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The Impact of Network Structure and Network Behavior on Inventor Productivity

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Abstract

Building on social network theory, we provide a deeper understanding of the causality between an inventor's professional network and her performance. By taking into account whether knowledge from a network has been important in the creation of an invention, we are able to disentangle the performance contributions of network structure and network behavior. Our data set combines information from an original survey of 204 inventors active in the tissue engineering industry and the European and German patent registers about 2,439 patents and 3,985 co-inventors working with the 204 focal inventors. The results indicate that network structure, i.e., the size of the network, the strength of the ties, and the inventor's position in a network as well as network behavior positively affect the productivity of inventors. Furthermore, not dealing with the endogeneity problem of network structure and behavior would have led to the conclusion that network behavior does not matter with respect to productivity.

The Impact of Network Structure and Network Behavior on Inventor Productivity

1 Introduction

Even though the benefits of social networks are represented in a long tradition of study (e.g., Granovetter 1973), this is still a subject that is a focus of today's research (e.g., Borgatti and Halgin 2011). Early social network approaches to explain innovation and product development (e.g., Allen 1977; Tushman 1978) revealed that individuals who are strategically positioned in a network can facilitate the dissemination of information and thereby foster innovation. Powell et al. (1996) argued that the network level should be analyzed to understand organizational learning. Scholars have also analyzed gains from different types of network ties and found weak ties, typically conveying non-redundant information, to be especially positively related to innovation performance (Granovetter 1973).

The causality between networks and innovation performance has, however, remained poorly understood. Innovation critically relies on the recombination of existing ideas or technological components in a novel manner (e.g., Nelson and Winter 1982; Fleming 2001). In this case, networks are of utmost importance because the combination of existing knowledge is facilitated by access to the knowledge¹ of the different actors within a network (Nerkar and Paruchuri 2005; Fleming et al. 2007a). However, causality could also go in the opposite direction, i.e., (past) performance may work as a signal to connect with others or to encourage them to share resources, thereby enabling inventors to shape their networks and relationships among units for their benefit (Bala and Goyal 2000; Ryall and Sorenson 2007). A two-sided relationship has been deemed to be important conceptually (Lee 2010) but has been neglected in empirical work. The latter could provide an explanation for the sometimes contradictory results of existing studies. Strong ties have, for example been shown to be positively but also negatively related to innovation performance (Reagans and McEvily 2003, Uzzi 1999, Rost 2006, Fleming et al. 2007a).

Furthermore, conceptual and empirical research has only considered access to relevant knowledge, in other words, the opportunity to engage in the exchange of knowledge (Granovetter 1973; Ahuja 2000; Fernandes et al. 2000; Obstfeld 2005). The fact that networks have the potential to provide access to critical resources (Zaheer and Bell 2005), however, does not mean that the actors within that network have actually used these resources. Even more importantly, availability does not mean that these resources were instrumental for innovative activity. Only considering the structure of a network and neglecting the behavior of the actors within it potentially overestimates the network structure-

¹ In the following, the terms “knowledge” and “information” are treated as synonymous.

performance relationship. Assume, for example, that an actor has a central position in a network. This leads to a higher visibility and, hence, to a larger probability that the actor will be assigned to prestigious projects, typically resulting in a higher observable performance. The high performance is, however, not caused by the resources supplied by the network. To provide a more comprehensive picture of the network-innovation performance relationship, information about whether information, once used, was instrumental in the making of an invention will be taken into account.

Overall, this paper fills two research gaps. First, it provides a deeper understanding of the causality between an inventor's professional network and her performance by employing adequate statistical methodology to address the inherent endogeneity problem. Second, by taking into account whether the employed knowledge has been important in the creation of an invention, we are able to disentangle the performance contributions of network structure and network behavior.

Our analysis is based on original survey data obtained from 204 inventors listed on German and European patent applications of companies that are active in the tissue engineering industry. Tissue engineering is characterized by multidisciplinary research that requires the combination of knowledge from different domains, such as biotechnology, biology and chemistry (Murray 2002). Furthermore, it is still an emerging industry that is highly dynamic, leading to rapid and frequent technological changes (Hüsing et al. 2003). These characteristics make it a particularly suitable setting for this paper. The survey data were matched with register information covering 2,439 patents filed at the German Patent and Trademark Office (GPTO) and the European Patent Office (EPO), including information about 3,985 co-inventors working with the 204 focal inventors. The combination of these data sources is unique and enables us to uncover largely novel patterns of network positions and relationships as well as trace performance, controlling for individual and organizational characteristics. Following the existing literature, we will focus our analysis on ego-networks².

This paper contributes key insights to social network research by analyzing the relationship between network structure and performance while allowing for a simultaneous relationship between the two. Additionally, this paper includes a measure of network behavior to capture whether the opportunities offered by a network to foster innovation have been taken advantage of and ultimately contributed to enhancing performance. It thereby makes important progress in research on networks. Finally, the paper links research on networks with the strategic management and innovation literatures to obtain a more comprehensive understanding of the management of creative invention processes.

² Ego-(centered) networks are built around a focal actor (called the *ego*). Ego-networks take into account the ties other actors within a network have with this ego as well as the ties between these other actors. In the literature, ego-networks are also referred to as personal networks (Wassermann and Faust 2009).

2 Theoretical Background

Borgatti and Halgin (2011: 1) define network theory as “mechanisms and processes that interact with network structures to yield certain outcomes for individuals and groups”. The authors propose a new theory of networks and distinguish between models of networks and types of outcomes. Network models comprise a *flow* and a *bond model*. In the former, ties are interpreted as pipes that allow items to “flow through a network according to certain rules” (p.5). The latter interprets a network tie as a bond that “aligns and coordinates action, enabling groups of nodes to act as a single node” (p. 7), which could increase the capabilities of the group. The two types of outcomes comprise *choice* and *success*. Choice refers to behaviors, attitudes or beliefs. Research explaining similar decisions of pairs of nodes, such as the diffusion of innovation (Davis 1991, DiMaggio and Powell 1983), falls into this category. Success refers to performance or rewards at the node or network levels. This paper provides flow-based explanations of success. In some cases, however, an unambiguous distinction between *choice* and *success* as outputs is not possible. Ahuja (2000), Fernandes et al. (2000), and Obstfeld (2005), for instance, argue that networks in which actors are densely linked support mutual trust and promote individual attachment to the group, thereby enhancing performance.

Social capital theory defines social capital as “the sum of resources, actual or virtual, that accrue to an individual or a group by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition” (Bourdieu and Wacquant 1992: 119). Social capital resources include those with individual utility, such as the possibility of exerting influence (Granovetter 1973; Burt 1992), and those with collective utility, such as a group’s coordination capabilities or the application of norms (Coleman 1988; Obstfeld 2005). Coleman (1990) notes that social capital, in turn, facilitates the actions of individuals within a social structure (for instance, a network) and creates value. In particular, being part of a network facilitates access to diverse information flows, which may ultimately increase performance (Nerkar and Paruchuri 2005; Fleming et al. 2007a). If a network provides valuable information that is also employed in the innovation process, a positive relationship between networks and performance seems to be plausible. Theoretical literature on the relationship between performance and network structure, however, also finds that productivity could work as a signal that encourages others to share resources or information (Ryall and Sorenson 2007). Hence, social capital theory already provides a first indication that network access and performance are involved in a self-reinforcing process. This complicates a causal interpretation of the observed relationships.

One of the fundamental arguments in social network analysis and social capital theory is that networks provide access to knowledge, which may otherwise be beyond an individual’s reach or costly to create, e.g., due to the localization of knowledge (Rosenkopf and Almeida 2003). Social network analysis is further based on the assumption of the “importance of relationships among interacting units” (Wasserman and Faust 2009: 4). However, whether information gained from network ties was

ultimately instrumental in enhancing innovative performance has remained poorly understood (Zaheer and Bell 2005). Theoretical research has focused on network structure, i.e., the number or strength of ties in a network or the network position of an actor and their role in facilitating knowledge flows, providing non-redundant information, or fostering innovation (e.g., Granovetter 1973, Coleman 1990, Borgatti and Halgin 2011). Empirical work also focused on access to potentially relevant knowledge (Ahuja 2000; Fernandes et al. 2000; Obstfeld 2005). An exception is represented by the literature on the extent to which network ties are actually used (Fleming et al 2007a, 2007b, Lissoni 2010) and on the motivation of actors to actively share knowledge (e.g., Dyer and Nobeoka 2000).

Against this backdrop, our study sets out to investigate the causal relationship between network structure and performance. In a second step, network behavior will be taken into account to disentangle the availability and the actual utility of network resources.

Relationship between Network Structure and Performance

Following Wasserman and Faust (2009), we define a network structure as the pattern of relationships within the entire network, comprising the network positions of actors (e.g., a broker position) as well as their relationships (e.g., the number and strength of ties). Within this paper, networks are restricted to work-related or professional networks that provide access to the knowledge of the different actors, i.e., inventors.

Social network analysis scholars find that weak ties provide access to non-redundant information. Strong ties, in contrast, supply information that is already known or otherwise accessible to the actor (Granovetter 1973). Consequently, weak ties are more valuable than strong ties in enhancing performance because weak ties better enable the actors within a network to recombine existing and new knowledge (Fleming et al. 2007a). However, from a social capital point of view, weak ties do not necessarily foster resource flows. Social cohesion and trust affect the willingness and motivation of individuals to invest time, energy, and effort into sharing knowledge with others. Therefore, strong ties could have an effect on performance that is as strong or even stronger (Reagans and McEvily 2003; Szulanski 1996; McEvily et al. 2003; Uzzi 1999; Rost 2006).

In 1992, Burt published her seminal work on structural holes. She argues that structural holes, which refer to the lack of connection between two nodes in a network and can be bridged by a broker, can provide access to valuable sources of knowledge. To be of value, the knowledge obtained from a particular source must differ at least to some extent from that obtained from another source or that is already available to an actor (Leiponen and Helfat 2009). Otherwise, actors could substitute different knowledge sources with one another, without deriving any benefit of sourcing complementary knowledge from multiple sources. Brokers, who represent the only connection between otherwise disconnected actors (Burt 1997; Hargadon and Sutton 1997; Podolny and Baron 1997; Zaheer and Bell

2005; Shipilov 2006) are perceived as strategic network positions that may enable actors to access and control critical resources from their ties (Portes 1998). Additionally, access to complementary, non-redundant information could facilitate knowledge (re-)combination and therefore innovation. Both attributes of broker positions may well lead to superior performance (Burt 1992; Nerkar and Paruchuri 2005; Obstfeld 2005).

However, structural holes can also have a negative effect on the flow of knowledge. Here, the same argument applies as in the case of weak ties: Networks that densely link actors support mutual trust and promote individual attachment to the group. This, in turn, may reduce barriers to resource mobilization, enhancing performance (Ahuja 2000; Fernandes et al. 2000; Obstfeld 2005). Networks characterized by structural holes may lack the required density and, consequently, also the required trust, leading to a decrease in peer effects (Fleming et al. 2007a; Lobo and Strumsky 2008).

Even though the studies summarized above differ with regard to whether the effect is positive or negative, they do agree on a causal effect of network structure on performance. However, several other studies assume the causality to go in the opposite direction, i.e., that performance shapes the structure of a network. First, scholars argue that more able actors are better able to secure the opportunities that lead to brokerage positions, i.e., they may be able to form network ties that grant them these potentially valuable positions within a network (Lee 2010). Actors may even strategically build networks or choose positions within a network to maximize payoffs (Bala and Goyal 2000; Ryall and Sorenson 2007).

Second, the perceived quality of actors based on past performance encourages others to share information or work with these actors (Lee 2010; Cross and Cummings 2004). Hence, past performance serves as a signal for other actors in a network (Gould 2002). Additionally, experts are assumed to possess more valuable knowledge and skills (van der Vegt et al. 2006). Because performance history, which is typically observable, reduces search costs, transaction costs, and uncertainty (Ejermo and Karlsson 2006), tie formation is positively correlated with performance history (Baum et al. 2005).

Even though existing research indicates a two-sided causality of network structure and performance, the majority of the existing theoretical and empirical literature has thus far implicitly assumed a one-sided relationship (Borgatti and Halgin 2011; Fleming and Juda 2004; Nerkar and Paruchuri 2005). One exception is provided by Lee (2011), who discusses the endogeneity problem conceptually but does not employ an econometric methodology that allows for a simultaneous relationship between the two constructs. He uses two separate models to test his hypotheses. Borgatti and Halgin (2011), in their conceptual paper, argue that knowledge about how a network reached a certain structure is not necessary to understand the consequences of that structure. The authors thereby completely neglect a potential endogeneity problem.

Another limitation associated with drawing causal inferences from network analysis that has thus far been disregarded in the literature is a possible selection problem. An organization's decision to hire an employee or to assign an employee to a particular project or team is not exogenous. Organizations assemble teams such that certain goals can be reached, i.e., to create a valuable invention. Selecting an inventor who has recently changed his employer would automatically lead to an increased network. Hence, an observed correlation between network structure and productivity would not reflect the true effect of the network. Ignoring such selection would cause the effect of network structure on performance to be biased (Singh and Agrawal 2011). To solve these methodological issues, we employ an instrumental variable (IV) model, using a Two-Stage Least Squares (SLS) estimator, in which we augment the initial OLS equation with additional equations, one for each endogenous variable capturing network structure.

Relationship between Network Behavior and Performance

Network behavior refers to the behavior of individuals within their networks, such as the use of the knowledge or the mode of communication.

Research analyzing the structure of a network as a determinant of knowledge sharing between the actors in the network (Burt 1992; Fleming et al. 2007a; Cross and Cummings 2004) implicitly assumes that opportunities to engage in knowledge sharing are ultimately used. Researchers who studied the relationship between networks and the performance of their actors (Ahuja 2000; Fernandes et al. 2000; Obstfeld 2005) also presume that the knowledge available in a network is employed in the innovation process and that it is important, i.e., causal to innovative performance. However, the availability of a network or resources within a network does not necessarily mean that actors were aware of the potential value of these ties or resources and that they used the resources to create innovations. Furthermore, even if other actors in a network possess relevant information, they do not necessarily share it (Dyer and Nobeoka 2000).

Lissoni (2010), for instance, analyzes the networks of 74 academic inventors (university scientists who also patent) and combines survey data with bibliometric data. He finds that the strength of relationships as well as the type of information exchanged with former or current co-authors varies considerably. Based on US patent citation data, Singh (2005) reports significant information flows between co-inventors listed on the same patents. Later, Fleming et al. (2007a and 2007b) conduct 16 interviews with inventors and find that some degree of technical interaction exists after co-inventorship. Additionally, the interviews reveal that the fact that co-inventors are still in contact does not necessarily mean that information relevant to future inventions flows through these ties. Reinhholt et al. (2011) use survey data on 750 consultancy employees and find that the degree of knowledge sharing within a network does not only depend on the availability of knowledge but also on the motivation and ability to share and take advantage of knowledge. The ability argument is in line with

the concept of absorptive capacity proposed by Cohen and Levinthal (1990). Overall, the existing literature provides the initial evidence that the availability of resources in a network is necessary but not sufficient to confirm an ambiguous network-performance link. To understand whether a possible relationship between network structure and performance still holds, once we account for network behavior, we add a variable to our regression model that captures whether the information provided by the network ties, once used, was instrumental for creating inventions.

3 Tissue Engineering Industry

Tissue engineering (TE) refers to a sub-field of red biotechnology and is defined as “an interdisciplinary field that applies the principles of engineering and life sciences toward the development of biological substitutes that restore, maintain, or improve tissue function or a whole organ” (Langer and Vacanti 1993: 920). In particular, it involves the production of cell-based drugs used for the regeneration of damaged bone, cartilage, skin, or the cardiovascular system as well as the production of cell-based diagnostic systems. Although often treated synonymously, TE depicts a sub-field of regenerative medicine, which aims at healing diseased tissues and organs.

TE was chosen as an industry for the underlying analysis because its multidisciplinary, i.e. requires the combination of knowledge from different domains, such as biotechnology, cell biology and polymer chemistry (Murray 2002). The TE industry is an emergent and highly dynamic field (Hüsing et al. 2003) characterized by frequent technological changes and the rapid diffusion of innovation. Additionally, TE is “an area where scientific and technical progress overlap”, which has a wide range of applications (Niklason and Langer 2001, Murray 2002: 1393). Companies active in TE are young, small, research-based and technology-oriented as well as highly dependent on human capital. To make inventions, scientists in the TE industry have to rely on a variety of knowledge sources, including publications, patents or personal contacts mainly with researchers from universities or state-owned research organizations. Due to severe competition, the exchange of information between firms active in TE is rare. Contacts with firms from other industries occur more often because the multidisciplinary of TE calls for knowledge flows from outside industry boundaries (Heibel 2012). Whereas the scientific literature conveys explicit knowledge, personal interactions are appropriate for transferring tacit and sticky knowledge, which is typically costly to acquire, transfer, and use (Von Hippel 1994). Overall, TE provides a particularly appropriate environment to study the relationship between knowledge flows within professional networks and innovation performance.

The empirical analysis of this paper relies on the German TE industry, which is the second largest TE industry in the world and the largest in Europe (Kirsten 2007). The German TE industry mainly consists of biotechnology companies. Several pharmaceutical companies are active in that field, as well. The first German TE company was founded in 1992, and the industry reached its peak in 2002 with 35 active TE firms. At the beginning of the 2000s, Germany provided an attractive environment for TE companies because at that time, the Federal Ministry of Education and Research (BMBF)

offered extensive funding for research in biotechnology. After 2002, the number of active TE companies decreased – mainly because of the close-down of the ‘Neuer Markt’³ in Germany in June 2003.

Between 1992 and 2008, 46 different TE companies were observed. At the end of 2008, only 28 companies were still active. Between 1995 and 2008, 18 companies ‘left’ the TE market, 8 because of bankruptcy and the remaining 10 because of acquisitions. Of these 46 companies, 44 were start-ups (mainly university spinoffs) and 2 were subsidiaries of large and established companies. Generally, large firms have been reluctant to enter the TE market because of a lack of experience with living cell technology, low profitability (i.e., TE products or treatments do not qualify for reimbursement from health insurance), and restrictions on stem cell research in Europe (Heibel 2012, Hüsing et al. 2003).

4 Data Source and Sample

4.1 Data Description

To answer our research questions, we require data on inventor productivity, inventor networks, and a number of other factors that potentially influence the productivity of inventors. Because no public dataset offered the required information, we conducted a survey of inventors who are active in the TE industry. We considered all companies that have been conducting R&D in the field of TE or have manufactured TE-related products. The survey data were then complemented with patent data from publicly available patent databases. This reduces the danger of a common method bias because key variables in the analysis are derived from different sources.

The TE industry – like other biotechnology industries – is characterized by a high patent propensity. This has the advantage that productivity as well as networks can be traced using patent data. A low patent propensity would lead to the underestimation of the productivity of inventors. Additionally, networks could be perceived as being small due to a lack of data rather than a lack of ties. Furthermore, 44 (out of 46) companies were specialized in TE. This facilitated the identification of inventors active in TE. Hence, large networks are not just an artifact of patents wrongly attributed to inventors. Finally, the fact that the German TE industry emerged approximately 1990 allows for the entire population of companies and inventors to be surveyed. In other words, inventor networks can be built based on the entire industry life cycle.

The identification of the inventors underlying the survey was carried out in three steps. First, based on Kirsten (2007) as well as an extensive search of web and industry reports, companies active in the TE industry until 2008 (46 companies) were identified. Second, all patent applications with priority dates

³ The ‘Neuer Markt’ was a segment of the Frankfurt stock exchange that listed the stocks of young high-tech companies, comparable to the Nasdaq in New York. It was opened in March 1997 and closed only six years later, after the dot-com bubble burst (von Kalckreuth and Silbermann 2010).

up to July 2008 filed by these companies and their founders (founder inventors), were identified from the esp@cenet and the DEPATISnet databases of the European Patent Office (EPO) and the German Patent and Trademark Office (GPTO). This procedure resulted in a list of unique 382 inventors active in 41 of the 46 TE companies.

Third, to identify the co-inventors of the 382 inventors, we searched for all DE and EP patent applications by these inventors with priority dates between 1982⁴ and July 2008 using the EPO and GPTO databases. After correcting for equivalent patents, 1,238 patents (9 patents per inventor on average; min=1; max=67) and 1,485 co-inventors (16 co-inventors per inventor on average; min=0; max=99) listed on these patents could be identified. This resulted in a population of 1,867 (1,485+382) inventors. For 1,340 of these inventors, a valid address could be found listed on the patent documents, or in the online version of the white pages as well as the internet. Hence, 1,340 inventors formed the sample frame of the following analysis.

Survey data – The survey data were collected through a self-administered survey of inventors. To develop the questionnaire, 10 semi-structured expert interviews were conducted. The questionnaire was pretested with 8 inventors and finally sent to the 1,340 inventors⁵ identified using the three-step procedure described above. The inventors received a cover letter asking them to complete either a paper or online questionnaire. In total, responses were received from 229 inventors, resulting in a response rate of 17%.⁶ Due to missing values, the final empirical analysis is based on the responses of 204 inventors.

Patent data – The survey data were supplemented with patent data, which was also obtained from the esp@cenet and the DEPATISnet databases of the EPO and the GPTO. Information from the patent databases comprises the technology classification of the patent applications and the application dates. Patent citation data were received from the ‘Patent Citation Project’ (Harhoff 2009) based on the PATSTAT database as of 10/2009.

To trace the networks and productivity of the inventors over time, we searched for all DE and EP patent applications by the responding inventors within the last ten years of their inventive activity. To avoid wrong matches, the patent documents were searched for manually, based on inventor and applicant names and addresses as well as the titles of the inventions. The search resulted in 2,439 patent documents. Based on these patent documents, we were able to identify 3,985 co-inventors of the surveyed inventors.

⁴ 1982 was chosen as the lower bound because it allows for the inclusion of patent applications (e.g., of founding inventors) from up to 10 years prior to the establishment of the first TE company.

⁵ A valid address could be found in the online version of the white pages for 1,340 of the 1,867 originally identified inventors.

⁶ A non-response analysis was conducted based on the full population (1,867 inventors). The results show that the place of residence significantly affects the probability that the inventors will answer the questionnaire. Hence, inventors with an address outside Germany at the time of the invention are underrepresented in the sample.

4.2 Definition and Measurement of Variables

- **Dependent Variable**

Productivity – We use inventor productivity as a performance measure. The variable is operationalized as an inventor’s cumulative fractional output divided by years of inventive activity (i.e., 10 years or less assuming that inventors started their careers at the age of 23). A way of justifying this measure would be to assume that inventors become active at the age of 23 and continue to work with constant productivity. To measure a coefficient for age instead of assuming a proportional relationship between age and the number of applications, age is also included in the regression. The number of fractional applications refers to the number of applications with respect to the size of the inventor team. To account for the quality of the inventions, we weighted the fractional patent counts with the number of citations these patents had received from subsequent patent filings (forward citations) within three years after publication of the search report (Harhoff et al. 1999). In particular, we define the productivity of inventor i , who has k patents, as:

$$productivity_i = \frac{\sum_{k=1}^K \frac{1}{n_{ik}} c_{ik}}{m_i}; \quad k \in [1; K]$$

where n_{ik} refers to the number of inventors listed on patent k of inventor i and c_{ik} refers to the number of citations received by patent k of inventor i plus one. In accordance with Price (1976), who counts the publication of a paper as its first citation “success”, the application of an EP or DE patent is considered to be its first patent citation. Adjusting the number of citations by adding one allows for the logarithm of this variable to be calculated. m_i denotes the inventor’s number of years of inventive activity.

- **Independent Variables**

Network structure

We analyze networks at the level of the individual actor. The measures representing the structure of a network were obtained from a network analysis based on co-authorships mentioned on patent filings (Balconi et al. 2004, Breschi and Lissoni 2005). Our network is non-directional, i.e., the relational tie between two actors in a network does not have a direction. The relations in our network are valued, i.e., relations can vary in strength. We use ego-(centered) networks, which are built around a focal actor (referred to as ego) and take into account the ties other actors within a network have with this ego as well as the ties between these other actors (Wasserman and Faust 2009). Figure 1 illustrates an ego-network of inventor B. Inventor B has 2 patents. Patent 1 was filed with 3 other inventors (A, C, D). Patent 2 lists 2 additional co-inventors (E, F).

[Insert Figure 1 about here]

Inventor networks constructed using patent data are based on two assumptions. First, inventors who are jointly listed on a patent, i.e., co-inventors, know each other and exchange information. Second, knowledge flows between former co-inventors continue to take place even if the two inventors no longer work together (Breschi and Lissoni 2004, Singh 2005). The empirical literature provides evidence that these two assumptions are reasonable. Lissoni (2010) surveyed 74 academic inventors in Italy to analyze their relationships with co-authors. 100% of the respondents confirm that their co-inventors are of known identity. Continued knowledge exchange with former co-inventors is indicated by 79% of the academic inventors and 46% of the inventors employed by firms. Furthermore, Fleming et al. (2007a, 2007c) conducted interviews with 18 inventors, 17 of whom confirmed that the network of co-inventors represents their actual professional network. 13 out of 18 inventors confirmed knowledge flows with former co-inventors even after the end of a joint project.

In the following, we use the patent data (European and German patent applications) of the inventors to operationalize network structure. For each inventor, co-inventors listed on patents filed during the 10 years prior to the year of the most recent patent filing were considered.

Number of ties – This variable is defined as the number of co-inventors of the focal inventor and can be interpreted as the possibilities an actor has to ‘catch’ information flowing through the network. In case of an ego-network, the number of ties equals the size of the network minus the focal inventor. Inventor B, displayed in Figure 1, has 5 ties, i.e., he is connected with each of his co-inventors. The measure corresponds to the actor’s degree centrality proposed by Freeman (1978). Because this measure depends on the years of the inventors’ inventive activity, we standardize the measure by multiplying the measure by $10/m_i$, where m_i refers to the number of years of inventive activity of inventor i .

Strength of ties – Following Rost (2006), we define the strength of ties as the number of co-inventorships a focal inventor has with a co-inventor. The network displayed in Figure 1 only contains ties that exhibit strength 1 because the figure does not indicate that inventor B repeatedly teamed up with one of his co-inventors. Granovetter (1973: 1361) defines the strength of interpersonal ties as a “combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie”. Hence, the strength of a tie can be interpreted as the quality of the tie. Because this measure depends on the number of ties of the inventors, we consider the average tie strength of an inventor by dividing the sum of the strength of ties by the number of ties. Like the number of ties, we weight the measure by $10/m_i$ to account for the inventors’ years of inventive activity.

Number of components – A network component is defined as a connected sub-graph in a graph (Wassermann and Faust 2009). Components in an inventor network are a focal inventor’s groups of co-inventors that are connected among themselves but not connected with other co-inventors of the focal inventor. The number of components therefore refers to the number of disconnected sub-groups

of co-inventors of a focal inventor and can be interpreted as the possibilities of an inventor to access non-redundant information. Figure 1 shows a network consisting of two components (ABCD and BEF). Inventor B is the broker who bridges the two components.

Network behavior

Importance of the network – Respondents were asked about the importance of discussions with other people in the creation of their most recent invention⁷. This variable is used as a proxy for the importance of interactions with people who are part of the inventor’s professional network. In particular, it can be assumed that a piece of information, perceived as important for inventive activity, had also been used to create an invention. A dummy variable was created, taking the value of 1 if the respondent regarded interactions as being very important or important for obtaining insights underlying the invention, and zero otherwise.⁸

- **Control Variables**

External sources – Respondents were explicitly asked about the importance of discussions with people from outside their organization. This variable is a proxy for the importance of interactions with people other than the respondents’ co-inventors. Hence the variable controls for contacts which are not part of an ego-network based on co-inventorships. Again, a dummy variable was created, taking the value of 1 if the respondent regarded interactions as important for obtaining insights underlying the invention, and zero otherwise.

Personal interaction – The variable provides information about the importance of personal interactions for the respondent’s inventive activity compared to communications through other channels such as email or telephone. The variable was obtained from the questionnaire. A dummy was created, taking the value of 1 if the inventors considered personal interactions to be very important or important and zero otherwise. This variable was included in the regression analysis because the literature confirms that the mode of communications is relevant to creative activity. For instance, Senker (1995) argues that the transfer of know-how requires personal interactions. Additionally, if inventors assign great importance to personal interactions, this could also influence the structure of their networks as well as their network behavior. To avoid biased results caused by personal characteristics such as an extraverted, communicative, or talkative nature, we include the variable as a control variable.

⁷ Although the answers to the questionnaire were related to specific patents, the answers are assumed to be transferable to all of an inventor’s patents. The results of the PatVal 1 survey, which asked multiple inventors to fill out more than 1 (up to five) questionnaire, showed that inventors rely on special sources of knowledge, possibly due to positive experiences in the past. Comparing the answers of inventors who filled out more than one questionnaire revealed that the answers for different inventions either matched completely or were at least highly correlated. The spearman correlation coefficients for different sources of knowledge ranged from 0.84 to 0.73 (Hoisl 2007).

⁸ A five-point Likert scale was employed to measure the importance of interactions with people from the network. The intervals 1 = “very important” and 2 = “important” were sorted into the first category (interactions are important).

Literature – We also control for the importance of scientific literature in the respondent’s inventive activity. The variable is used as a proxy for the science dependence of an inventor’s work. Additionally, Balconi et al. (2004) and Breschi and Catalini (2010) find that the network structure differs between industrial and academic inventors. To capture both aspects, we include a dummy variable that takes the value of 1 if the respondent regarded scientific literature as (very) important for her inventive activity, and zero otherwise.

Age – We control for the age of the inventor at the time of her last patent filing to estimate a coefficient for age instead of assuming the coefficient to be 1, i.e., to take a proportional relationship between adjusted patent counts and age for granted. To account for a possible non-linear relationship between age and productivity, we also include a squared term in the regression. Furthermore, age is an important control variable to avoid biased coefficients of network-related variables. For instance, Lissoni (2010) found that older inventors are more likely to take on broker positions.

Gender – The gender of an inventor was included in the regression because female inventors were shown to exhibit a lower observable productivity, which is attributable to balancing family and work or moves after marriage (Ginther 2004, Ginther and Kahn 2006). Additionally, Ibarra (1992) found that women’s networks are different and that women also behave differently within networks. A dummy variable was created, taking the value of 1 for male inventors and zero for female inventors.

Education – The questionnaire contained a question asking the respondents for their highest attained degree. Because the share of inventors active in the biological sciences who have attained a doctoral degree is greater than in other industries, we created three dummy variables, taking the value 1 if the inventor attained a post-doctoral (e.g., a habilitation), doctoral or lower degree (e.g., a diploma, bachelor or master degree). Because the attained level of formal education reflects an individual’s cognitive ability and knowledge structures (Pelled 1996), inventors with higher educational attainment may exhibit greater productivity. Additionally, Murray (2004) and Fleming and Frenken (2007) find that networks of inventors exhibit ties to fellow students. This could again impact network structure.

Mobility – The respondents indicated whether they changed their employer between 1997 and 2006. The respondents could choose between “no change”, “one change”, “two changes”, “three changes”, and “more than 3 changes”. The answers were consolidated, resulting in a dummy variable taking the value of 1 if inventors changed their employer at least once within the given time period. Again, this variable was included for two reasons. Hoisl (2007) showed that mobile inventors are more productive in the post-move period. Additionally, a recent change in employers should lead to an increase in the network (Murray 2004, Fleming and Frenken 2007). However, even though Agrawal et al. (2006) showed that social relationships can outlive mobility, after a while, the inventor should “lose” at least some of her ties to former colleagues.

Private firm – We further control for the type of organization the inventor is employed by. In particular, we include a dummy variable that takes the value 1 if the inventor is employed by a private firm and zero otherwise (e.g., state-owned research organizations, hospitals, or universities).

Large organization – Studies indicate the presence of systematic differences in research conducted by small and large organizations (Nelson 1959). To control for this type of variation in our data, we follow prior studies (e.g., Rosenkopf and Almeida 2003) and include a variable indicating the number of employees. The information was obtained from the questionnaire⁹. We created a dummy variable that takes the value 1 if an organization has more than 500 employees and zero otherwise.

Temporal concentration – We added control variables for temporal effects, i.e., these measures reveal whether an inventor continued to consistently invent during the 10 years of inventive activity considered in this analysis or whether he developed his inventions within a short period of time. Additionally, these variables control for an increasing patent propensity observable in almost all industries after 1990 (Hall 2004). Three variables were added to the regression, indicating the share of priority filings prior to 1990, between 1990 and 1999, and between 2000 and 2010.

4.3 Descriptive Statistics

Descriptive statistics and the correlation matrix are reported in Table 1. Correlations between independent variables are relatively low, indicating that the collinearity of covariates should not be a concern. Figure 2 provides a histogram of our dependent variable, showing that the distribution of inventor productivity is right skewed. Inventor productivity varies between 0.01 and 3.82, with an average of 0.48. The inventors in our sample have between 1 and 102 ties, with an average of 18.5. The strength of ties varies between 1 and 10, with an average of 1.80. Inventors in the sample dispose of between 1 and 7 components, with an average of 1.91. 87% of inventors indicated that information from their professional network was important or very important for their inventive activity. Information from sources outside their professional network (discussions with people from outside the own organization) was considered to be important or very important by 51% of the respondents. Personal interaction was regarded as important or very important by almost all inventors in our sample (96%). The scientific literature was perceived as important or very important for inventive activity by 79% of the inventors.

The age of the inventors varies between 24 and 77 years, with an average of 47 years. 84% of the inventors in our sample are male and 16% are female. 59% of the inventors indicated that they have attained a doctoral degree and 25% have a post-doctoral degree. Furthermore, 46% of the respondents changed their employer between 1997 and 2006. 64% of the inventors were employed by a private

⁹ The questionnaire asked for the number of employees, providing nine different categories: 1 = 1-5 employees; 2 = 6-10 employees; 3 = 11-25 employees; 4 = 26-50 employees; 5 = 51-100 employees; 6 = 101-500 employees; 7 = 501-1000 employees; 8 = 1001-5000 employees; 9 = more than 5000 employees.

firm at the time of the survey and 54% by a large firm (more than 500 employees). Finally, in line with the emergence of the TE industry in Germany, the shares indicating the temporal concentration of inventive activity show that, on average, the majority of the patents were filed between 2000 and 2010 (62%), 35% were filed between 1990 and 1999 on average, and only an average of 3% were filed prior to 1990.

[Insert Table 1 and Figure 2 about here]

5 Model Specification and Estimation Results

Due to the skewness of the productivity distribution, which is known from the literature (Lotka 1926), a logarithmic transformation of the dependent variable is used. In a first step, the following log-log specification is estimated using an OLS regression.

$$\log(\text{productivity}) = \beta_0 + \sum_{l=1}^3 \beta_{1,l} \cdot \log(\text{network structure}_l) + \beta_2 \cdot \text{network behavior} \\ + \sum_{h=1}^H \beta_{3,h} \cdot \text{controls}_h + \varepsilon$$

Due to the two-sided causality between network structure and productivity, which was described in the theory section, the OLS estimators $\hat{\beta}$ are inconsistent for β . To obtain consistent estimates for β , we use an instrumental variables (IV) approach. In particular, a Two-Stage Least Squares (2SLS) regression is used. The IV estimator $\hat{\beta}_{IV}$ is consistent for β if instruments can be found that are correlated with the endogenous regressors but uncorrelated with the error term ε . Hence, in the IV model, the three endogenous variables are instrumented with variables we expect to affect the productivity of the inventors either through our network measures or not at all. The IV model regresses productivity on the fitted values of the endogenous variables (Angrist and Pischke 2008, Cameron and Trivedi 2009). To obtain unbiased standard errors, 2SLS estimates are constructed simultaneously. 2SLS is implemented in software routines such as STATA. We use the *ivreg2* command, as proposed by Baum et al. (2007).

In the following, the instruments for our endogenous variables *number of ties*, *strength of ties*, and *number of components* will be described:

- The number of ties was instrumented by the interaction *large organization * private organization* and a dummy variable taking the value 1 if the most recent invention of the respondents had *not* been an *invention in TE*. We justify the adoption of the first instrument on the grounds that the interaction of two explanatory variables can be used as instrument as long as it has no direct effect on the dependent variable, i.e., productivity (Wooldridge, 2002). Inventors employed with large private firms profit from the availability of potential ties within their organizations. Hence, they can build large networks at a low cost (Ejeremo and Karlsson 2006, Hussler and Rondé 2007). We do

not expect the interaction to have a significant effect on inventor productivity because the type and size of an organization only affects productivity indirectly, i.e., via systematic differences in the organization of research processes. In particular, inventors in large R&D departments in the chemical and pharmaceutical industries are highly specialized and play a smaller role in any single R&D project but are involved in different projects at the same time, leading to more patent filings per inventor (Kim et al. 2004). However, we control for this difference by using fractional patent counts.

The second variable “*no TE invention*” qualifies for an instrument because the sample was constructed such that each inventor has made at least one TE-related invention. Inventors whose last invention was not in the field of TE could have recently diversified into another technical field or the TE invention in the past represented a ‘side-trip’ into a new field. Being active in different technology areas, however, enables inventors to increase the size of their networks, i.e., to add ties to their networks (Murray 2004, Fleming and Frenken 2007). Although the literature has shown that knowledge recombination across technical fields leads to more valuable inventions (Miller et al. 2007), it does not necessarily affect the accumulated productivity of the inventors because quality may be achieved at the expense of quantity. Additionally, TE is defined as an industry with applications in different technical areas (Heibel 2012); hence, boundary spanning should be a characteristic inherent to most inventors active in that industry.

- The strength of ties was instrumented by three dummy variables indicating whether the inventors were in charge of *choosing their co-inventors* of their most recent invention or whether another party chose the co-inventors (reference group), or whether the focal inventor was the only inventor listed on the patent. Additionally, it was instrumented by a dummy variable taking the value 1 if the inventor’s *residence was in Germany* at the time of the survey.

The former variable is assumed to work as an instrument because inventors who can choose with whom they want to work¹⁰ typically choose colleagues they like or get along with very well. This is confirmed by Rank and Tuschke (2010), who find that friendship ties between managers increase the likelihood that these managers will collaborate with each other. Additionally, repeated interaction reduces risk and monitoring costs in teams (Ejeremo and Karlsson 2006). Both friendship and repeated interactions should result in sustained and strong ties (Granovetter 1973).

Whether inventors can put together their teams by themselves or can at least take part in the decision about team composition depends on their position within an organization as well as the management style of an organization, i.e., whether the management approach is rather participatory and cooperative or hierarchical. However, whether an organization chooses a participatory management style does not depend on its employees (or their productivity) but rather on the

¹⁰ We assume that inventors who could put together their teams for the last invention were also authorized to choose their co-inventors for earlier projects.

executive management and the organizational context (Jago and Vroom 1982, Dulewicz and Higgs 2005). One could, of course, argue that very productive inventors are more likely to put together their teams. However, Heibel (2012) could not find a significant effect of the participation decision of inventors regarding team composition and inventor productivity.

The second variable used as an instrument for the strength of ties is the country of residence of the inventors. In particular, if an inventor lives in Germany, he should be able to create stronger ties with inventors who are active in the German TE industry than if she lived abroad. A possible explanation is spatial proximity (Rosenkopf and Almeida 2003) as well as the fact that these inventors speak the same language, which should facilitate communication. However, it is not reasonable to believe that German inventors are more or less productive than inventors living in other countries.

- The number of components was instrumented by variables indicating the *shares of inventions* the respondents made in *chemistry and pharmaceuticals, instruments, or other technical areas*. Whereas the former two represent technical areas to which TE inventions are typically assigned, the latter category comprises other technical areas in which TE inventions may nevertheless be applicable.

Inventors who are active in different fields, typically referred to as “boundary spanners” (Rosenkopf and Nerkar 2001), have worked with different groups of inventors. In particular, the fact that networks are technology- or industry-specific should enable them to increase the number of components. Studies on the formation of networks highlight that organizations predominantly form cohesive ties that lead to homogenous clusters (Mowery et al., 1998; Stuart and Podolny, 1996). This should apply to the networks of individuals as well.

As previously mentioned, the ability to work in different technical fields does not necessarily affect the accumulated productivity of the inventors. First, invention quality may be achieved at the expense of quantity. Second, the fact that TE is characterized by multidisciplinaryity, i.e., requires the combination of knowledge from technical fields such as biotechnology, cell biology or polymer chemistry (Murray 2002), should, in principle, qualify inventors to become boundary spanners.

If inventors repeatedly work with the same co-inventors, we have to assume that for those observations, the error terms are correlated. To accommodate the correlation, a cluster regression is used. The cluster estimator adjusts the variance-covariance matrix to account for correlations between observations for the same dyad and triad of inventors (i.e., the same pair or trio of co-inventors). Hence, the following regression is based on 204 inventors working in 190 different inventor teams.

The results of the OLS and 2SLS models predicting inventor productivity are reported in Table 2. To explore the impact of our variables, we introduce them sequentially. Models 1 to 3 report the results of the OLS regression. Models 4 and 5 summarize the results of the 2SLS regressions. Model 1 only

contains the control variables. Models 2 and 4 incorporate variables that capture the network structure and Models 3 and 5 further include network behavior. All specifications employ models with standard errors clustered for dyads or triads of co-inventors.

[Insert Table 2 about here]

In the following, unless otherwise specified, the results of Model 5 will be reported. The results show that network structure significantly affects inventor productivity. In particular, a 10% increase in the number of ties increases productivity by 1.1%. A 10% increase in the strength of ties increases productivity by 3.8%. Finally, a 10% increase in the number of components increases productivity by 3.2%. The effects of the number and the strength of ties are significant at the 10% level and the effect of the number of components is significant at the 5% level. Whereas network behavior, i.e., the importance of information obtained from the network is not significant in the OLS regression model (Model 3), the effect becomes significant after instrumenting the endogenous variables capturing network structure (Model 5). In particular, if an inventor perceived the information he received from ties within his network to be instrumental for his inventive activities, his productivity increases by 7.5%. Furthermore, after incorporating the importance of the information, the size of the effect of the strength of ties decreases by 12%. The size of the effect of network components increases by 9.4%.

Three control variables exhibit a significant effect. First, if personal interactions were considered to be important for inventive activity, the inventor's productivity decreases by 29%. A possible explanation for this negative effect could be that personal interaction – compared to interaction via telephone or email – is very resource intensive. This could lead to a decrease in output quantity. Additionally, personal interaction may be required if there are conflicts within a team or problems regarding the project. This could also decrease inventive output. Furthermore, we have to note that 96% of the respondents considered personal interaction to be important, leading to low variation in the variable. Before adding the network variables (Model 1), the two dummies capturing the level of education do not significantly affect inventor productivity. This finding is in line with Hoisl (2007). The level of education significantly decreases productivity once we incorporate network measures (Model 5).

6 Discussion and Conclusion

The goal of this paper was to provide a deeper understanding of the causality between an inventor's professional network and her performance by employing adequate statistical methodology to address the endogeneity of network structure. Second, by taking into account whether the knowledge available in a network was important for making an invention, we were able to disentangle the performance contributions of network structure and network behavior.

The results indicate that network structure, i.e., the size of the network, the strength of the ties, and the inventor's position in a network, positively affects the productivity of inventors. Whereas the existing

literature had already provided evidence of a significant relationship, existing methodology has not allowed for a causal interpretation of the results. Additionally, the results were – in part – contradictory. For example, Fleming et al. (2007b) find that weak ties enhance performance due to the possibility of transferring non-redundant information, whereas Szulanski (1996) finds that strong ties are particularly valuable for the transfer of sticky information and consequently increase productivity. Furthermore, whereas Leiponen and Helfat (2009) show that a broker position enhances productivity, Obstfeld (2005) argues that more densely linked networks, which do not exhibit structural holes (i.e., actors cannot hold broker positions) increase productivity. Not accounting for the endogeneity problem possibly ‘caused’ these differences in outcomes.

Furthermore, we show that once we instrument endogenous variables, network behavior, i.e., whether the inventor assigned importance to the information he received from his network becomes significant. The latter variable represents a proxy for whether information provided by network ties was actually used. Not dealing with the endogeneity problem would have led to the conclusion that network behavior does not matter with respect to productivity.

These outcomes have a number of theoretical and practical implications. First, the results of this study contribute to the social network research by providing a better understanding of the relationship between network structure and productivity. Additionally, network behavior has neither been the subject of an empirical test, nor has it been considered in contemporary theorizing about productivity. Our results thus provide an important empirical validation of its relevance in the underlying context. Our study further provides implications for research on strategic management. In particular, the importance of the utilization of a network links network-related research with research on strategic capabilities, e.g., absorptive capacity (Cohen and Levinthal 1990).

Our results also provide practical implications for R&D management. Given the positive effect of the size of a network as well as the strength of ties, organizations should support the building of networks and the establishment of strong ties – for instance, by using intranets to connect employees and fostering repeated interaction through repeated joint projects. Furthermore, the importance of network components, i.e., the number of an actor’s groups of co-inventors not linked among each other, means that organizations should foster boundary spanning, which may well lead to an increase in the number of components. Because building networks is time and resource consuming, firms should also consider network structure- and network behavior-related information when hiring employees.

Although the empirical setting in this study provides major advantages over the existing literature, a few limitations must be noted. First, as with many other studies in this field, we cannot employ experimental (or at least quasi-experimental) data. Hence, we cannot completely rule out possible selection effects. Second, our study is partly based on patent data. In particular, network structure is operationalized using patent data. These data allow us to trace the inventive history of individuals. However, we also note that patent data provide incomplete coverage of innovative activity because not

all outcomes of R&D processes are patented or patentable (Cohen et al. 2000). We attempted to address this limitation by choosing an industry characterized by high patent propensity as well as taking into account national (DE) as well as regional (EP) patent filings. Nevertheless, we cannot rule out that the inventor networks are incompletely represented by our data. Furthermore, networks of inventors do not only consist of their former co-inventors. In particular, not all persons who have a stake in solving a technical problem are ultimately listed on the patent document. Additionally, networks do not only include colleagues but also other actors, such as people employed in other organizations (e.g., suppliers) or friends. Hence, even though existing empirical studies and our own interviews indicated that the professional network of an inventor represents an important source of knowledge and thereby enhances inventive activity, the derivation of implications for employees outside R&D may be limited. Finally, TE provided a very attractive setting for our analysis. However, the industry is unique because it is characterized by high science dependency, multidisciplinary, and highly qualified inventors. It is also a rather young industry. Although our results are certainly applicable to other emerging high-tech industries like nanotechnology, clean technology, or IT, implications may be limited in mature industries such as the mechanical engineering or automotive industries.

Further research should broaden the definition of network to include actors other than actual and former co-inventors. Additionally, further research should consider additional industries or conduct a multi-industry study to determine whether network structure and network behavior effects differ among industries. Finally, other studies should look more deeply into the actual utilization of networks – maybe even into the importance of knowledge acquired from specific ties.

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Table 1 - Descriptive Statistics and Correlation Matrix (N = 204)

Variables	Mean	Std.Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1 productivity	0.48	0.63	0.01	3.82	1											
2 number of ties	18.50	17.27	1	102	0.69	1										
3 strength of ties	1.80	1.13	1	10	0.34	0.44	1									
4 number of components	1.91	1.26	1	7	0.29	0.11	-0.13	1								
5 importance of the network	0.87		0	1	-0.01	0.02	-0.05	-0.07	1							
6 external sources	0.51		0	1	-0.05	-0.05	-0.02	0.07	-0.04	1						
7 personal interaction	0.96		0	1	-0.14	0.05	0.02	-0.05	0.41	0.03	1					
8 literature	0.79		0	1	-0.12	-0.08	-0.06	0.00	0.01	0.02	-0.05	1				
9 age	47.12	10.12	24	77	0.15	0.04	-0.18	0.22	-0.11	0.07	-0.04	-0.13	1			
10 gender	0.84		0	1	0.09	0.03	-0.11	0.14	0.02	0.001	-0.03	-0.03	0.20	1		
11 doctoral degree	0.59		0	1	0.03	0.19	0.14	-0.13	-0.03	-0.02	-0.004	0.06	-0.21	-0.18	1	
12 post-doctoral degree	0.25		0	1	-0.15	-0.22	-0.19	0.16	-0.04	0.11	0.08	-0.09	0.22	0.10	-0.70	1
13 mobility	0.46		0	1	-0.08	-0.16	-0.05	-0.03	0.07	0.01	0.07	0.05	-0.44	-0.08	0.07	0.03
14 private firm	0.65		0	1	0.25	0.28	0.07	-0.14	0.02	-0.02	-0.16	0.09	0.0004	0.01	0.35	-0.52
15 large organization	0.54		0	1	0.06	0.13	-0.05	0.01	0.08	0.06	-0.09	0.09	-0.08	-0.001	0.03	-0.03
16 share prio yr < 1990	0.03	0.16	0	1	-0.01	-0.02	-0.01	-0.06	-0.03	0.10	-0.08	0.02	0.30	0.09	-0.01	0.05
17 share prio yr 1990-1999	0.35	0.35	0	1	0.05	-0.05	-0.11	0.08	0.05	-0.05	0.10	-0.05	0.19	0.11	-0.10	0.06
18 share prio yr 2000-2010	0.62	0.37	0	1	-0.04	0.06	0.11	-0.05	-0.03	0.005	-0.06	0.04	-0.30	-0.15	0.10	-0.08

Variables	13	14	15	16	17	18
13 mobility	1					
14 private firm	0.05	1				
15 large organization	-0.27	-0.01	1			
16 share prio yr < 1990	-0.13	0.05	0.08	1		
17 share prio yr 1990-1999	-0.19	-0.04	-0.01	-0.07	1	
18 share prio yr 2000-2010	0.23	0.01	-0.02	-0.36	-0.91	1

Note: Pearson correlation coefficients (for two continuous variables), point biserial coefficients (for one continuous variable and one dummy variable) and phi coefficients (for two dummy variables) (N = 30,550); * significant at the 1% level

Table 2 - OLS Regression Model and Instrumental Variables Model of Productivity (N = 204)

VARIABLES	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)
	OLS	OLS	OLS	2SLS	2SLS
log(productivity)					
<i>Network Structure</i>					
log(number of ties)	#	0.133*** [0.028]	0.131*** [0.028]	0.109* [0.063]	0.108* [0.062]
log(strength of ties)	#	0.424*** [0.080]	0.429*** [0.080]	0.437* [0.241]	0.383* [0.231]
log(number of components)	#	0.180*** [0.052]	0.184*** [0.052]	0.288* [0.151]	0.315** [0.150]
<i>Network Behavior</i>					
importance of the network (dummy)	#	#	0.067 [0.044]	#	0.075* [0.039]
<i>Knowledge Sources</i>					
external sources (dummy)	0.005 [0.043]	-0.014 [0.031]	-0.011 [0.031]	-0.016 [0.031]	-0.014 [0.031]
personal interaction (dummy)	-0.252* [0.146]	-0.246* [0.129]	-0.291** [0.128]	-0.244** [0.115]	-0.293** [0.114]
literature (dummy)	-0.091 [0.070]	-0.070 [0.049]	-0.073 [0.049]	-0.070 [0.047]	-0.074 [0.047]
<i>Inventor Characteristics</i>					
log(age)	0.890 [2.251]	8.754*** [2.489]	8.811*** [2.397]	8.220* [4.984]	7.159 [4.691]
log(age) squared	-0.084 [0.301]	-1.120*** [0.327]	-1.127*** [0.315]	-1.057 [0.646]	-0.920 [0.608]
gender (dummy)	0.045 [0.052]	0.032 [0.037]	0.030 [0.037]	0.024 [0.043]	0.017 [0.042]
doctoral degree (dummy)	-0.070 [0.077]	-0.117** [0.057]	-0.112* [0.057]	-0.109** [0.055]	-0.099* [0.055]
post-doctoral degree (dummy)	-0.115 [0.087]	-0.136** [0.066]	-0.131** [0.065]	-0.129** [0.064]	-0.122* [0.063]
mobility (dummy)	0.020 [0.056]	0.085* [0.045]	0.082* [0.045]	0.069 [0.047]	0.057 [0.048]
<i>Characteristics of the Organization</i>					
private organization (dummy)	0.141** [0.055]	0.003 [0.041]	0.005 [0.041]	0.026 [0.062]	0.041 [0.062]
large firm (dummy)	0.065 [0.046]	0.028 [0.037]	0.026 [0.037]	0.030 [0.039]	0.027 [0.040]
<i>Temporal Concentration (reference group: share priority year (2000-2010))</i>					
share priority year < 1990	-0.098 [0.139]	0.054 [0.107]	0.057 [0.100]	0.076 [0.118]	0.078 [0.112]
share priority year (1990-1999)	0.006 [0.059]	0.049 [0.043]	0.043 [0.044]	0.041 [0.043]	0.032 [0.044]
Constant	-1.635 [4.142]	-17.345*** [4.728]	-17.483*** [4.557]	-16.304* [9.672]	-14.245 [9.107]
R-squared	0.147	0.560	0.564	0.548	0.542
F test	3.349	11.48	10.90	5.39	5.24
F test 1st-stage: number of ties	-	-	-	2.73 (p=0.010)	2.73 (p=0.010)
F test 1st-stage: strength of ties	-	-	-	2.49(p=0.018)	2.47 (p=0.019)
F test 1st-stage: no. of components	-	-	-	2.51 (p=0.017)	2.49 (p=0.018)
Hansen J statistic	-	-	-	0.333(p=0.988)	0.316 (p=0.989)

OLS and IV regression analyses, clustered standard errors in brackets / *** p<0.01, ** p<0.05, * p<0.1

Instruments (Models 4 and 5): no TE invention; cooperation decision inventor; no cooperation; share chemistry/ pharma; share instruments; share other, d_Germany

Figure 1 - Ego-network of inventor B

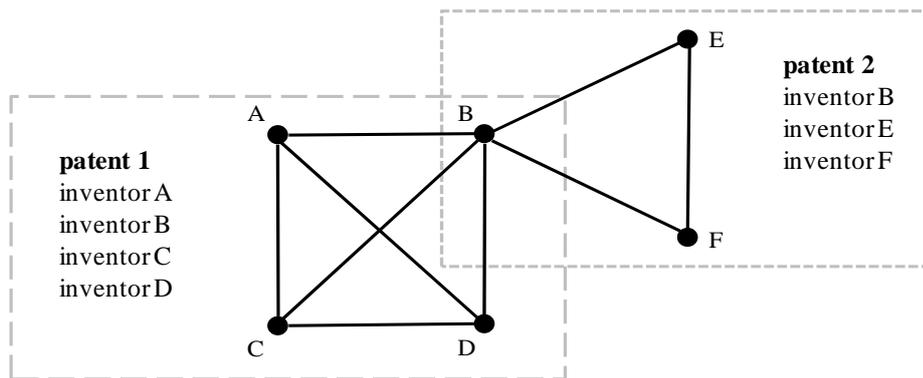


Figure 2 - Distribution of inventor productivity (N = 204)

