considered. Since we control for the absolute number of patents in figure 1(b), these differences do not surprise us, but make us feel more comfortable in analyzing the knowledge base according to co-occurrences in the following.

This analysis provides a static picture of the German knowledge base covering patenting activities over a seven year period. It represents the strengths of the German innovation system in automobiles and chemicals as rather distinct subsystems with instruments connecting the knowledge base. However, our primary interest lies in the changes that occurred during that period. The late 1990s were characterized by major advances in fields such as IT, semiconductors, or biotechnology and we wonder how these advancements changed the technological knowledge base. For that purpose, we display changes in the importance of technologies according to three different variables in figure 2. Overall, correlations of these variables between different years suggest quite a stable structure (they range between 0.89 and 0.99), but we can observe significant changes for some fields.

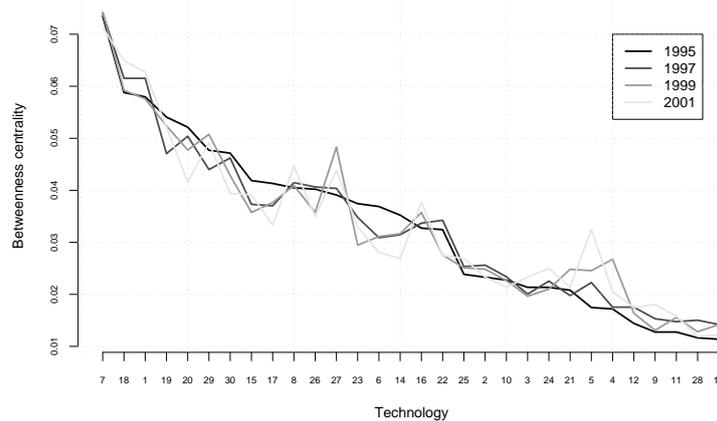
In figure 2(a) technologies are sorted in descending order of the number of patents in 1995 and values for subsequent periods (1997, 1999, 2001) are plotted in that order. We can observe a deepening of the knowledge base in the sense that strong patenting fields such as transport (27), analysis (7), and electrical machinery (1) all show increasing numbers of patent applications. Some fields become decidedly stronger such as engines (24), telecommunications (3), or information technology (4). Figure 2(b) visualizes changes in the degree centrality of technologies, i.e. how strong a technology is connected to any other. Here, we see that analysis (7) remains the most central technology, transport (27) is becoming more connected, while a sharp decrease in connections is observed for the chemical industry (17). While this type of centrality accounts for the relevance of a technology for other fields, it does not take into account the whole structure of the knowledge base. The high values in transport, for example, arise because of its strong relations to mechanical elements but not to the multitude of other fields. As such, we consider betweenness centrality to be a better indicator for key technologies. In social network analysis, betweenness centrality is measured as the frequency with which a node is positioned between pairs of other nodes on the shortest path connecting them. For the knowledge base of Germany we find analysis (7), chemical engineering (18), and electrical



(a) Number of patents



(b) Degree centrality



(c) Betweenness centrality

Figure 2: Changes in the importance of technological classes for the German knowledge base

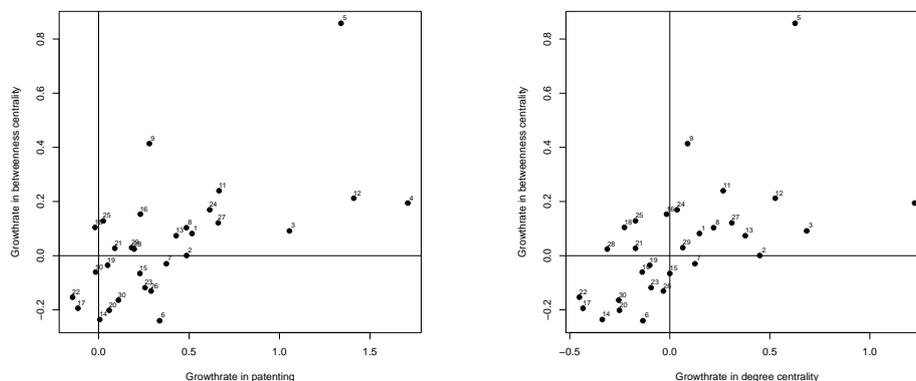


Figure 3: Scatterplot of growthrates in patenting, degree and betweenness centrality of technological classes

machinery (1) to be the three most important and persistent key technologies. The most drastic increase in this measure appears for semiconductors (5), where betweenness more than doubles.

To provide a more structured impression of the development of technological positions within the knowledge base, we calculate growth rates of the number of patents, degree, and betweenness centrality between 1995 and 2001. In figure 3, where these growth rates are plotted against each other, two interesting cases appear. IT (4) and semiconductors (5) seem to follow quite distinct patterns in terms of integration with other technological fields. While IT shows high increases in patents and in degree centrality, betweenness centrality shows only a slight increase. Contrary, semiconductors shows a very high growth rate in betweenness centrality while patents and degree centrality increase less pronounced.

4 Inventor networks in IT and semiconductors

One question that arises from the exercise above, is on the relation between i) the integration of a specific technology – or its development – within the knowledge base and ii) the organization of the innovation process within a specific technology. One can imagine that the organization of the innovation process differs between technologies that deepen their specific knowledge base and those that widen its knowledge base in establishing connections to other fields. The development of patents that link different technological fields clearly needs different capabilities than the development of patents that only touch one field. Apparently, competencies for widening knowledge might not be found within a single person but we should expect them to arise from the collaboration within teams of inventors. As such, we hypothesize that a field that is increasingly

central within the knowledge base, should also be characterized by increasing interaction between inventors.

To provide an answer to this question, we analyze inventor networks in the two fields identified in the previous section as showing quite distinct developments: IT (4) and semiconductors (5). For the purpose of comparison it is fortunate that these two fields belong to the same sector and are also quite similar in terms of the number of patents and inventors. Furthermore, the top applicants show up in both technologies. Siemens, Bosch, and Infineon are among the top 5, Philips, Daimler and Fraunhofer are among the top 10 applicants in both fields.

To reconstruct inventor networks, we relate inventors by common team membership as documented on patents; i.e. two inventors are related if their collaboration is documented by their common naming on the same patent (Balconi et al., 2004; Fleming et al., 2007). Since knowledge exchange between individuals does not occur at one point in time, the common procedure in constructing such networks is to consider patents from more than one year. We decided to take three-year moving windows², which implies fewer connections than in longer periods but provides us with more observations to analyze the development of the networks. This also implies the assumption that relationships between team members are broken up if they are not renewed in terms of collaboration.

In table 1, we present descriptive statistics of these two networks for the years 1997 to 2001 to analyze gradual changes in the network structure. A comparison of the development of the inventor networks in these two technologies shows some interesting features. Information technology is the larger network in terms of inventors and also grew faster between 1997 and 2001. The growth rate of the IT network between the first and last year is 0.795, while the semiconductor network grew by 0.464. Since information technology was chosen because of its sharp increase in patenting, this result does not surprise us. However, the connectedness of the two networks shows strong differences. One indicator of the connectedness of a network is the share of actors within the main component. Components are connected parts of the network and the main component is simply the one with the highest number of members. The formation of large components has been analyzed by Fleming and Frenken (2007) for regional networks. In IT, we observe no such formation with the number of inventors starting at 28 in 1997, peaking at 107 in the following year, and declining to a value of 59 in 2001. Given the size of this network this is a very small main component and accordingly we observe a share in the range between 1% and 3% of all inventors within that main component. This volatility implies a high fragility of this largest connected part of the network. The picture of semicon-

²Fleming et al. (2007) e.g. use a five-year moving window.

Table 1: Dynamics of the inventor network in IT and semiconductors

	1997	1998	1999	2000	2001
Information technology (4)					
Nodes	2946	3430	4146	4584	5287
Number of components	1460	1716	2067	2277	2533
Size of main component	28	107	87	53	59
Share in main component	0.95%	3.12%	2.10%	1.16%	1.12%
Isolates	784	952	1138	1272	1379
Share of isolates	26.61%	27.76%	27.45%	27.75%	26.08%
Centralization	0.0102	0.0195	0.0140	0.0098	0.0109
Density	0.0007	0.0006	0.0005	0.0004	0.0004
Mean degree	1.9579	2.0093	2.0014	2.0414	2.1865
Semiconductors (5)					
Nodes	2122	2394	2694	2849	3107
Number of components	754	813	887	908	934
Size of main component	78	256	291	334	475
Share in main component	3.68%	10.69%	10.80%	11.72%	15.29%
Isolates	307	341	363	397	404
Share of isolates	14.47%	14.24%	13.47%	13.93%	13.00%
Centralization	0.0199	0.0242	0.0200	0.0220	0.0179
Density	0.0014	0.0013	0.0012	0.0012	0.0011
Mean degree	2.9161	3.1997	3.2858	3.5114	3.5558

Note: Networks are reconstructed from patent applications within a three-year window up to the specified year.

ductors is a different one. Here, the share of inventors in the main component starts at 3.7% and continually rises up to 15.3% in 2001. This result meets our expectation of an increased connectedness in a technology that becomes more central within the knowledge base.

If we consider interdisciplinary teams to be a reaction to technological opportunities that arise from an increased pervasiveness, isolated inventors who have no contacts to other actors should also be less common in a widening technology compared to a deepening one. Again, meeting our expectations, the share of isolated inventors in IT is almost twice as high compared to semiconductors and it seems to be much easier to generate novelty as a single inventor in IT than it is in semiconductors.

Centralization is not so much a measure of connectedness than of the concentration of inventive activities among inventors. In table 1, we report the centralization measure based on degree centrality, i.e. on the number of linkages of an actor. The theoretical minimum of this index is 0 for a ring structure or any network in which every actor has the same number of linkages and its maximum is 1 for networks in which all actors are connected to a single, central actor (star network). In both networks centralization takes rather low values between 0.01 and 0.025 and is always higher in the semiconductor network.

The network density is defined as the number of all linkages divided by the

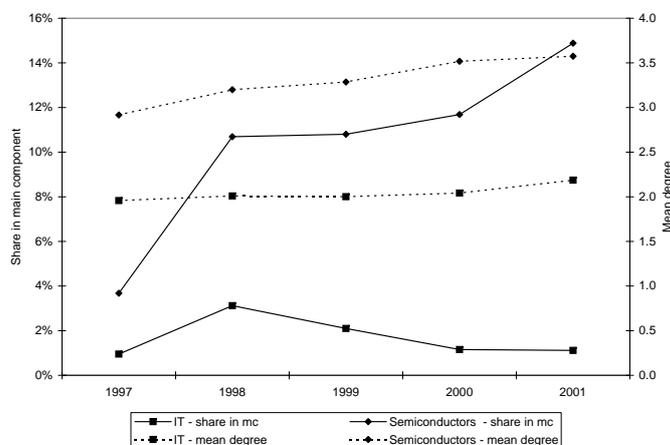


Figure 4: Connectedness of inventor networks in IT and semiconductors

number of possible linkages and gives an impression of the connectedness of the network. This measure is somewhat problematic in comparing networks of different sizes as the number of possible linkages increases geometrically while the actual number of linkages usually does not since inventors are constrained in their capacities to have contacts to other actors. Therefore, we also report the mean degree, i.e. the average number of ties. In both networks the mean degree increases steadily, indicating a general tendency towards an increasing relevance of teamwork which is in line with the results by [Wuchty et al. \(2007\)](#). But again, we observe sharp differences between both technologies. While in IT the mean degree is comparably low and increases only slightly from 1.96 in 1997 to 2.18 in 2001, values in semiconductors increase twice as fast and at a higher level from 2.92 to 3.56 in semiconductors.

The central statistics for our comparison of the connectedness in the inventor networks of IT and semiconductors are presented in figure 4 to illustrate the sharp differences in the share of inventors within the main component and the mean degree.

5 Conclusions

Many scholars have performed research on how sectors, industries, or technologies are interrelated and how knowledge flows from one field to the other or how certain fields draw on the knowledge produced in other fields. Quite often this research comes with an explicit or implicit criticism on existing classifications of industry, but few consider these relations to be of a changing nature. We performed an exploratory exercise to get an idea of how such a process might

be explained and which consequences it might have for the organization of the innovation process. More specifically, we analyzed the relationship between the changing position of technologies within the knowledge base and the changes within the underlying inventor networks, i.e. the structure of actors that produce new knowledge and thereby not only constitute but also actively change the knowledge base and react to new opportunities.

In addition to existing explanations of increasing team size, we could identify another mechanism where the nature of technological opportunities plays an important role for the incentives to form larger teams in the process of innovation. If opportunities within a specific domain are still abundant, innovation deepens the existing knowledge and networks play only a minor role. Whenever opportunities arise from broadening the field of applications or from drawing on the knowledge of a variety of technologies, interdisciplinary teams are formed which constitute larger network structures among inventors. We propose that the nature of technological opportunities is driving the process that determines if a certain field develops towards a key technology.

This research has to be viewed as a first step into the analysis of a co-evolution of technology and invention networks and certainly has its limitations. Patents as a data source have to be viewed critically and some of these drawbacks might well affect our results. Many innovations are not patented which is the reason why we can only observe the tip of the iceberg of actual relations in the innovation process. The fact that patents are increasingly used for strategic purposes (Cohen et al., 2000; Blind et al., 2006, 2009) might also mislead us, since no teams of inventors are needed for patents that do not reflect actual progress in knowledge production. For the analysis of such a co-evolutionary process, the time span that we covered is certainly short and similar studies will have to test our results with developments in more technological areas.

Appendix

Table 2: Concordance between IPC and technology codes

	Industry Technology	IPC-Code
I.	ELECTRICAL ENGINEERING	
1.	Electrical machinery and apparatus, electrical energy	F21; G05F; H01B, C, F, G, H, J, K, M, R, T; H02; H05B, C, F, K
2.	Audiovisual technology	G09F, G; G11B; H03F, G, J; H04N-003, -005, -009, -013, -015, -017, R, S
3.	Telecommunications	G08C; H01P, Q; H03B, C, D, H, K, L, M; H04B, H, J, K, L, M, N-001, -007, -011, Q
4.	Information technology	G06; G11C; G10L
5.	Semiconductors	H01L, B81
II.	INSTRUMENTS	
6.	Optics	G02; G03B, C, D, F, G, H; H01S
7.	Analysis, measurement, control technology	G01B, C, D, F, G, H, J, K, L, M, N, P, R, S, V, W; G04; G05B, D; G07; G08B, G; G09B, C, D; G12
8.	Medical technology	A61B, C, D, F, G, H, J, L, M, N
9.	Nuclear engineering	G01T; G21; H05G, H
III.	CHEMISTRY, PHARMACEUTICALS	
10.	Organic fine chemistry	C07C, D, F, H, J, K
11.	Pharmaceuticals, cosmetics	A61K, P
12.	Biotechnology	C07G; C12M, N, P, Q, R, S
13.	Agriculture, food chemistry	A01H; A21D; A23B, C, D, F, G, J, K, L; C12C, F, G, H, J; C13D, F, J, K
14.	Materials, metallurgy	C01; C03C; C04; C21; C22; B22; B82
15.	Surface technology, coating	B05C, D; B32; C23; C25; C30
16.	Macromolecular chemistry, polymers	C08B, F, G, H, K, L; C09D, J
17.	Chemical industry and petrol industry, basic materials chemistry	A01N; C05; C07B; C08C; C09B, C, F, G, H, K; C10B, C, F, G, H, J, K, L, M; C11B, C, D
IV.	PROCESS ENGINEERING, SPECIAL EQUIPMENT	
18.	Chemical engineering	B01B, D (without -046 to -053), F, J, L; B02C; B03; B04; B05B; B06; B07; B08; F25J; F26
19.	Materials processing, textiles, paper	A41H; A43D; A46D; B28; B29; B31; C03B; C08J; C14; D01; D02; D03; D04B, C, G, H; D05; D06B, C, G, H, J, L, M, P, Q; D21
20.	Handling, printing	B25J; B41; B65B, C, D, F, G, H; B66; B67
21.	Agricultural and food machinery and apparatus	A01B, C, D, F, G, J, K, L, M; A21B, C; A22; A23N, P; B02B; C12L; C13C, G, H
22.	Environmental technology	A62D; B01D-046 to -053; B09; C02; F01N; F23G, J
V.	MECHANICAL ENGINEERING, MACHINERY	
23.	Machine tools	B21; B23; B24; B26D, F; B27; B30
24.	Engines, pumps, turbines	F01B, C, D, K, L, M, P; F02; F03; F04; F23R
25.	Thermal processes and apparatus	F22; F23B, C, D, H, K, L, M, N, Q; F24; F25B, C; F27; F28
26.	Mechanical elements	F15; F16; F17; G05G
27.	Transport	B60; B61; B62; B63B, C, H, J; B64B, C, D, F
28.	Space technology, weapons	B63G; B64G; C06; F41; F42
29.	Consumer goods and equipment	A24; A41B, C, D, F, G; A42; A43B, C; A44; A45; A46B; A47; A62B, C; A63; B25B, C, D, F, G, H; B26B; B42; B43; B44; B68; D04D; D06F,N ; D07; F25D; G10B, C, D, F, G, H, K
30.	Civil engineering, building, mining	E01; E02; E03; E04; E05; E06; E21

Source: ISI OST INPI classification (update 2005) (Schmoch, 2008).

References

- Almeida, P. and Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, 45(7):905–917.
- Balconi, M., Breschi, S., and Lissoni, F. (2004). Networks of inventors and the role of academia: An exploration of italian patent data. *Research Policy*, 33:127–145.
- Blind, K., Cremers, K., and Mueller, E. (2009). The influence of strategic patenting on companies’ patent portfolios. *Research Policy*, 38(2):428–436.
- Blind, K., Edler, J., Frietsch, R., and Schmoch, U. (2006). Motives to patent: Empirical evidence from germany. *Research Policy*, 35(5):655–672.
- Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, 39(1):61–74.
- Boschma, R. A. and ter Wal, A. L. J. (2007). Knowledge networks and innovative performance in an industrial district: The case of a footwear district in the south of italy. *Industry and Innovation*, 14(7):177–199.
- Breschi, S. and Lissoni, F. (2003). Mobility and social networks: Localised knowledge spillovers revisited. Working Paper 142, Cespri.
- Breschi, S. and Lissoni, F. (2009). Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. *Journal of Economic Geography*, 9(4):439–468.
- Breschi, S., Lissoni, F., and Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. *Research Policy*, 32(1):69–87.
- Buenstorf, G. (2007). Evolution on the shoulders of giants: Entrepreneurship and firm survival in the german laser industry. *Review of Industrial Organization*, 30(3):179–202.
- Buenstorf, G. and Klepper, S. (2009). Heritage and agglomeration: The akron tyre cluster revisited. *Economic Journal*, 119(537):705–733.
- Cantner, U. and Graf, H. (2004). Cooperation and specialization in german technology regions. *Journal of Evolutionary Economics*, 14(5):543–562.
- Cantner, U. and Graf, H. (2006). The network of innovators in jena: An application of social network analysis. *Research Policy*, 35(4):463–480.
- Cohen, W. M. and Levinthal, D. A. (1989). Innovation and learning: the two faces of r&d. *Economic Journal*, 99(397):569–596.
- Cohen, W. M., Nelson, R. R., and Walsh, J. P. (2000). Protecting their intellectual assets: Appropriability conditions and why u.s. manufacturing firms patent (or not). Technical report, NBER Working Paper No. W7552.
- de Solla Price, D. J. (1963). *Little Science, Big Science*. Columbia Univ. Press, New York.

- Dosi, G. (1982). Technological paradigms and technological trajectories : A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3):147–162.
- Dosi, G. (1988). The nature of the innovative process. In Dosi, G., Freeman, C., Nelson, R., Silverberg, G., and Soete, L., editors, *Technical Change and Economic Theory*, pages 221–238. Pinter, London.
- Fleming, L. and Frenken, K. (2007). The evolution of inventor networks in the silicon valley and boston regions. *Advances in Complex Systems*, 10(1):53–71.
- Fleming, L., King, Charles, I., and Juda, A. I. (2007). Small worlds and regional innovation. *Organization Science*, 18(6):938–954.
- Guimerà , R., Uzzi, B., Spiro, J., and Amaral, L. A. N. (2005). Team assembly mechanisms determine collaboration network structure and team performance. *Science*, 308(5722):697–702.
- Jaffe, A. B. (1989). Characterizing the "technological position" of firms, with application to quantifying technological opportunity and research spillovers. *Research Policy*, 18(2):87–97.
- Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108(3):577–598.
- Johnson, D. K. N. and Mareva, M. (2002). It's a small(er) world: The role of geography and networks in biotechnology innovation. Wellesley College Working Paper 2002-01.
- Jones, B. F. (2005). The burden of knowledge and the 'death of the renaissance man': Is innovation getting harder? Working Paper 11360, National Bureau of Economic Research.
- Klepper, S. (1996). Entry, exit, growth, and innovation over the product life cycle. *American Economic Review*, 86(3):562–583.
- Klepper, S. and Thompson, P. (2006). Submarkets and the evolution of market structure. *RAND Journal of Economics*, 37(4):861–886.
- Malerba, F. and Orsenigo, L. (1997). Technological regimes and sectoral patterns of innovative activities. *Industrial and Corporate Change*, 6(1):83–117.
- Mowery, D. C., Oxley, J. E., and Silverman, B. S. (1998). Technology overlap and interfirm cooperation: Implications for the resource-based view of the firm. *Research Policy*, 27(5):507–523.
- Nesta, L. and Saviotti, P. P. (2005). Coherence of the knowledge base and the firm's innovative performance: evidence from the u.s. pharmaceutical industry. *Journal of Industrial Economics*, 53(1):123–142.
- Nesta, L. and Saviotti, P.-P. (2006). Firm knowledge and market value in biotechnology. *Industrial and Corporate Change*, 15(4):625–652.

- Pavitt, K. (1984). Sectoral patterns of technical change: Towards a taxonomy and a theory. *Research Policy*, 13:343–375.
- Saviotti, P. P. (2004). The knowledge-base of the firm in biotechnology based sectors: Properties and performance. *Revista Brasileira de Inovação*, 3(1):129–166.
- Scherer, F. M. (1982). Inter-industry technology flows and productivity growth. *Review of Economics and Statistics*, 64:627–634.
- Schmoch, U. (2008). Concept of a technology classification for country comparisons. Final report to the world intellectual property organisation (wipo), WIPO.
- Singh, J. (2003). Social networks as drivers of knowledge diffusion. Technical report. Available at SSRN: abstract id = 431872.
- Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*, 51(5):756–770.
- Sorenson, O. (2003). Social networks and industrial geography. *Journal of Evolutionary Economics*, 13:513–527.
- Sorenson, O. (2004). Social networks, informational complexity and industrial geography. In Fornahl, D., Zellner, C., and Audretsch, D. B., editors, *The Role of Labour Mobility and Informal Networks for Knowledge Transfer*. Kluwer, Dordrecht.
- Teece, D., Rumelt, R., Dosi, G., and Winter, S. (1994). Understanding corporate coherence: theory and evidence. *Journal of Economic Behavior and Organization*, 23:361–377.
- Wuchty, S., Jones, B. F., and Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, 316(5827):1036–1039.
- Zander, U. and Kogut, B. (1995). Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. *Organization Science*, 6:76–91.
- Zucker, L., Darby, M., and Armstrong, J. (1998a). Geographically localised knowledge: Spillovers or markets? *Economic Inquiry*, 36:65–86.
- Zucker, L. G., Darby, M. R., and Brewer, M. B. (1998b). Intellectual human capital and the birth of u.s. biotechnology enterprises. *American Economic Review*, 88(1):290–306.