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An empirical enquiry into co-patent networks and their stars: The case of cardiac pacemaker technology

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ABSTRACT

Scientific research concerning R&D staff structures has already been based on networks as they are mapped by co-patent data. The present paper combines the method of patent analysis with network analysis techniques and shows by means of a patent sample from cardiac pacemaker technology, that the different communication functions a star inventor accomplishes in their network are mirrored not only by quantity, but also by quality of patents. The mere patent quantity has a significant positive impact on the size of an inventors' personal network and the number of inventors they can directly pass information to. But more importantly, there is significant empirical evidence that high technical specialisation has a positive impact on an inventor's potential to mediate between others as well as on the efficacy to reach them on short notice. For the latter, likewise the number of citations received is a positive predictor. Thus, we characterise stars as industrious, well-known technical specialists and contradict the general assumption that generalists would be the ideal gatekeeper in an R&D network.

1. Introduction

Co-patent networks are reflections of existing knowledge flows between companies, R&D departments or inventors. These networks display stars, who are important actors in their field of technology. Their early detection and development can be considered as main issues for HR management in R&D. However, the characteristics of stars within the surroundings of their co-patent networks have not yet been fully explored. Against this background, the present work engages in matching instruments of network analysis with patent analysis techniques. It seeks to determine patent predictors of star inventors in co-patent networks. The focal point is to answer the question if and to what extent patent quality characteristics mirror the different roles stars take in their network: their basic functions being the maintenance of large personal networks, the mediatorship between individuals and the ability to reach everybody on short notice. Patent research here insinuates that patent quality will furnish appropriate predictors that distinguish common inventors from stars. Especially the frequently employed predictor citations received, as well as the technical range inventors cover, and their ability to bridge geographical distances should explain the stardom of an inventor.

In the following paragraphs, Section 2 at first creates the theoretical framework of the present work. Section 3 introduces the methodical approach, whereas Section 4 presents an empirical example from the cardiac pacemaker technology. Section 5 gives a summarising conclusion. The results of this work help understanding the evolution of prominence in some inventors that we call stars within a technology field. By identifying the driving forces, HR management in R&D can support their selection processes by looking for specific characteristics of the candidates. Knowing which factors explain the emergence of the much sought for 'network capital', facilitates personnel selection, early development of inventors and appropriate team composition. The study thereby attempts to make a contribution to the empirical foundation of essential communication characteristics of R&D networks and their inventors.

2. Theoretical framework

2.1. Relevance and success factors of collaboration

Collaboration in R&D appears in many different forms. It can be formally arranged in teams or projects and it may likewise happen informally through unscheduled, random contacts or get-togethers. Collaboration takes place in order to work on scientific discoveries as well as to conduct clinical trials, beta testing or to realise the transfer of knowledge and resources between researchers. A minimum of two individuals working together can thereby be understood as collaboration (Mindruta, 2008). In

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this context, it is widely agreed that the increase of technical complexity and the challenges of globalised markets necessitate the extensive use of collaboration especially in R&D (Wuchty et al., 2007; Zhenzhong and Yender, 2008). This growing importance is underlined in patent statistics by the increasing number of inventors on patent documents. Considering for example patent applications at the German Patent Office in the last decade, the number of inventors has risen from 1.96 inventors per patent application (1995) to 2.32 within the next ten years (DPMA, 2005). Similar results could be obtained for American patents at the United States Patent Office, USPTO (Zhengzhong and Yender, 2008; Wuchty et al., 2007) as well as concerning patents of European and Asian countries (Hussler and Rondé, 2007; Zhenzhong and Yender, 2008). The main advantages of collaborative work are possible synergies and cross-fertilisation, as well as the natural increase of creativity and cross-thinking between collaborators (He et al., 2009).

There are different factors that facilitate or promote the collaboration of companies or inventors.

First and foremost, scientific popularity, visibility and recognition are promoting factors for the emergence of collaboration and professional excellence. Outstanding reputation will lead to increased willingness of others to collaborate. Companies as well as inventors attract valuable collaboration partners more easily, the better their reputation presents itself and the better known in their technological community they actually are (Merton, 1968). Companies that for example support collaboration between industry and academia may especially attain image effects based on academic involvement and thus make themselves more attractive for future company alliances or as future employers. More than that, company collaborations with academic researchers usually entail higher quality than company to company collaborations (Balconi et al., 2004; Mindruta, 2008).

In addition, the degree of specialisation as well as the need for complimentary knowledge influence the inclination to collaborate (Balconi et al., 2004; Mairesse and Turner, 2005). The higher a company's specialisation and the subsequent need for partners with different technological backgrounds, the more will they seek contact to their counterparts. In this context even geographical distances matter less, the more specialised and demanding the sought for knowledge is (Hussler and Rondé, 2007). The technical fit is most important, since the search for collaborators is not random, but a strategic process. In this process partners sort themselves by attributes which are relevant for the respective innovation (Mindruta, 2008).

Third, geographic proximity plays an important role. Researchers naturally have a higher propensity to collaborate when working in the same laboratory or in the same region than if they were further apart. Knowledge exchange becomes easier once the inventors face no or only marginal spatial barriers. It can therefore be important for companies, to locate in regions where there are similar or complementary technological specialisations to their own, from which they can benefit. Likewise should inventors and research departments who are to collaborate on a regular basis, not be separated by large geographical distances. This holds for company to company collaborations as well as for collaborations within a company (Hussler and Rondé, 2007; Mairesse and Turner, 2005; Zucker et al., 2006).

2.2. Characteristics of co-patent networks

Co-patenting can be understood as a visible result of inventive collaboration in R&D and signifies that an inventor is listed on a patent not on his or her own, but with at least one other inventor. Collaboration in this sense is the tracking of work relations, or even more precise, information channels, along which information has flown in the process of patenting an invention. Literature distinguishes co-patent networks and co-publication networks. While the former focus on inventors and their patents, the latter are dedicated to researchers and scientists who publish their work in scientific literature. Co-patenting is held more relevant for industry researchers, i.e. applied research, whereas publications are more prominent among academia. The examination of these collaboration activities helps the mapping of ties within technology fields and depicts knowledge maps that could hardly be traced outside a company or institution but with publicly available patent or publication data (Balconi et al., 2004; Hussler and Rondé, 2007; Mina et al., 2007).

Despite the objection that patents are by definition static and possibly incomplete criteria to measure knowledge flows (since there may be many non-patentable work results), they offer the next best solution when company internal information about communication, work or social structures between individuals is absent. This will be regularly the case when external researchers examine collaboration structures in R&D, when companies monitor competitors or if within a company relevant communication information remains undisclosed or incomplete. Patents mirror the results of collaboration that appears always within a social context. In the process of inventing, the social links an inventor has influence their decisions substantially. Social interaction like leadership effects and peer effects in their research group play an important role concerning collaboration structures and disclosure of knowledge (Bercovitz and Feldman, 2004). The method of extracting information from patent statistics thus cannot be doubted generally; the variety of patent studies is reference for that. On the contrary, there is even empirical evidence that structures around inventors examined by patent statistics are largely identical with structures revealed by expert surveys in R&D. In a study by VITT for instance, members of R&D departments name in interviews the same inventors as key inventors in their technology field, who could before be identified externally by patent statistics (Vitt, 1998).

As regards the characteristics of co-patent networks, they generally show high fragmentation at the beginning of their emergence, but become increasingly connected and less fragmented over time. They consist of different components in which every inventor can be reached by another (i.e. there the graph in one component is connected), but the components are not connected among each other. The more components there are, the more fragmented is the co-patent network. A component minimum depicts collaboration links resulting from 1 patent. In this case a co-patent network would consist of as many components as there are patents. A component at most covers all patents and inventors of a technology field, which will however practically rather not be the case. Still there is empirical proof that the main component covers the majority of actors, only a minority is usually disconnected or part of the smaller components (Barabási et al., 2002; Cotta and Merelo, 2007; Heinze, 2006; Liu et al., 2005; Newman, 2001, 2004). Components are thereby defined as subsets of actors who are connected to each other, but not with the rest of the network. The main component is the largest of these subsets (Wasserman and Faust, 2007).

While there are only few pioneers in the introductory stage of an industry, many inventors enter the network in the growth stage and thenceforth (Haupt et al., 2007). Network theory shows in this context, that during the evolution of a network new links are added according to two basic principles: time and preferential attachment. Thus, the 'oldest' inventors have a good chance to be the centres of their respective co-patent network. Likewise the inventors with many links benefit from a great chance to generate new connections (principle of preferential attachment). This process finally also results in the typically scale-free nature of collaboration networks, i.e. the distribution of the inventors' links follows a power law. There will be many inventors with comparatively few collaboration partners, while only few are extensively connected to other inventors. They are the hubs whose absence would reduce the density of the network substantially, whereas density is understood as the number of all realised links divided by the number of all possible ones (Wasserman and Faust, 2007). Based on the existence of hubs is also the small-world-phenomenon that usually characterises collaboration networks. Co-patent networks show properties in this regard, if despite large network sizes many actors can be reached in a few 'hops' via comparatively few intermediaries (Goh et al., 2002; Newman, 2004). If two inventors generate a patent together, their distance is 1. Should any two inventors never have collaborated, their distance is measured by the number of intermediaries (other inventors) between them. In case they belong to two different, unconnected components of the network, their distance would be infinite.

Differences in collaboration networks are however notable with respect to industry specificities. In the chemical and electronics sector the network density is higher (more links of inventors due to larger team sizes) than in process and mechanical engineering or consumer goods. Likewise the number of patents (e.g. measured as average number of patents per inventor) is higher in the chemical or electronics branch in comparison to other industries (Balconi et al., 2004). The medical branch takes a special position, since innovations may not only come from biomedical research, but also from other fields like electronics, chemistry, etc. (Mina et al., 2007). It is therefore the more important, to confine the empirical example to a definable invention that is largely free of industry overlaps. According to expert knowledge the author had access to, this is the case for the groundbreaking invention of the cardiac pacemaker.

2.3. Characteristics of stars

From a company perspective, stars are company members who embody great value to the employer due to their outstanding performance and the resulting monetary and social returns they generate. They are able to secure a company's lead in developing new technologies or establishing recent ones; they can be seen as brains of a company. Stars are thus consequently characterised by professional excellence and outstanding quality of work (Cotta and Merelo, 2007; Goeree et al., 2007).

In innovation management literature, stars are often characterised as individuals with specific communicative abilities in the innovation process. They are often described as technological gatekeepers (see similarly the definitions of promotors or champions in pertinent literature). They act as outstanding R&D protagonists who have the ability to develop and enforce the innovation process substantially. Gatekeepers in particular work independently from specific innovation projects, i.e. independently from one single invention or one individual patent. They act as information brokers for both internal and external sources and thus abolish communication barriers within a company or technology field. Gatekeepers are thus considered sociometric stars in their research community (Hauschildt and Schewe, 1997; Vitt, 1998). In order to meet these requirements, stars hold central positions in their network, or more precise, comply with different centrality roles in their surrounding networks: First, they must maintain an extensive list of contacts, in order to gather and spread information quickly to many other inventors. Second, they must be in a position to mediate between research partners, who were otherwise unknown to each other. An inventor with a large ego-network, but without further, indirect (or second class) connections would not be in the position to be an information broker or mediator for other inventors. Third, stars must reach other participants of the network efficiently, i.e. the paths to any other inventor within a network must not be too long. Thus, stars cover different aspects of network centrality, in classic network theory they are also known as degree, betweenness and closeness centrality in collaboration networks. These three aspects or communicative roles are by definition not free of overlaps. However, they do cover different characteristics that make an inventor prominent in the network and underline the fact that stars are altogether important bonding actors in their R&D department and technology field (Wasserman and Faust, 2007).

Statistics suggest that the share of stars in a company only amounts to a small percentage of all inventors (approximately 6–12%), depending on company size. In large firms, their share is estimated to be found on the lower end of this range at about 6%, whereas small firms usually possess a bigger share. Star inventors generate the majority of patents in terms of quantity and quality (about 2/3 of all patents; Ernst et al., 1999). This matches basic findings in bibliometrics, whereupon in a defined group of individuals there are always only few people who achieve outstanding results (Lotka, 1926). The gain or loss of a star of that kind, e.g. after restructuring a company, merger or acquisition, must thus be of substantial importance to a company, not only because of the loss of potential future valuable patents, but also for disruptions in the information channels. There is empirical proof that the loss after merger activities had in fact devastating effects on company performance in both respects (Vitt, 1998), which makes the early attachment and development of stars and talents the more important.

3. Methodical approach

3.1. Derivation of propositions

Summing up, there is a clear notion that stars should be characterised by a high centrality in their networks. We assume that they possess many contacts, and/or take mediator positions and/or position themselves close to many other inventors. We thus prompt the question whether the particular positions they fill can be interpreted as a function of characteristics detectable in their work. Since the observable work results in the present study are patents, we aim at finding support for the notion that patent indicators can be predictors for network centrality. There, especially quality indicators are of interest. The position of an inventor in their network will be influenced by the principles of time and preferential attachment, but should also be positively dependent on the quality of their work, i.e. their patents (Freeman, 1979). It is after all quality that distinguishes star inventors from the mere industrious ones (Vitt, 1998). Our fundamental proposition 1 can be thus be derived:

(1). The quality of an inventor's patents is a positive, significant predictor of the inventor's centrality in the co-patent network.

However, patent quality can be understood as collective term that is represented by many possible indicators. While specificity of tasks, academic background of inventors, renewal times of patents etc. as such can only with difficulty be observed, we concentrate on other, clearly detectable aspects the quality of patents implicates. Comparatively easy to obtain and thoroughly tested indicators are for example passive (or in other words received) citations, but also the technical breadth or IPC-range of an inventor, or the geographical range they cover by their collaborations (Carpenter et al., 1981; Harhoff et al., 1999; Haupt, 2005, 2007; Hussler and Rondé, 2007; Trajtenberg, 1990). We expect all of these variables to make a positive contribution to the explanation of the selected centrality variables. Nevertheless, there is no definition for one single kind of centrality. On the contrary, there are different aspects of central network positioning detectable, which render an inventor star in comparison to their fellow inventors. For these different roles an inventor plays (maintaining a large personal network, act as mediator, reach others quickly), each quality indicator may be important to a different extent.

For example, if an inventor is particularly well-known by others and has a large number of contacts at their command, this may be traceable especially by the number of citations he or she receives. The citations with which one inventor (or the patent itself) values the other, gives proof of the relatedness of the current patent to the prior one, but it also shows that one inventor is acquainted with the other to some extent. Thus, the following is assumed:

(1a). The number of citations an inventor receives is a particularly positive, significant predictor of the size of an inventor's personal ego-network within the co-patent network.

In addition to that, the stars' holding of mediator positions in the network was declared before. In order to fill this role, stars might possess a particularly broad technical knowledge, since they pass on information from varying sources and must be able to refine and process them. They can accordingly be assumed to be rather generalists than specialists, since the tasks they accomplish may not be specific or task-idiosyncratic, but rather general. As we mentioned before, gatekeepers are described in literature as not belonging to a single project, but to work independently and subordinately. Their technical universality, visible e.g. by the IPC-classification of their patents, should accordingly be a positive indicator of their mediator potential. Hypothesis 1b can thus be developed as:

(1b). The IPC-range an inventor covers is a particularly positive, significant predictor of the inventor's mediator potential in the co-patent network.

A constitutional characteristic of a star must also be the efficiency with which an inventor can reach any other participant in the network. Only if the connecting path to a target person is comparatively short, i.e. includes not too many intermediaries, information can be passed on quickly while reducing the danger of loss of information. Thus, featuring a foreign or geographically distant inventor in the personal network (meaning an inventor outside one's own federal state, if we consider US patents), will very likely increase the efficiency with which even far away, company-external inventors may be reached. As we suggested before, the bridging of distances may be needed for certain types of idiosyncratic tasks. Against this background, Hypothesis 1c claims the following:

(1c). Patenting with geographically distant inventors is a particularly positive, significant predictor of the inventor's the efficacy with which they can reach others in the co-patent network.

In order to further clarify the measures used, the variables will be presented formally in the next part.

3.2. *Definition of measures*

In order to test the before mentioned propositions, measures for the suggested communication functions, which are degree, betweenness and closeness centrality in a network, need to be illustrated. They serve as dependent variables in linear regression analysis (OLS) that will be conducted in the following. Furthermore, the discussed patent quality indicators will be defined. For the purpose of testing these predictor variables appropriately, however, we also present control variables that need to be considered. It is time as well as scale effects regarding the number of patents per inventor that have to be controlled for in the regressions. Both were previously described to belong to the constitutional principles of network evolution: An early entry in the network as well as the possession of many patents (principle of preferential attachment) may influence the centrality of an inventor to a substantial extent. This study is, however, particularly interested in contributions predictor variables make beyond time and quantity effects, considering the fact that stars distinguish themselves primarily by their quality of work.

Looking at centrality in social network analysis, three established measures can be distinguished: degree centrality, betweenness centrality and closeness centrality (Freeman, 1979; Wasserman and Faust, 2007). They embody different communication functions stars realise in their network. First, we can introduce an inventor's centrality or prominence in the network by the number of contacts to whom there are direct links through joint patents. This variable is known as degree. It equals the size of an inventor's personal or ego-network:

$$DEGREE = d(n_i)$$

where d is the number of collaborators adjacent to inventor n_i, i.e. there is a link between them due to one or more patents in which both collaborated (Wasserman and Faust, 2007). Moreover, centrality is measured by betweenness, i.e. the likelihood that an actor in the network will be a potential mediator between any two individuals, because he or she lies on (one of) the shortest paths between them (the two, it must be assumed, do not "know" each other by a direct link). This variable is computed as betweenness:

$$BETWEENNESS = \sum_{j<k} g_{jk}(n_i)/g_{jk}$$

where the denominator g_{ik} is the overall number of shortest paths that exist between actors j and k, while $g_{ik}(n_i)$ is the number of shortest paths that include the initial inventor i (Wasserman and Faust, 2007). For example, inventors j and k are connected via 3 possible paths in the network. 1path runs through 2 further inventors (i.e. has length 2) and 2 paths go through only 1other inventor(i.e. path length 1). The number of shortest paths g_{ik} is thus 2; the first and longer path does not need to be considered. If we further imagine that only 1 of these two shortest paths involves inventor i, he or she has a chance of 1/2 to be selected as mediator between j and k. The resulting betweenness of inventor i is thus 0.5.

Furthermore, network centrality is expressed by the swiftness, efficacy, or in other words: path length, with which an inventor can reach others in the network. The variable closeness centrality or closeness thus computes path lengths to other inventors in the network:

$$CLOSENESS = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1}$$

where $d(n_i, n_j)$ is the number of shortest paths that link actor i and j. The total distance that i is from all other actors j in the network is conclusively measured as the sum of all shortest paths between possible inventor pairs. Since this sum is rather small for inventors who can reach others quickly via short ways and large for inventors, who are rather distant from the others, the inverse is calculated to turn the result into a closeness centrality measure

Table 1
Variables of the empirical model.

Variable	Description	Formal expression	Explanation
DEGREE	Centrality measure	$d(n_i)$	Number of collaborators
BETWEENNESS	Centrality measure	$\sum_{j<k} g_{jk}(n_i)/g_{jk}$	Mediator potential
CLOSENESS	Centrality measure	$\left[\sum_{j=1}^{g} d(n_i,n_j)\right]^{-1}$	Efficacy to reach others in the network
ENTRY	Time measure (control variable)	T_i^{first}	Year T in which the first patent of inventor i was filed (entry into the network)
DUMMY	Time measure (control/ dummy variable)	T_i^{group}	Time span in which inventor i first entered the network $T_i^{group}=0$ for all inventors before 1990 $T_i^{group}=1$ for all inventors from 1990 to 2005
OUTPUT	Quantity measure (control variable)	$\sum P_i$	Number of patents p granted to inventor i
NETCIT	Quality measure	$\sum Z_i - \sum Z_{ii}$	Cumulative number of citations Z QUOTE that inventor i received from the patents of other inventors j; minus self-citations that came from patents of inventor i
IPCRANGE	Quality measure	$\sum IPC_i$	Number of IPC-subclasses, in which an inventor's patents were filed (e.g. A61N for pacemakers in the German classification system)
COLOC	Quality measure	$d(n_i)^{foreign}/d(n_i)$	Share of foreign inventors among an inventors collaborators (as measured by dissimilar country codes in the inventor addresses)

that assigns large values to central inventors and vice versa (Wasserman and Faust, 2007).

Apart from these network centrality variables, the mentioned control variables regarding time and patent quantity need to be defined. Time can be represented by the entry year of an inventor in the co-patent network, i.e. the first publicly noticeable appearance on a patent document in the specific field of technology is noted. In doing so, the seniority of an inventor is accounted for. Even if there is no information about the productivity of the inventor throughout the years, an early filing of one or more patents allows in inventor to collect more links and higher credit than a late entry into the network. Thus, the time variable entry can be computed as

$$ENTRY = T_i^{first}$$

where T is the year in which the first patent of inventor i was filed. Patent quantity in turn can be measured by counting the absolute number of patents an inventor generated in the period under consideration:

$$OUTPUT = \sum P_i$$

which defines the sum of patents P granted to inventor i.

Regarding patent quality measures we can refer to established statistical measures from pertinent literature. Generally the use of multiple indicators is suggested in order to reduce the variance of results (Lanjouw and Schankerman, 2004). The collection of commonly drawn upon measures is yet difficult. Renewal times or lawsuits can neither be observed from an external perspective, nor can they be calculated by database. Beyond that, increasing numbers of patents are filed at the European or World Patent Office in the last years and exhibit thus per se an international character. Consequently, these are not appropriate quality criteria. Instead, patent quality is often measured by citations received from other patents (also called "passive" or "forward citations") or their IPC-range. Both are approved measures that can be considered stand-alone indicators of patent quality. While citations received point out how visible and technically important the inventive knowledge and its inventors are, a large IPC-range is taken as a sign of great technological diversity and thus broad applicability of the invention or, respectively, the inventor. The latter is also associated with great quality or value of an inventor to a company (Carpenter et al., 1981; Harhoff et al., 1999; Haupt, 2007; Trajtenberg, 1990, Zucker and Darby, 1998). Sometimes, a positive bias in favour of well-known, prominent (chiefor senior) researchers is argued (Ernst et al., 1999; Merton, 1968). If an inventor is named on a patent, however, it has to be assumed that he or she contributed to the invention, whether technically or regarding organisational questions. The quality measures net citations and IPC-range will therefore be computed as follows:

$$NETCIT = \sum Z_i - \sum Z_{ii}$$

where ΣZ_i depicts the cumulative number of citations Z that inventor QUOTE received from all other patents. ΣZ_{ii} defines so-called self-citations coming from patents of inventor i themselves, referring to his or her own patents. These self-citations need to be deduced from the overall number of citations in order to limit artificial inflation of citations due to heavy self-citing (Haupt, 2005). The IPC-range of an inventor is furthermore given as

$$IPC\_RANGE = \sum IPC_i$$

where the number of different IPC-subclasses, in which an inventor's patents were filed is counted (e.g. regarding the German classification system A61N would be most relevant for cardiac pacemakers and counts as one entry). Nonetheless, implications of collaborating with geographically distant inventors were noted before. The overcoming of large distances indicates a technologically specific, demanding and in its results valuable collaboration (Zhenzhong and Yender, 2008). Based on this supposition, the share of foreign collaborators can also be taken into consideration when looking at patent quality of an inventor. We thus build a co-location variable that similarly has been the focus of other studies (Hussler and Rondé, 2007):

$$COLOC = d(n_i)^{foreign}/d(n_i)$$

where the share of foreign inventors $d(n_i)^{foreign}$ among all inventors collaborators is computed. The distinction between 'foreign' and 'domestic' research laboratories can thereby be made by dissimilar country codes in the inventor addresses given in patent documents. Table 1 summarises the variables defined so far.

If and to which extent the factors time, patent quantity and patent quality are decisive in taking inventors to their later network position, will be calculated by conducting a multiple linear regression analyses. Three empirical cases will be constructed, in which the place of the dependent variable is respectively taken by degree, betweenness or closeness. The control variables are time and patent quantity, whereas the indicators of patent quality (in the different forms of citations, IPC-range and the share of foreign collaborators) serve as independent variables (enter-method).

4. Empirical study

4.1. Outline of the patent sample

The empirical examination of the previously presented propositions is based on a patent sample from cardiac pacemaker technology. This choice was made due to the advantage that appertaining patents are clearly technically definable and industry specific. They can be outlined clearly by the search string *pacemak$* in patent databases, according to expert knowledge the author had access to.

The present patent sample originates from data of the US Patent Office (USPTO) and covers the beginning industrial life cycle of cardiac pacemakers in the 1970s until the still continuing maturity stage of today (Boettcher et al., 2003; Haupt et al., 2007). The sample was generated on 15.11.2007 by searching for "pacemak$" in abstract, title or claims of patent documents registered with the US Patent Office database (issued patents only; accessible via www.uspto.gov). Citations are based on DOCDB data of the European Patent Office(as of calendar week 39 in 2006). All interpretations of patent documents and citation data were realised with the help of MyPATAS (2007), software developed by the Jena Patent Information Office. Due to reasons of necessary simplification, only the most sizeable applicant in the field of cardiac pacemaker technology is considered. This is undertaken purposely to limit the fragmentation of the sample and to largely avoid bias that arises due to different organisational structures, firm cultures or research strategies that different companies might follow. The choice of only one applicant increases the coherence of the studied population. As patent database research shows, the enterprise Medtronic Inc covers nearly one fourth of all patents in the cardiac pacemaker field between 1974 and 2005 (415 patents). It is thus by far the largest applicant and may be considered to possess high technological impact, which justifies the selection of the company for the present study. The successor companies in the ranking are Pacesetter Inc (219 patents, 11% of pacemaker patents) and Cardiac Pacemakers (139 patens, about 7%). Fig. 1 illustrates Medtronićs patent life cycle, which stands exemplary for the pattern of the whole branch (Haupt et al., 2007). As the patent life cycle shows, the American-based company Medtronic is one of the historical co-founders of the product cardiac pacemaker.

The company today entertains by their own statement 45 R&D facilities, manufacturing facilities and distribution centres all over the world, which cover different medical fields besides the production of cardiologic devices. As Medtronić s headquarters are located in Minneapolis/Minnesota, likewise more than half of the mentioned research, manufacturing and distribution facilities are (see also the publicly available http://www.medtronic.com/about-medtronic/locations. By examining the country codes on the inventorś addresses on the patent applications in the sample, it becomes apparent that as much as 80% of the inventors in the cardiac pacemaker field are Minnesota based, while most others are located in Arizona, California or the Netherlands in Europe. We thus conclude that research regarding cardiac pacemakers may be centred in Minnesota, but is clearly influenced also by other, geographically distant research laboratories. The common practice to file patents under headquarter addresses instead of the actual research laboratory location can be neglected; only geographical data of inventors addresses are here considered. An error-free allocation of inventors to (footnote continued) individual research facilities is at the same time not possible and therefore omitted. The patent sample embraces large geographical distances within the US and overseas. Nevertheless, it can be implied that the collective company affiliation is accompanied by a concerted patent strategy and communication practices in all locations, and that in some cases efforts were taken to level these distances.

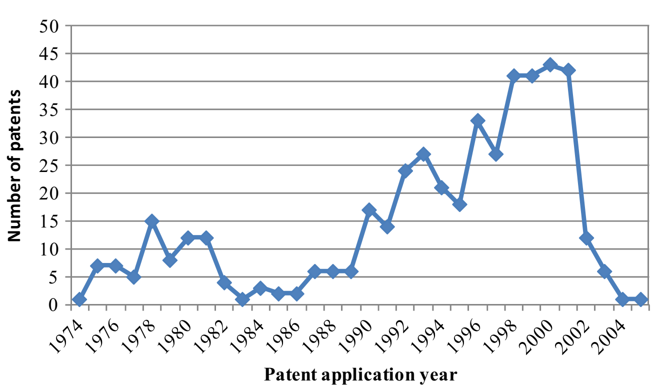

Fig. 1. Patent life cycle of cardiac pacemaker technology. (Assignee: Medtronic)

4.2. Mapping the co-patent network

Mapping the co-patent network of the 445 inventors and their relations through 415 patents from 1974 to 2005, we can distinguish 23 different components in the co-patent network. The main component, i.e. the largest connected fraction of the network with 288 inventors covers the majority of the population (69.9%). 66 of all inventors are entirely unconnected (16%), they are called isolates. With a density of .0049, the pacemaker co-patent network matches results of other patent studies (Balconi et al., 2004; Cotta and Merelo, 2007; Liu et al., 2005; Newman, 2001). Although dominated geographically by Minnesota based inventors, links exist likewise between them and inventors from other locations.

However, the fragmentation of the network indicates that the sample has to be further modified in order to avoid additional bias. First, to make network embedding measures in fragmented networks comparable, only connected graphs are looked at (Wasserman and Faust, 2007). Disconnected graphs, e.g. by the consideration of more than one component or isolates (whose distance to each other is by definition infinite because no tie connects them) increases the bias in centrality measures. The network can be trimmed in this respect by removing inventors who are located outside the main component. In doing so, we neglect inventors who exhibit an infinite distance to the main component in the network. To limit further time bias in the patenting and citation process, the population will be restricted according to its period under examination. In literature there are different suggestions, ranging from the comparison of time slices or the consideration of a fix time window after each patent application (Lanjouw and Schankerman, 2004). Since the former method downsizes the testable inventor sample substantially and the latter one complicates data collection to a large extent, we decide in favour of another solution. In the present paper time bias shall be accounted for by removing patents that were filed later than the end of the growth stage in 1998 from the sample. Thus, recent patents with little time to generate citations are entirely excluded and the possibility of ongoing granting processes is neglected. Concurrently the variable entry year acts as control variable in the regressions and thus should eliminate remaining differences between older and newer patents. Accounting for time in the regression after all simulates an equal entry year for all inventors and thus an equally long time window for all inventors.

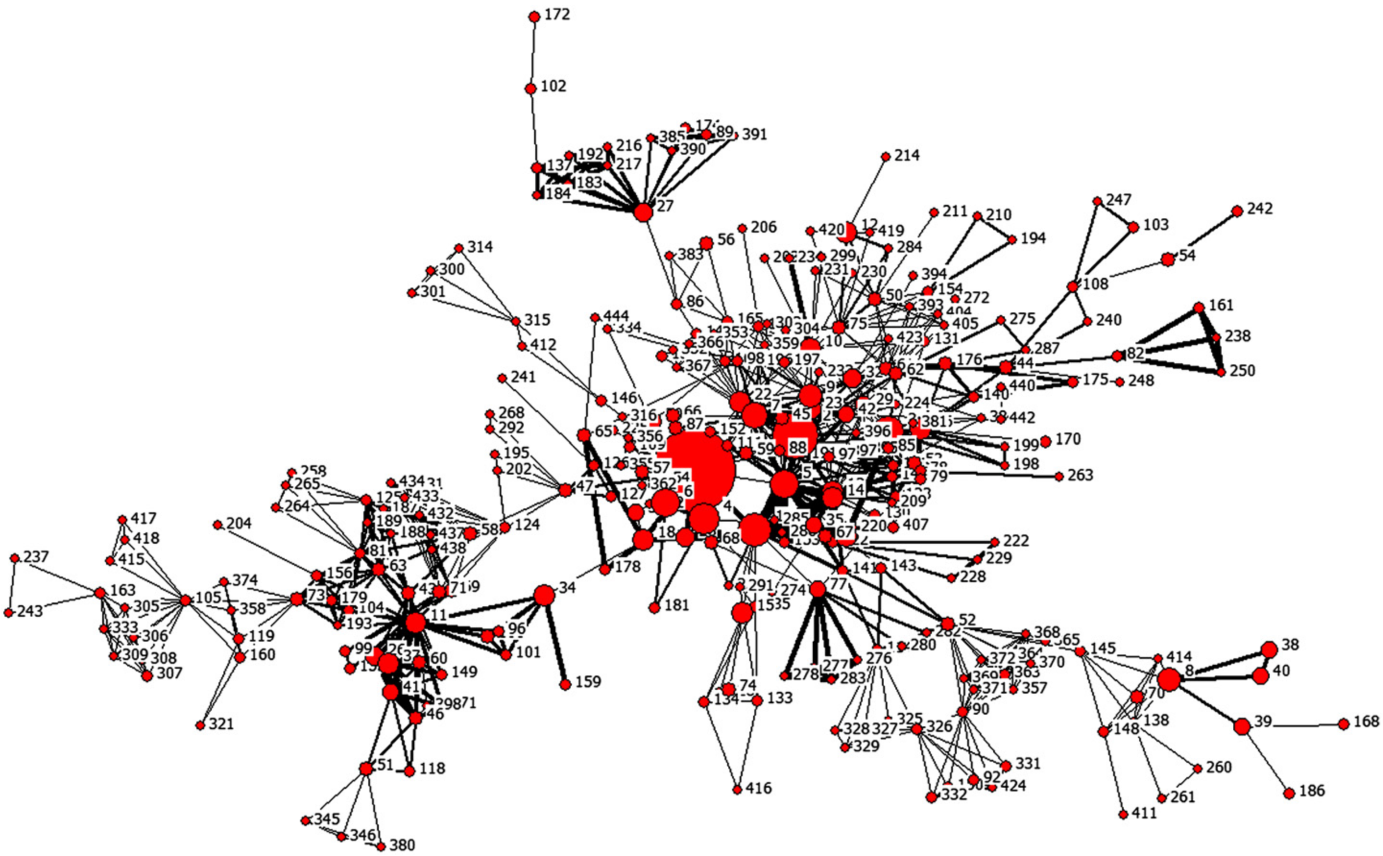

Fig. 2. Co-patent network in cardiac pacemaker technology, main component. (based on patents issued for Medtronic Inc. (application dates between 1976 and 1998); Graphic computed via Netdraw 2.054, spring embedding layout; Borgatti et al., 2002).

To fulfill further implications of regression instruments and to limit the largely skewed nature of some measures, outliers of the dependent and independent variables were identified and subsequently removed. This reduces the variance in the variables and improves the quality of later results (Backhaus et al., 2008). Outliers are thereby defined as inventors who show statistically higher (or lower) values than the population mean plus three times standard deviation. The inventor population is thus eventually reduced to 211 relevant inventors, all connected within the main component. They still cover 47% of all regarded inventors. Network density now amounts to .0123 and is thus more than twice higher than the original network, i.e. the modified main component is better connected. The average distance of all inventors did not change substantially (distance being measured between mutually reachable nodes only). The network exhibits small world properties, i.e. any two inventors are on average two steps or two patents away from each other. Fig. 2 illustrates the co-patent network (consisting now only of one main component) graphically.

4.3. Results and discussion

In order to test the propositions, both dependent and independent variables are analysed beforehand by descriptive statistics and correlation statistics. Tables 2 and 3 present the overviews.

The average inventor has entered the network in 1991, few years after the beginning of the growth stage. On average, each inventor holds 3 patents, receives 87 citations and files patents in 2 different patent subclasses. The average inventor does rather not patent with foreign inventors from geographically distant areas. They collaborate on average with 5 other inventors, i.e. have 5 direct contacts in the network (see degree) and have about 12 times the chance to be an information broker or mediator for others (see betweenness). The inventor with the lowest closeness centrality needs more than 2400 steps to reach all others in the component, while the inventor with the greatest closeness manages this by 950 steps.

Looking at the correlation statistics among predictors, the variable ENTRY shows negative significant correlations to OUTPUT, NETCIT and COLOC, indicating that an early entry year can be associated with a higher number of patents, citations and share of foreign collaborators. There is one positive and significant coefficient between ENTRY and DEGREE, all others being non-significant. However, it becomes obvious by the graphical depiction of the patent life cycle that the amount of patents within the technology field increased substantially from 1990 henceforth. There is a discontinuity in the graph detectable (see Fig. 1) that suggests later inventors might have been part of a new inventive impulse, a new inventive era that separates inventors gaining their first patents before 1990 from those generating their patents thereafter. Although no distinct technical reason was detectable by the author in the patent documents, inventors patenting after 1990 seem to have obtained by far more patents than their pioneering counterparts before 1990. This will be taken account for by inserting a dummy variable in the later following regressions. We assign value 0 to the inventor group who entered the network before 1990 and value 1 to the other group that first patented from 1990 thenceforth. The resulting regression coefficient of the dummy variable will thus describe the difference of the group "from 1990" in comparison to the reference group "before 1990" (with respect to the dependent variable).

Apart from moderately positive and significant correlations of OUTPUT with IPCRANGE and the centrality variables, OUTPUT

Table 2
Descriptive statistics main component (N=211 inventors).

	Min	Max	Mean	St. error	St. deviation
ENTRY	1974	1998	1991.47	.440	6.394
OUTPUT	1	15	3.05	.191	2.770
NETCIT	0	785	87.19	6.880	99.941
IPCRANGE	1	6	1.61	.063	.922
COLOC	0	1	.078	.014	.197
DEGREE	1	28	5.67	.307	4.464
BETWEENNESS	.000	162.000	11.667	2.0128	29.237
CLOSENESS	.000416	.001053	.000712	.000009	.000137

Table 3
Correlation analyses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) ENTRY							
(2) OUTPUT	−.139*						
(3) NETCIT	−.264**	.713**					
(4) IPCRANGE	.032	.237**	.000				
(5) COLOC	−.259**	−.095	.055	.035			
(6) DEGREE	.156*	.620**	.462**	.121	−.111		
(7) BETWEENNESS	−.008	.421**	.247**	−.014	−.086	.624**	
(8) CLOSENESS	−.021	.365**	.395**	−.146*	−.078	.359**	.301**

Pearson (*Correlation is significant at the .05 level (2-tailed). **Correlation is significant at the .01 level (2-tailed)).

shows the highest correlation in the table with regard to NETCIT (.713**). This signifies that there are overlaps in the content of these two variables. A high number of patents is apparently often associated with a large amount of citations received, i.e. there are scale effects. Nevertheless no variable shall be excluded at this stage, especially so since the patent output serves as control variable that controls the impact of patent quantity on patent quality measures. Instead it will be of particular interest, whether the variable NETCIT can contribute significantly to the explanation of the dependent variables, if OUTPUT is regarded at the same time. Possibly the variances of the two measures overlap too much, i.e. we measure the same issue by both variables (so-called multicollinearity; Backhaus et al., 2008). If the beta-coefficient of NETCIT is insignificant (or even negative due to occurring multicollinearity), the variable might be deleted from the model since we must assume that the scale effect of NETCIT (already covered by OUTPUT) is so high as to not contribute any additional information to the model. Still, the correlation is by no means high enough as to expect that NETCIT could not contribute additional information. Although there is a chance that with an increasing number of patents also the number of citations rises, there may be many patents with no or only few citations, whereas some patents collect uncommonly many citations. We thus hope that the variable NETCIT will additionally contribute explanatory power regarding the dependent variables. The remaining correlation coefficient of OUTPUT towards COLOC is negative, but non-significant.

As for OUTPUT, the variable NETCIT is likewise moderately positive and significantly related to all three network centrality measures. The correlation is yet weaker than in the case of OUTPUT. Furthermore, NETCIT shows no correlation to the variable IPCRANGE and only a small positive coefficient towards the variable COLOC. Both coefficients are, however, non-significant. The IPC-range shows a negative and significant relationship towards one of the centrality measures, CLOSENESS. The relationship between IPC-range and betweenness is likewise negative, but there the correlation coefficient is non-significant. This suggests that a rather narrow IPC-range might be positively associated with network centrality, contradictory to previous derivations. There are positive correlations of IPCRANGE and COLOC as well as DEGREE, they are yet non-significant. Regarding the variable COLOC all coefficients with regard to centrality are negative and non-significant, i.e. they may not have any statistically traceable effect in the present sample. Among the dependent variables there are overall moderately positive, significant coefficients between the dependent variables, the centrality measures. This is neither unexpected nor hindering, since the chosen measures reflect the prominence and communication possibilities of an actor in the network only through different aspects of centrality, which are by definition not free of overlaps.

Looking now at the regression results (Table 4), three significant regression models emerge. While the variance of degree centrality (R^2=.453**) was best explained by the chosen model, betweenness and closeness centrality arrived at a significant R^2 as well (R^2=.217** and R^2=.233**). Contrary to the expectations but conjecturable after the correlation analyses, ENTRY marks a positive and significant impact on DEGREE (.246*), i.e. in terms of number of contacts a later entry in the network (or later start of patenting) yields a higher degree centrality. As was assumed before, the beta-coefficient of DUMMY is positive (.209); it is however non-significant. This signifies that we have reason to assume that the inventor group who entered the network 1990 thenceforth, per se exhibits higher DEGREE values than those before 1990. In general, this may capture the discontinuity that was already described regarding the patent life cycle of the patent population. It may likewise be supposed, that the growing size of the ego networks goes back to an increased division of labour and/or a growing complexity of technical tasks in the pacemaker field in the 1990s. This effect may well be found in patent samples from other technology areas as well. However, the beta coefficients between ENTRY and BETWEENNESS (.134) as well as ENTRY and CLOSENESS (.153) reflect the previously expected negative effect (although non-significant). They support the initial assumption that an early entry into the network does indeed

Table 4
Regression statistics (ordinary least squares).

	Standardised coefficients DEGREE Beta	Standardised coefficients BETWEENNESS Beta	Standardised coefficients CLOSENESS Beta
ENTRY	.246*	−.134	−.153
DUMMY	.029	.217	.262*
OUTPUT	.580**	.560**	.245*
NETCIT	.120	−.128	.254**
IPCRANGE	−.026	−.157*	−.216**
COLOC	.009	.007	−.043
(R^2)	(.453**)	(.217**)	(.233**)

(*Regression is significant at the .05 level (2-tailed). **Regression is significant at the .01 level (2-tailed)).

foster larger centrality values. At the same time the dummy variable for the time bias is in the two latter cases positive (.217 for betweenness and .254* for closeness, the latter of which is also significant). Here we again note that the inventor group that started patenting from 1990 henceforth benefited from a time advantage and positions themselves more central in the network than the earlier pioneers.

The beta coefficients for the predictor OUTPUT is comparatively large and in all cases of centrality significant (degree: .580**; betweenness: .560**; closeness: .245*). The number of patents is thus a considerable and constituting predictor regarding the evolution of collaboration networks and the emergence of their central actors. By obtaining many patents, much of the communication possibilities of the inventors in the network can be explained. This is admittedly largely due to the construction of co-patent networks. Still it has to be noted, that the number of patents plays for example a comparatively minor role with regard to CLOSENESS. The beta-coefficient amounts here to only half of the other values. While for the gathering of a large ego-network as well as for the taking of mediator positions patent quantity is decisive to a more substantial extent, it is less so for the efficacy to reach others.

The regression coefficients regarding the patent quality variables are with regard to some variables positive, but in many places insignificant, and altogether not continuously on the positive side. Basic Hypothesis 1 is thus not entirely supported. There are positive (non-significant) coefficients in 2 of 3 cases for NETCIT (in connection with DEGREE and CLOSENESS), i.e. it may be assumed that the net citations received do tend to be a generally positive predictor of network centrality in these cases. COLOC shows 2 positive beta coefficients in relation to DEGREE and BETWEENNESS, they are yet non-significant. Altogether contradicting the previous suppositions is the result regarding IPCRANGE. There, all coefficients are negative, and even significant in the cases of BETWEENNESS and CLOSENESS. The single effects of the quality variables on all three centrality measures shall be examined closer in the following.

Considering the regression model for the dependent variable DEGREE, we detect significant predictors only in the variables ENTRY and OUPUT. The possession of a large personal network, i.e. the maintenance of many personal contacts thus goes back primarily to a high quantity of inventions. Besides, inventors with a large DEGREE entered the network only after the pioneering years, when the growth stage fully started and allowed for growing team sizes due to increased complexity of tasks. The variable NETCIT does not contribute significantly to the explanation of degree centrality, it shows however a positive regression coefficient. Against this background, Hypothesis 1a cannot be entirely rejected. However, the variable NETCIT does not supply any additional information that would not have been measured by OUTPUT. Our previous expectations were accordingly not met.

Regarding BETWEENNESS, i.e. the mediator potential an inventor shows in their network, the variables OUTPUT and IPCRANGE contribute significantly to the explanation of the dependent variable. Whereas the control variable OUTPUT is again a strong positive indicator for mediator potential, the BETWEENNESS of an inventor is negatively dependent on IPCRANGE. Hypothesis 1b must thus clearly be declined. However, the IPC-result shows that it is interestingly rather specialists than technical generalists who are able to take mediator positions in the network. The assumption, that only technically broad knowledge might serve the processing and refining of information between other partners, is thus made obsolete. Instead, generalists show lower centrality values. Mediator positions are really filled with specialists, who will presumably be best able to decide which complementary knowledge is needed for an innovation project. Specialists moreover will be engaged by many other inventors due to their deep technical knowledge they show on particular subjects. We thus conclude that generalists may after all not reach the professional excellence that takes them to central network positions.

Considering the regression model for the dependent variable CLOSENESS, significant contributions by DUMMY, OUTPUT, NETCIT and IPCRANGE can be observed. While the former show a positive impact, the latter IPCRANGE is again negatively related. Again those actors possess high closeness to others, who started patenting only after the beginning of the growth stage in 1990 and who generated many patents. As before, closeness centrality is negatively dependent on IPCRANGE. It is again rather specialists who are close to many others in the network. Specialist inventors with a narrow IPC-range may be sources of important specialist knowledge, the need for which puts them in a position that shortens the distances to other network participants. Additionally, this time inventors with many citations received show higher closeness centrality. The variable NETCIT does here contribute positively to the explanation of the dependent variable, despite the further remaining effect of the control variable OUTPUT. The impact of NETCIT is even stronger than the latter's coefficient, i.e. a prominent scientific reputation (expressed by citations) predicts better the efficacy to reach others on short paths than the sheer amount of patents an inventor generated. It is, as Merton calls it, the especially visible actors who are known to many others in their technology field, who can in turn also easily reach many others on short ways (Merton, 1968). Moreover, a study of Nerkar/Paruchuri supports the assumption that stars are often rewarded by being the focus of later citations of others and thus connect themselves continuously better in the network (Nerkar and Paruchuri, 2005). Regarding the variable COLOC, however, only a (small) negative and non-significant effect can be detected, i.e. high closeness to others in the network is rather not associated with contacts to foreign inventors. Hypothesis 1c must thus be again rejected. However, since we could not find substantial proof for the impact of the variable COLOC, empirical research might be extended in future to populations with less domestically characterised, more foreign-oriented inventor networks (see also Fig. 2; Hussler and Rondé, 2007).

All regression models were tested for compliance with statistically required premises (Backhaus et al., 2008). According to Backhaus et al. (2008), the premises of linearity, expectancy value of error variable unequal to zero, homoscedasticity and normality of error variables must not be violated. This procedure indicated that the CLOSENESS-model entirely complied with regression requirements (referring also to residual diagnostics and scatterplots of residuals on the predictor variables), whereas the DEGREE and BETWEENNESS-models needed more loose interpretation in that respect. While this weakens the power of results of the first two centrality measures, we still maintain the results for closeness centrality, that are supported in their direction by the results of degree and betweenness centrality.

5. Conclusion

In summary, the assumption that stardom in a co-patent network is a traceable function of patent quality, does find empirical support, although no continuous empirical affirmation. The evolution of a co-patent network is by definition strongly affected by time and the mere number of patents an inventor contributes to their field of technology. However, patent quality has an additional impact on some aspects of communication functions a star inventor covers.

Looking at different roles or communication functions a star inventor takes in their network, we state that patent quality is for each role or aspect of centrality that stars fulfill decisive to a different extent: for example, regarding the maintenance of extensive personal networks that spread information to a large amount of contacts on a direct way, the number of patents an inventor files has the biggest impact. No significant evidence could be found at this stage for the influence of patent quality. This may be explained by the fact that the here measured degree centrality puts emphasis on direct contacts (absolute number), but ignores the connectedness with regard to the rest of the network. Against this background, there are plain scale effects, i.e. inventors with many patents tend to possess a large personal network of collaborators. Patent quality there only comes into practice when the interplay of stars with all other inventors of the network is looked at.

Considering the mediator potential an inventor encompasses, i.e. the filtering and passing on of information to partners otherwise unknown to each other, it is patent quantity, but moreover technical specialisation that are crucial. As a result of the empirical analysis, an inventor with many patents, who is highly specialised on one technical subject matter, will be able to suit a mediator position. Thus, it is not the generalists who act in this sense as gatekeepers or communication mediators in a network (see in contradiction e.g. Nikulainen, 2007). Instead it can be argued, that the (communicative) tasks an inventor has to fulfill at this stage are so idiosyncratic, as to not fit generalists. Specialists might be overall better able to decide about the necessity and kind of knowledge an innovative project requires. In consequence, specialists will also be able to evaluate incoming information more appropriately than generalists, due to the expert knowledge they show. We must further assume that generalists may not have enough technical expertise as to put themselves in any information broker or mediator position. They may simply not develop the necessary excellence.

Aiming at reaching others in the network on especially short notice, i.e. having short and efficient paths to other inventors, inventors again show a high number of patents, high technical specialisation but moreover also a high number of citations received. Again it is not the generalists who are characterised by great efficacy to reach other network participants, but technically specialised inventors who patent only in a narrow IPC-range. We observe that specialists are more able to shorten paths to other network members, than their more general counterparts are. They can presumably also themselves supply specific knowledge that is needed for different innovation projects. Thus they are acquainted and connected with different research groups and can accordingly reach other inventors in the network comparatively quickly. Generalists are here rather pushed to the frame of the network, whereas specialists position themselves in the centres. Regarding closeness, likewise the reputation (that we here see expressed by citations received) plays an important role. The recognition and followership that the citations by others implicate minimise the steps an inventor needs to reach any random inventor.

Based on the results, we generally reason that concerning selection, development and bonding issues companies should put emphasis on inventors who are of course not clear seniors, but who enter a field of technology only after the first insecurities of the pioneering years and distinguish themselves by high patent activity and clear technological specialisation. It has to be specifically assumed, that professional generalists will much less likely found the centres of a technological network, than professional specialists. Thus, the development of technological specialisation and excellence in inventors has to be paramount for R&D management. Technological generalists will rather act at the outskirts of a network, not contributing enough to move to the centre. Furthermore, the number of patents and citations should be closely monitored, to select the most promising candidates for strategically important R&D tasks. Accompanying measures like incentives to share knowledge, build contacts and sharpen professional knowledge by specialist trainings will be additionally helpful. However, there is more research to be conducted on these grounds, e.g. with respect to personal backgrounds, scientific affiliations or other factors that might be supportive in taking star positions in a technology field. Based on additional interviews and further data collection an even more complete picture of star-factors could be drawn up in an extended study, which likewise remains to be verified for other industry branches.

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