Network embeddedness, geographical co-location or both?

The impact of distinct and combined proximity effects on firm-level innovation output in the German Laser Industry

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ABSTRACT:

Empirical and theoretical contributions provide strong evidence that firm-level performance outcomes in terms of innovativeness can either be determined by the firm's position in the social space ("network effects") or by the firm's position in the geographical space ("co-location effects"). Even though we can observe quite recently first attempts in bringing together these traditionally distinct research streams (Whittington et al. 2009), research on interdependent network and geographical co-location effects is still rare. Consequently, we seek to answer the following research question: considering that the effects of social and geographic proximity on firm's innovativeness can be interdependent, what are the distinct and combined effects of firm's network and geographic position on firm-level innovation output? We analyze the innovative performance of German laser source manufacturers between 1995 and 2007. We use an official database on publicly funded R&D collaboration projects in order to construct yearly networks and analyze firm's network positions. Based on information on population entries and exits we calculate various types of geographical proximity measures between private sector and public research organizations (PRO). We use patent grants as dependent variable in order to measure firm-level innovation output. Empirical results provide evidence for distinct effect of network degree centrality. Distinct effect of firm's geographical co-location to laser-related public research organization promotes patenting activity. Results on combined network and co-location effects confirms partially the existence of interdependent proximity effects, even though a closer look at these effects reveals some ambiguous but quite interesting findings.

Key words: geographical co-location, networks positioning, innovation output

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Introduction[4]

Management studies emphasize the importance of knowledge and learning processes for the competitive advantage of firms (Grant 1996, Kogut/Zander 1992). In his analysis of firm's learning processes Malerba (1992, p. 847) highlights the importance of two different knowledge channels for the firm: internal and external knowledge sources. Internal knowledge sources refer to processes of knowledge generation within the firm such as research and development activities. On the other hand, other economic actors within the industry (competitors, customers, suppliers, etc.) or public research and development (R&D) organizations constitute external sources of knowledge. In rapidly changing environments the ability to identify and exploit various sources of knowledge becomes increasingly important (Cohen/Levinthal 1990). Following Polanyi (1958) scholars have recognized that relevant knowledge is tacit and context-dependent. These fundamental characteristics turn external knowledge difficult to access and to assimilate. In this context proximity to external knowledge sources may enable access and assimilation of knowledge and foster learning and innovation processes (Amin/Wilkinson 1999).

Boschma (2005, p. 62) introduces five proximity dimensions: cognitive, organizational, social, institutional and geographical proximity. Interestingly, he claims that "geographical proximity per se is neither a necessary nor a sufficient condition for learning to take place (…) it facilitates interactive learning (…) by strengthening the other dimensions of proximity". Moreover, he emphasizes that proximity facilitates learning and innovation; however, due to a lack of openness, proximity may have a negative impact on innovation. Finally, Boschma (2005) stresses the little understanding of possible combined effects of the various proximity dimensions. This paper aims at contributing to the body of research exploring the role of social and geographical proximity in the exploitation of external knowledge sources by analyzing distinct as well as combined proximity effects on the innovative performance of firms. However, this endeavor requires a clear distinction of both proximity concepts. Boschma (2005) defines social proximity "in terms of socially embedded

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relations between agents at the micro-level". We concentrate in the following on a very specific form of social proximity which can be defined as formalized relationships between organizations in a well-defined population which provide interorganizational knowledge transfer channels or learning arenas in order to accomplish joint research and development activities. On the other hand, geographical proximity is defined as "the spatial or physical distance between economic actors" Boschma (2005). This distinction is, to some extent, in line with the theoretical contribution provided by Visser (2009) who analyzes and discusses different effects of networks and clusters on innovation and learning. However, this contribution focuses on the benefits of knowledge spillovers due to co-location to other organizations which do not necessarily require local interactions between actors.

Economic sociologists highlight the importance of social proximity effects and argue that membership in complex collaborative structures may have a positive impact on various dimensions of firm-level performance outcomes (Baum et al. 2000). For instance, a large number of theoretical as well as empirical studies indicate that the structural configuration of interorganizational networks and the occupation of strategically important positions within complex network structures exert a positive impact on resource access (Gulati 2007), knowledge transfer (Grant/Baden-Fuller 2004) and interorganizational learning processes (Hamel 1991, Nooteboom 2008). Besides, we have strong empirical support for the consequences of network positioning on firm performance in terms of innovativeness (Powell et al. 1996, Ahuja 2000, Stuart 2000).

Economic geographers have studied whether geography and proximity influence the extent to which knowledge spreads across agents. Oerlemans/Meeus (2005) point out that this body of research on can be grouped in two strands: a strand with a focus on spatially mediated knowledge spillovers (Feldman 1993, Audretsch/Feldman 1996) and contributions focusing on spatial (or face-to-face) interaction and interactive learning (Maskell/Malmberg 1999, Saxenian 1994). To explore the impact of geographic proximity to knowledge sources on firm's innovativeness we take the knowledge spillovers' perspective. This perspective stresses that proximity influences companies' possibilities to benefit from knowledge spilling over from research and development activities taking place outside of the boundaries of the firm (Audretsch 1998). Also empirical studies from this research strand suggest that physical proximity of firms to external knowledge sources enhances innovative and economic performance (Jaffe, 1989; Audretsch/Feldman 1996; Audretsch/Dohse 2007).

This brief review of contributions from the field of economic sociology and economic geography suggests that performance outcomes in terms of innovativeness can be influenced by the firm's position in the social space (due to various types of "network effects") and by the firm's position in the geographical space (due to "localised knowledge spillovers effects"). Even though some notable studies on interdependent effects between various proximity dimensions have been conducted in the past (Torre/Rallet 2005; Nooteboom 2008; Oerlemanns/Meuss 2005), especially research on interdependent social and geographical proximity effect is rare (Zaheer/George 2004; Whittington et al. 2009). More precisely, it is still widely unexplored to what extent interdependencies between "social proximity" and "geographical proximity" determine the ability to tap and utilize external knowledge sources in order to increase firm's innovative output. Although we can observe quite recently first attempts in bringing together these traditionally distinct research streams (e.g. Whittington et al. 2009), we still face more questions than answers. For instance, previous empirical studies fail to test interdependent effects between various dimension of geographical and social proximity in terms of distance to different types of actors in the innovation process or various types of strategic network positions. Furthermore most previous studies do not incorporate the inherent industry and network dynamics sufficiently. Moreover, the vast majority of empirical findings are based on data for the biotechnology industry (Owen-Smith/Powell 2004, Whittington et al. 2009). Existing empirical findings have to be tested based on data from other industries. Results can diverge in substance due to differences in the degree of industries technological maturity, different industry life-cycle stages and differences in firm size distribution across industries.

We choose the German Laser Industry in order to contribute to a deeper understanding of distinct and combined proximity effects on firm-level innovation output for several reasons. First, the German Laser Industry can be characterized as a science based industry (Grupp 2000) in which firm's ability to innovate is a key factor of firm performance and success. Second, laser technology requires knowledge from various academic disciplines such as physics, optics and electrical engineering (Fritsch/Medrano 2009). Consequently, the German laser industry provides rich an opportunity to study the nature of knowledge spillovers as well as knowledge transfer and learning processes in interorganizational R&D networks.

To sum up, this contribution puts forward the following research question: considering that the effects of social and geographic proximity on firms' innovativeness can be interdependent, what are the distinct and combined effects of firm's network position and geographic position on firm level innovative output in the laser industry? In order to answer the outlined research question we analyze social and geographic proximity of the full population of German laser source manufacturers between 1995 and 2007. To the best of our knowledge we did not find any empirical study analyzing interdependent social and geographical proximity effect in the German Laser Industry. We use official data from the German Federal Ministry of Research and Technology (BMBF) on publicly funded R&D collaboration projects to obtain yearly data on interorganizational networks and analyze structural network patterns and firm's network positions. Based on exact information on firm's population entries and exits we calculate various types of geographical proximity measures. We use patent data – more precisely, patent grants – as an indicator for firm's innovative output.

The paper is organized as follows: the next section provides a literature review on relevant issues in order to derive our research hypothesizes. Next, a description of the main characteristics of the German Laser Industry follows, together with a brief presentation of the data sources used in this paper. In the same section we discuss methodological issues and specify the dependent and independent variables. Thereafter descriptive statistics, econometric issues and econometric estimations are presented. After discussing the results and key findings the paper closes with a short discussion on the limitations of the results and possibilities for further research.

Theory and hypothesis development

Network structure, network positioning and innovation output

Alliances and networks have gained significantly in importance over the last decades. A large body of research exploring the types, the determinants and the effects of these collaborative arrangements and hybrids has emerged. Especially the amount of survey-based case studies and cross-sectional research on interorganizational networks has constantly risen since the early 1980s[5]. For instance, researchers have extensively discussed structural collaborative forms on a dyadic level ranging from short-term supply contracts, licensing and franchise agreements, consultancy contracts to consortia, long-term partnerships and joint ventures (Inkpen 2001, Brass et al. 2004). Likewise, motives for collaborative agreements like cost

[5] For an overview of early efforts in alliance and network research see (Osborn/Hagedoorn 1997; Gulati 1998; Kudic 2010).

savings (Hagedoorn 2002), risk reduction (Hagedoorn 1993, Sivadas/Dwyer 2000), time savings (Mowery et al. 1996 p. 79), reputation and status (Stuart 1998, Stuart et al. 1999, Stuart 2000, Gulati et al. 2000), knowledge access (Rothaermel 2001, Grant/Baden-Fuller 2004) and interorganizational learning (Hamel 1991, Khanna et al. 1998, Kale et al. 2000) have been at the center of the debate. International business (Johanson/Mattsson 1988) as well as entrepreneurship scholars (Larson 1992, Larson/Starr 1993) have emphasized the relevance of interorganizational networks as an important strategic option to enter international markets (Axelsson/Easton 1992). Moreover, economists have especially used transaction cost arguments to explain the existence of hybrids (Thorelli 1986, Jarillo 1988), focused on contractual agreement behind various types of collaborative partnerships (Reuer/Arino 2003, 2007) and analyzed interorganizational governance issues (White 2005, Oxley/Sampson 2004, Kudic/Banaszak 2009). Other scholars focus predominantly on the consequences of network structure and network membership. A large number of empirical and theoretical contributions provide strong evidence that structural network characteristics such as network density, structural holes, and structural equivalence can influence performance of industries and firms within these industries (Gulati et al. 2000, p.205). With other words, firm's structural position within the overall industry network affects various dimensions of firm-level performance (McEvily/Zaheer 1999; Zaheer/Bell 2005). For instance, past studies examine consequences of network membership and alliance network composition on various dimensions of startup's early performance such as year-to-year revenue growth, employee growth or firm survival rates (Baum et al. 2000). In this paper we are interested in the interrelationship between network structure, network positioning and innovation output. Previous studies have explored the importance of structural network characteristics for the firm's innovation generating process (Podolny/Stuart 1995, Shan et al. 1994, Powell et al. 1996). However, these studies did not directly examine the role strategic positions in network structure as a predictor of firm-level innovation output. Quite recently, scholars have started to analyze the impact of various types of network positions in interfirm or interorganizational network structures on the firm's innovative performance (Ahuja 2000, Owen-Smith/Powell 2004, Gilsing et al. 2008, Whittington et al. 2009). Nonetheless, it is remarkable the vast majority of past as well as contemporary network studies focus on the biotech industry. The analysis of network structures and consequences of network embeddedness for other science-based industries is clearly underrepresented. Especially the characteristic features and the science-based nature of the Laser Industry dispose use to formulate the following general hypothesis:

H.1.: In the German Laser Industry, a firms structural positioning within an interorganizational R&D network influences its innovative performance output

The structural positioning of firms within interorganizational network reflects in several ways. A central debate in network literature focus on the relevance of sparsely connected network structures – "structural hole theory" (Burt 1992, 2005) – and densely connected network structures – "closure theory" (Coleman 1988) – and subsequent effects for embedded network actors. Recent theoretical (Burt 2000) as well as empirical (Rowley et al. 2000) studies sensibilize for the partial compatibility of both theories. Consequently, we consider brokerage as well as closure tendencies in our subsequent analysis. Nonetheless we draw our attention on the latter strand of literature in order to derive the following two hypothesizes. On the one hand, the number of the firm's direct partners is assumed to have an impact on innovation output. This perspective focuses on the most visible actors in the network and gives us a good idea of the firm's network involvement and the degree to which a firm is directly connected to other actors. The degree of connectedness allows us to specify the extent to which firms gain innovation experience of being directly well connected to other laser source manufacturers or laser-related public research organizations. High-degree firms occupy advantageous network positions because they have access to a broad variety of resources and knowledge stocks due to multiple network ties. Especially in science-based industries it is of vital importance to have access to various types of information and knowledge. A high number of direct partners and a densely connected ego-network lower the risk of dependence to other organizations due to the existence of redundant ties and optional knowledge channels to relevant partners. These considerations allow the formulation of our first hypothesis:

H.1.1.: In the German Laser Industry, the higher the number of firm's direct partnerships, the greater the subsequent innovative performance

On the other hand, we put forward the argument that not simply the count of ties but rather the quality of collaborative partnerships matters. The eigenvector centrality provides an appropriate indicator to identify connections to other strategically important organizations in the network. Empirical research provides evidence that particularly linkages to prominent strategic alliance partners and other organizations exert a positive impact on firm's performance due to interorganizational endorsement effects (Stuart et al. 1999). According to this perspective, we argue that firms gain innovation experience from being connected to other well-connected, highly prominent firms or laser-related public research organizations.

To sum up, the second perspective puts forward the argument that the quality and not simply the number of partnerships to other organizations matters. The arguments discussed above enable us to formulate the second hypothesis:

H.1.2.: In the German Laser Industry, the higher the firm's connectedness to influential and well connected collaboration partners, the greater the firm's subsequent innovative performance

Geographic proximity and innovation output

To explore the impact of geographic proximity to knowledge sources on firm's innovativeness we draw on the literature of localized knowledge spillovers. As already introduced above, this strand of research stresses that knowledge spills over from research and development activities and, more importantly, that the ability to assimilate these knowledge spillovers is influenced by distance (Breschi/Lissoni 2001). In general terms, this research strand has not deepened into the mechanisms that articulate the assimilation of localized knowledge spillovers. However, it is most suitable for our purpose of evaluating the distinct and combined effects of social and geographical proximity on firm performance since other strands focusing on face-to-face interaction to explain the geography of innovation (Maskell/Malmberg 1999, Saxenian 1994) involve (at least implicitly) other proximity dimensions identified by Boschma (2005) such as social or cognitive proximity.

The literature on regional knowledge spillovers stresses (and in some cases assumes) that physical proximity of firms to external knowledge sources enhances innovative performance. Audretsch/Feldman (1996) provide strong empirical evidence for the propensity of innovative activity to cluster. The propensity tends to be higher in industries where new knowledge (in terms of R&D expenditures and skilled labor) plays an important role. Even though Audretsch/Feldman adopt the state as unit of observation, their analysis implicitly assumes that physical proximity of firms to external knowledge sources enhances innovative performance at the firm level. Interestingly, clustering forces are influenced by the stage of the industry life cycle. In another contribution Feldman (1993) chooses the firm as level of analysis to analyze the determinants of firm's innovation output. Her results strongly support the relationship between the geographical proximity of innovative inputs external to the firm (such as corporate R&D activities carried out by other companies and R&D activities from PROs) and firm's innovative output. In other words, the co-location of firm near external knowledge sources enhances innovation performance. This effect varies with firm size.

Especially small firms seam to benefit from the proximity to sources of knowledge spillovers. These arguments substantiate the formulation of the following hypothesis:

H.2.: In the German laser industry geographic proximity to other profit and non-profit organizations influences firm's innovative performance

Jaffe (1989) and Acs et al. (1992) provide interesting results concerning the contribution of knowledge spillovers from public research organizations (PROs) to innovation. Using patents (Jaffe 1989) and direct counts of innovation outputs (Acs et al. 1992), these studies give evidence for the positive impact of knowledge spillovers from universities on corporate innovative activity. According to Jaffe (1989), this effect is particularly significant in the areas of drugs and medical technology, electronics, optics and nuclear technology. Drawing on these results we aim at testing the following hypothesis:

H.2.1.: Firm’s geographic proximity to laser-related public research organizations enhances firm’s innovative performance

In their overview of the literature on localized knowledge spillovers Breschi/Lissoni (2001) identify a number of contributions studying the mechanisms underlying knowledge spillovers’ transmission at the local level. Even though pure knowledge externalities at the local level may be present and may promote the concentration of innovative activity (as suggested by the empirical work introduced above on local knowledge spillovers), a number of other market and non market mechanisms exist enabling knowledge transmission and knowledge reuse among firms of the same industry at the local level. These mechanisms include local labor markets (Almeida/Kogut 1999, Zucker et al 1998), local markets for technologies (Lamoreaux/Sokoloff 1999) and the low propensity of skilled workers to relocate in space (Breschi/Lissoni 2009). From these arguments we elaborate the following hypothesis:

H.2.2.: In the German laser industry firm’s geographic proximity to other profit organizations active in this industry enhances firm’s innovative performance

Interdependent effects of social and geographic proximity

In his theoretical contribution Boschma (2005) stresses the relevance of the different dimensions of proximity and their interdependence. For instance he argues that geographical proximity is more likely to stimulate social proximity because co-location favors face to face interaction and trust building. Moreover, geographical proximity may also be complementary to other forms of proximity in the process of interorganizational learning. However, the way in which the different dimensions of proximity influence each other is quite unclear. Whittington et al. (2009) take one step further and analyze empirically the combine effect of social and geographic proximity dimensions on innovation performance. More precisely, they study whether the effects of these two dimensions are independent, substitutes or complements (Whittington et al. 2009, pp. 97-98). Assuming that proximity enhances firm level innovation, their hypothesis development follows this line of argumentation: Independent effects of social and geographical proximity on innovation would imply that both proximity dimensions influence innovation through unrelated mechanisms. In other words, the effects of positioning in the geographical and social space on innovative performance do not influence each other. Substitute effects of social and geographical proximity on innovation advocate the argument that geographically isolated firms may compensate their disadvantages in innovation through interorganizational cooperations. In this case, social proximity may compensate for geographical disadvantages. Finally, complementary effects of social and geographical proximity on innovation imply that geographical proximity can enhance the benefits of collaborative efforts (social proximity). Keeping these three possibilities in mind in order to derive our last set of hypothesizes we argue that these dimensions are not independent - they are complementary or substitutes - and can affect each other in several ways. On the one hand geographical proximity among firms and between laser firms and public research organizations is of vital importance and facilitates access and use of knowledge spillovers. Knowledge spillovers provide firms with general knowledge form surrounding organizations in a densely crowded geographic area. Co-located firms benefit from knowledge that is “in the air” which may be transfer through chanels such as mobility of inventors in local labor markets (Breschi/Lissoni 2001). Knowledge spillovers provide valuable information and increase the awareness of firms about new industrial and technologiucal trends. Consequently, firms who benefit from knowledge spillover increase their general technological understanding. This enhances at the same time their ability to access knowledge through interorganizational transfer processes and to learn in network relationships. On the other hand, firms largely benefiting from collocation effects may lose their awareness about alternative external knowledge channels such as interorganizational cooperations. These two line of arguments leads to the following hypothesis:

H.3.: In the German Laser Industry, the effects of social and geographical proximity are interdependent.

Due to the science based nature of the laser technology industry, innovation processes involve different type of actors. On the one hand public research organizations active in various scientific disciplines – physics, optics, electrical engineering etc. – primarily focused on generating scientific knowledge and, on the other hand highly specialized high-tech companies producing technological solutions for industrial purposes. we argue that the knowledge spilling over from the research activities of these organizations differs. Co-location to laser producer manufactures allows access to industry oriented knowledge whereas co-location to PROs enables access to scientific knowledge spillovers. To sum up, the benefits in terms of knowledge spillovers of being co-located to PROs may differ from the benefits of being co-located to laser source manufactures. This leads to the following two hypothesizes:

H.3.1.: In the German Laser Industry, the effects of social proximity and geographical proximity to other laser source manufactures on innovation are interdependent

H.3.2.: In the German Laser Industry, the effects of social proximity and geographical proximity to other laser related public research organizations are interdependent

Data and Methodology

Our analysis focuses on the population of German source manufacturers between 1990 and 2010. The acronym **LASER** stands for **L**ight **A**mplification by **S**timulated **E**mission of **R**adiation. We choose the German Laser Industry for this research project for several reasons. First, the industry can be characterized as a science based industry (Grupp 2000) in which firm’s ability to innovate is a key factor of firm performance and success. Second, systemic innovation theory (Freeman 1987, Lundvall 1982) has given rise to the insight that technological innovation is the result of a collaborative process and highlight the importance of exchange processes between various types of organizations (Schwartz et al. 2010). In the laser industry knowledge from various academic disciplines, particularly physics and electrical engineering, is required (Fritsch/Medrano 2009). Thus laser industry provides a rich opportunity to study structural characteristics of interorganizational R&D networks. Data gathered on publically funded R&D collaboration projects for the full population of German laser source manufacturers between 1990 and 2010 substantiate this argument and indicate that R&D collaborations between science and laser source manufacturers are an important mode of knowledge accessing and knowledge acquiring processes. For the purpose of this paper we use three main data sources: industry dynamics data, data on social/geographical proximity and patent data.[6]

Industry data: German laser industry (1990-2010)

Exact information on German laser industry dynamics (yearly firm entries and firm exits) stem from a proprietary data-set compiled by Guido Buenstorf. This data set contains full population of German laser source manufacturers between 1969 and 2005 (Buenstorf 2007). Based on this initial data set we use two sources to gather additional data on firm entries and exits after 2005. The first source provides data from the German official company register ("Bundesanzeiger Daten") and the second source is the yearly published Laser Industry business directory published by the b-Quadrat publishing company ("Europäischer Laser Markt Daten"). We decompose the internal organizational structure of all laser source manufacturers in the data set in order to identify and separate laser active firm-level units within these integrated economic entities. Furthermore, we include predecessors of currently exiting firms in our sample. Firm exits due to mergers and acquisitions or failures as well as different modes of population entries like for instance new company formation or spin-offs out of existing firms were treated differently. Changes of firm name and legal status over time have been considered. The full data set includes 217 laser source manufacturers in a time slot between 1990 and 2010. Figure 1 illustrates the industry dynamics[7] and yearly firm entries and exits for German laser source manufacturers between 1990 and 2010. We differentiate between different legal forms (GmbH, GmbH Co., GmbH Co. KG, OHG, Aktiengellschaft) and consider this information by including dummy variables in our estimations (legdumm). The data set includes information on the age of the firms. We include two variables (age, age^2) in our estimations to control for the effect of the maturity of the firm on innovation performance. Finally, we use the data to construct yearly time slots and gather additional data on various dimensions of social as well as geographical proximity.

6 For details on the data sources and variables see appendix I.

7 For a detailed analysis of evolutionary change patterns of the German laser industry between 1969 and 2005 (cf. Buenstorf 2007).

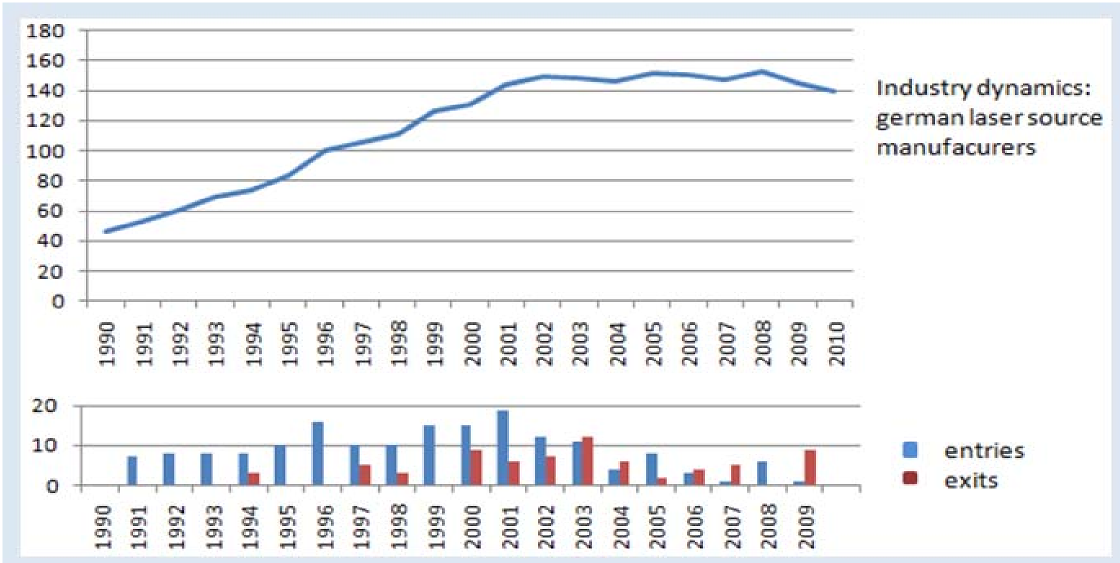


Fig. 1: Industry dynamics: German laser source manufacturers between 1990 und 2010, source: authors own illustration.

Network data and social proximity measures

In order to measure social proximity we obtain data on publicly funded R&D Projects available through an official database from the German Federal Ministry of Research and Technology ("Förderkatalog")[8]. This data source encompasses information on more than 110.000 completed and still ongoing subsidized research projects and provides detailed information on starting point, duration and involved project partners.[9] We identify for the population of 217 German laser source manufacturers 317 research projects whereas some of these projects includes up to 29 project partner from various industry sectors, non-profit research organizations and universities. For R&D projects with more than two partners we assume that all nodes are directly linked to each other. In order to construct an interorganisational R&D network we apply the "expanding selection method" according to Doreinan and Woodard (1992). Beginning with an initial list of 217 laser source manufacturers we add all non-profit research organizations and universities active in the field of laser search to our sample as long as these organizations establish several links to the firms on our starting list. In contrast to the "snowball sampling method" (Frank 2005, Knoke/Yang 2008) we did not include organizations with just one link. Consequently we lock out several

[8] http://foerderportal.bund.de/foekat/jsp/StartAction.do (Accessed in April-Mai 2010)

[9] Other complementary raw data sources on collaboration activities of firms exist. These will be exploited in the near future to complete the data set.

laser-related profit as well as non-profit organizations even if they were involved in one of the 317 research projects. Firms from other industry sectors involved in the research projects considered were excluded as well. Following this procedure we identify 138 laser-related public research organizations (fig. 2). Especially universities (UNI) and applied contract-research institutes (Frauenhofer Institutes) are dominant in our enlarged sample. The number of Technical Universities, Helmholtz Institutes, Leibniz Institutes and Max-Plank Institutes involved in research partnerships with German laser manufacturers is significantly smaller.

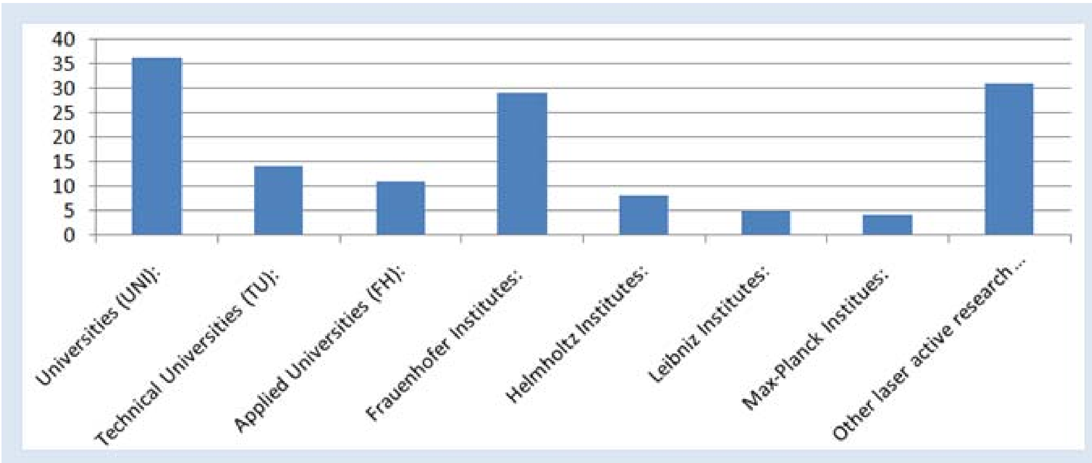


Fig. 2: Laser-related public research organizations, source: authors own illustration.

Finally, we end up with a total number of a total number of 355 network nodes and 317 multi-partner research projects. For R&D projects with more than two partners we assume that all project partners are directly linked to each other. We decompose all multi-partner research projects into dyadic partnerships and construct yearly interorganizational networks. This converted data set allows us to capture and quantify structural network characteristics over time and to account for several key network variables that may influence the innovative performance of laser source manufacturing firms in the period under observation. Fig 3 illustrates the evolution of the interorganizational laser industry network between 1995 and 2007[10]. Entries and exits of nodes and ties are considered on a yearly basis. In 1995 the structure of the network is characterized by a high degree of fragmentation and consists of three network components. The overall density of the network increases over time. In 2007 we can observe the formation of a densely connected network core and a sparsely connected

[10] We use the software package UCINet 6.2 and NetDraw 2.0 for constructing and visualizing the network (Borgatti et al 2002). For the econometric estimations we use data between 1995 -2007. Thus, we illustrate the evolution of the network for this narrowed time slot.

periphery. The emergence of a core-periphery structure is consistent with evolutionary network change pattern in other science based industry sectors like for instance in the US-biotech industry (Powell et al. 2005).

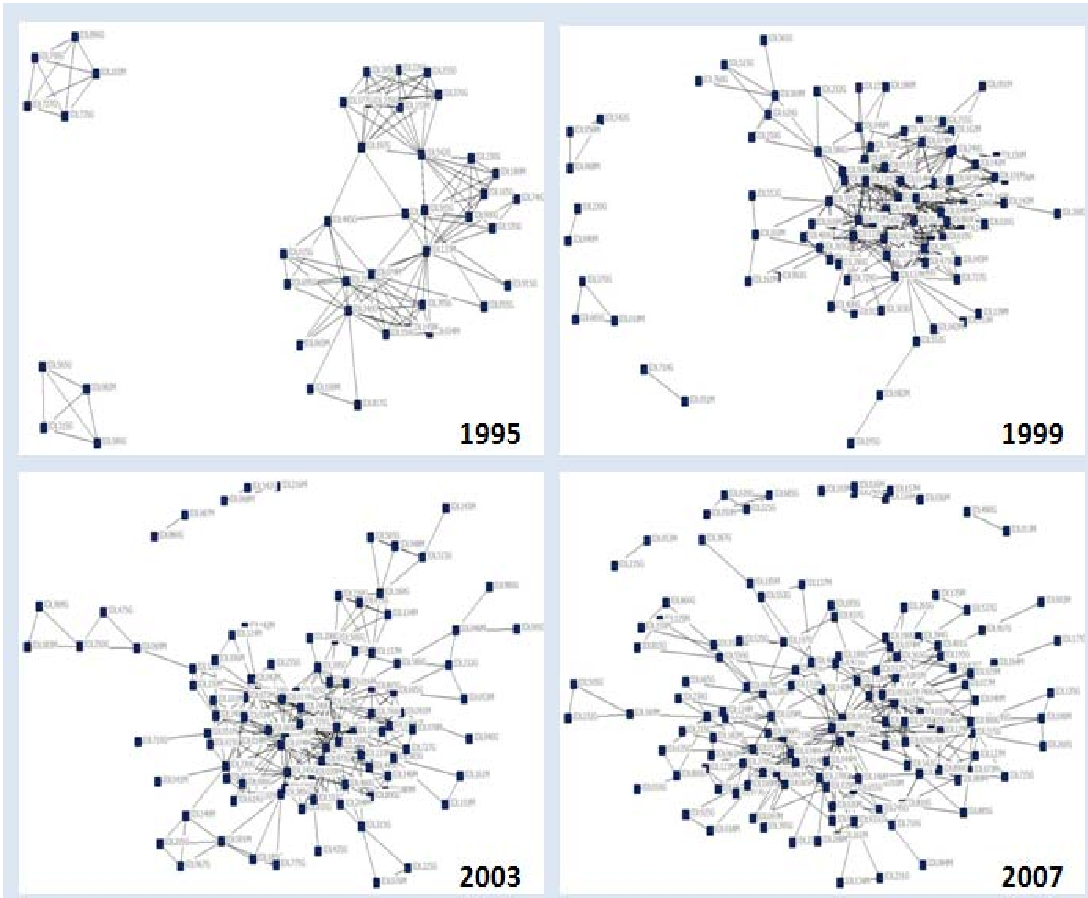


Fig. 2: Structural evolution of the interorganizational R&D network in the German laser industry, source: authors own illustration.

However, in this paper we are predominantly interested in measuring the positions of network actors over time. Social network analysis provides a suitable methodological framework for the empirical analysis of network structures (Wasserman/Faust 1994, Carrington et al. 2005, Knoke/Yang 2008). We calculate multiple centrality measures for the full sample of German laser manufacturers on a yearly basis using the network analysis software package UCINet 6.2 (Borgatti et al. 2002). With regard to our first set of hypothesizes (H1./H1.1./ H1.2.) we focus in the following section on two centrality measures: degree centrality and network centrality.

We use the degree centrality (Freeman 1979) because it is a suitable measure of network insolvent in the sense of being well-connected to other nodes in the same network. The degree centrality measures the direct number of ties one particular network node possesses. We use dichotomized symmetric adjacency matrices in order to calculate the normalized degree measures for all yearly networks between 1990 und 2010. The normalized degree centrality is defined as the degree divided by the maximum possible degree (Wasserman/Faust 1994). Calculated values are expressed as a percentage. According to this measure a node obtains a central network position if the degree is higher compared to other actors in the network. However, even though the degree centrality focuses on the most visible actors in the network and gives us a good idea of network involvement the measure considers solely direct network ties or actor's direct adjacent choices (Wasserman/Faust 1994, p.178). We generate the variable (degree). This measure allows us to specify the extent to which firms gain innovation experience of being well connected to other laser source manufacturers and laser-related public research organizations respectively.

As a second centrality measure we choose the eigenvector centrality (Bonacich 1987) as an indicator of status and prestige of an actor in the network (Wasserman/Faust 1994, p.204 ff). Some scholars argue that centrality of network actor is not simply determined by the direct number of ties; instead the eigenvector centrality a focal actor is determined by the centrality-value of each node it is connected to (Wasserman/Faust 1994). Again, we use dichotomized symmetric adjacency matrices to calculate normalized eigenvector centrality values whereas the normalized eigenvector centrality is defined as the scaled eigenvector centrality divided by the maximum difference possible and centrality values are expressed as a percentage. Thus, in order to measure the status of the firm we calculate the variable (eigenvec). The measure can be used to quantify the extent to which well-connected firms gain innovation experience from being connected to other well-connected high-status firms or laser-related public research organizations.

Whittington et al. (2009, p.104) report similar substantive results in model runs when replacing eigenvector centrality with betweenness centrality measures. Betweenness centrality is a measure for strategically important positions in the network (Wasserman/Faust 1994, p.184). According to this measure firms are central if they connect previously unconnected components or if they are located between many other directly connected organizations in the network. Thus, firms with high betweenness centrality values (between) can facilitate, appropriate or impede information and resource flows in the network (Whitington et al. 209,

p. 104). Consequently we calculate the variable (between) and include this measure in our analysis.

Geographical proximity measures

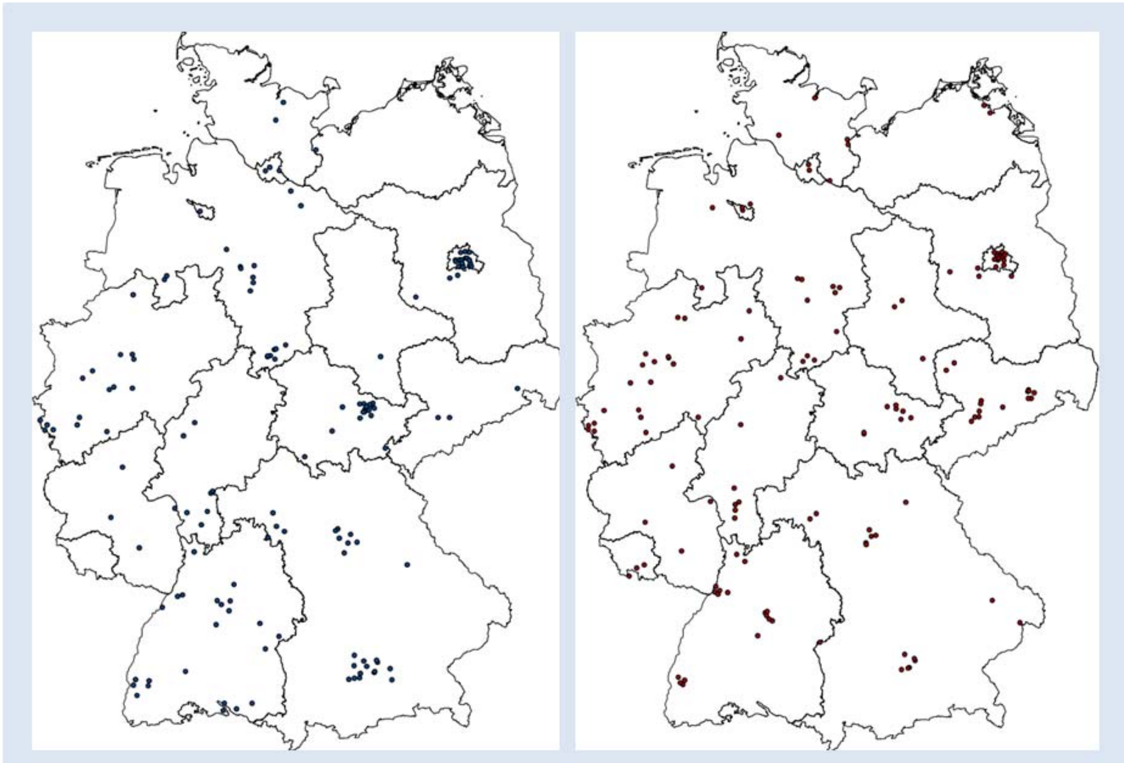
In order to calculate geographical proximity measures, we gather address data and ZIP-codes for the full population of German laser source manufacturers and laser-related public research organizations for each year in the period under observation. Following Sorenson and Audia (2000) we calculate the average distance from a focal firm to every other alter firm in the sample in each year as given in Equation (1).

$$(1) \quad LD_{it} = \sum_{j} \frac{1}{(1 + d_{ijt})}$$

Where j indexes all firms except for firm i and d_{ij} is the distance between firm i and firm j in year t. In a first step we generate the firm proximity variable ($prox_{firm}$). This measure increases as a firm's proximity to other laser source manufacturers in the sample increases. We use GPS-Coordinates (latitudes and longitudes) for the address of the firm and calculate the distance in kilometers between each pair of firms using Equation (2).

$$(2) \quad d_{ijt} = C\left\{\arccos\left[\sin(lat_i)\sin(lat_j) + \cos(lat_i)\cos(lat_j)\cos\left(\left|long_i - long_j\right|\right)\right]\right\}$$

The latitude (lat) and the longitude (long) are measured in radians to ensure that the results are measured in kilometers. In a second step we generate variable ($prox_{pro}$). We perform the same procedure as outlined above to operationalize the geographical closeness to 138 identified laser-related public research organizations. Figure 3 shows the regional distribution of German Laser Source Manufacturers and laser-related public research organizations based on the considerations above in 2007.



Laser Source Manufactures 2007 Laser related PROs 2007

Fig. 3: Regional distribution of German Laser Source Manufacturers and laser-related public research organizations in 2007, source: authors own illustration.

Patent data as measure of innovation output at the level of the firm

A lot has been written about the empirical challenges of measuring innovation processes. Despite the methodological constraints related to the use of patents to measure innovation performance (Patel/Pavitt 1995), patent indicators are commonly used in the analysis of innovation processes (Jaffe 1989, Jaffe et al. 1992). Following other research contributions analyzing innovative performance of firms and industries, we use patent counts per year (patcount) as a proxy for innovation output (Ahuja 2000, Whittington et al. 2009, Stuart et al. 1999). Fritsch and Medrano (2009) show for a sample of West German laser source producers in a time span between 1969 and 1980 that 86 percent of the patents filled were assigned to inventors from the private sector. Thus, we argue that patents as an inductor of laser technology inventions are a meaningful measure of firm level innovation output. To build time series of patent counts for the period 1978-2009 we consider the application year of the patent grants (rather than the year in which the patent was granted). Patent counts include granted patents from the German Patent Office and from the European Patent Office (including Euro-PCT patents). The EPO Worldwide Statistical Database (Version September 2009) was used as patent information source. This version of the database includes patent documents published until September 2009. Due to the length of the patent procedures before a patent is granted, the availability of data on granted patents for the years 2006-2009 is limited. For the patent data gathering process we used the names of the companies in the sample and assigned a patent to a company if its name appeared as a patent applicant and either the patent applicant or the inventor had an address in Germany. To deal with spelling issues in the database search procedure we prepared a list containing various ways of spelling of each firm's name. Additionally, for the allocation of yearly patent counts to each company we traced changes in corporate names, changes in the legal status of the firms, organizational changes and the establishment of spinoffs and considered them accordingly.

The potential effects of previous experience in patenting on innovative performance are captured through the cumulative number of patent counts since 1978 (or since the establishment of the company) (cumulative counts). Again, we take the corporate history of the firms in the sample into account for the construction of this variable. As suggested by previous empirical contributions using patent counts as an innovation proxy, we expect a positive effect of patenting experience on firm's innovative output.

Empirical Model

Table 1 presents the descriptive statistics of the dependent and independent variables. For the econometric estimation we use a narrow sample between 1995 and 2007 due to data availability issues related to incomplete data on R&D collaborations before 1995 and patents after 2007[11]. In order to test the hypotheses derived in the previous sections we model counts of patents using the 13 years of pooled cross section data for an unbalanced panel of 207 German laser industry firms described in the data section. Hence, the unit of analysis is a firm in a given year. We observe a total of 1694 such firm years between 1995 and 2007. On average, we have 8.18 observations per firm.

[11] Strategies to deal with the data availability problem are discussed in the last section.

Table 1: Variable Definition and Summary Statistics

Variable definition		Mean	Sd.	Min	Max
ENDOGENOUS VARIABLE					
Patcount	patents of firm I in year t	0.5159	2.1183	0	31
CONTROL VARIABLES					
Age	age in years	34.7887	23.1792	1	80
age2	age squared	1747.2110	1847.2750	1	6400
log(Cumulative Counts)	cumulative patent counts	0.8200	1.3718	0	5.70711
Legdummy 1	=1 if firm is GmbH & Co.	0.0035	0.0594	0	1
Legdummy 2	=1 if firm is GmbH & Co. KG	0.0555	0.2290	0	1
Legdummy 3	=1 if firm is Aktiengesellschaft (AG)	0.0756	0.2644	0	1
Legdummy 4	=1 if firm is OHG	0.0083	0.0906	0	1
Legdummy 5	=1 if firm is other organizational form	0.0177	0.1319	0	1
dummy1996	=1 if firm is observed in 1996	0.0590	0.2358	0	1
dummy1997	=1 if firm is observed in 1997	0.0620	0.2412	0	1
dummy1998	=1 if firm is observed in 1998	0.0655	0.2475	0	1
dummy1999	=1 if firm is observed in 1999	0.0744	0.2625	0	1
dummy2000	=1 if firm is observed in 2000	0.0773	0.2672	0	1
dummy2001	=1 if firm is observed in 2001	0.0850	0.2790	0	1
dummy2002	=1 if firm is observed in 2002	0.0880	0.2833	0	1
dummy2003	=1 if firm is observed in 2003	0.0874	0.2825	0	1
dummy2004	=1 if firm is observed in 2004	0.0862	0.2807	0	1
dummy2005	=1 if firm is observed in 2005	0.0897	0.2859	0	1
dummy2006	=1 if firm is observed in 2006	0.0891	0.2850	0	1
dummy2007	=1 if firm is observed in 2007	0.0868	0.2816	0	1
NETWORK VARIABLES					
Eigenvec	Eigenvector centrality	0.0302	0.0777	0	0.592
Between	Betweenness centrality	0.0055	0.0250	0	0.407
Degree	Degree centrality	0.0206	0.0513	0	0.472
PROXIMITY VARIABLES					
$Prox_{pro}$	Proximity to PROs in km	1.2150	0.9494	0.3335	4.1888
$Prox_{firm}$	Proximity to other laser firms in km	1167.9540	573.3318	0.2744	9.3684
INTERACTION VARIABLES		36.9469	103.2660	0	860.7060
eigenvec *x* $prox_{firm}$	Interaction term	6.2106	29.5261	0	624.7450
between *x* $prox_{firm}$	Interaction term	24.8449	67.4958	0	675.9900
degree *x* $prox_{firm}$	Interaction term	0.0408	0.1402	0	1.6964
eigenvec *x* $prox_{pro}$	Interaction term	0.0058	0.0269	0	0.4965
between *x* $prox_{pro}$	Interaction term	0.0264	0.0885	0	1.3443
degree *x* $prox_{pro}$	Interaction term	36.9469	103.2660	0	860.7060

Source: author's own calculation

Econometric Issues

As can be seen in Table 1 the endogenous variable of our count data model $patcount_{it}$ shows strong empirical evidence for overdispersion since the sample mean of patents is about 0.52 and much smaller than the sample variance of about 4.49. We test the significance of overdispersion using the procedure proposed by Cameron and Trivedi (1990) and reject the null hypothesis of no overdispersion with a p-value of 0.000.

There are several ways to deal with overdispersion in count data models. Commonly, overdispersion induced by unobserved heterogeneity is accounted for by estimating negative binomial models instead of the intuitive standard Poisson Model. The negative binomial model is more general than the Poisson model, because it allows for increased dispersion by incorporating an additional parameter α and reduces to the Poisson Model as $\alpha \to 0$ (Winkelmann 2003). In Table 3 we provide estimation results for the so-called NB2 model which explicitly models the variance as $Var(patcounts_{it} \mid \mu, \alpha) = \mu(1 + \alpha\mu)$. Since, unlike the Poisson Model, the NB2 Model is not consistent if the variance specification is incorrect we additionally provide Poisson estimation results with robust standard errors in Table 3.

Results

The following section provides preliminary estimation results[12]. Following Whittington et al. (2009) we estimate different models. All models show high overall significance indicated by likelihood ratio tests given separately in Table 2. Regarding the goodness of fit measures depicted in Table 2 there is no clear picture. We interpret all models with caution and with the specific econometric issues in mind which we discussed in the previous section.

Table 2: Model Diagnostics

Model	***Model I***		***Model II***		***Model III***	
Estimation Technique	Poisson	NB2	Poisson	NB2	Poisson	NB2
LogLikelihood	-1314.7472	-1067.5938	-1295.6132	-1062.5151	-1286.2668	-1058.1446
AIC	2671.4944	2179.1875	2643.2264	2179.0302	2636.5337	2182.2892
BIC	2785.6262	2298.7542	2784.5325	2325.7711	2810.4488	2361.6392
LR-Test	770.62362	432.18331	890.34191	442.34066	985.98284	451.08161

[12] The data gathering process has not been completed jet. This concerns especially the collection of collaboration data but also other elements of our data base are still under construction. See footnote 10.

Table 3: Estimation Results

	Model I				Model II				Model III			
Estimation Technique	Poisson		NB2		Poisson		NB2		Poisson		NB2	
	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value
Control Variables												
Age	-0.0303	0.0004	-0.0049	0.6398	-0.0230	0.0158	-0.0042	0.6912	-0.0237	0.0144	-0.0058	0.5846
Age2	0.0002	0.0270	-0.0001	0.6819	0.0001	0.2208	-0.0001	0.5792	0.0001	0.2456	-0.0001	0.6305
Log(Cumulative Counts)	0.7644	0.0000	0.8003	0.0000	0.7596	0.0000	0.7976	0.0000	0.7634	0.0000	0.7986	0.0000
Legdummy 1	-0.4617	0.1290	-0.2397	0.7656	-0.4620	0.1601	-0.2125	0.7903	-0.3295	0.3164	-0.0784	0.9219
Legdummy 2	0.0546	0.8143	0.0740	0.7697	0.1155	0.6212	0.0933	0.7139	0.1273	0.5902	0.1377	0.5892
Legdummy 3	0.6015	0.0013	0.6850	0.0013	0.6990	0.0004	0.7890	0.0003	0.6721	0.0009	0.7813	0.0004
Legdummy 4	0.3501	0.4368	0.4094	0.5018	0.6070	0.1960	0.6110	0.3281	0.8207	0.0735	0.9331	0.1540
Legdummy 5	-1.5859	0.0977	-1.3839	0.1891	-1.6152	0.0922	-1.4291	0.1750	-1.6047	0.0950	-1.4018	0.1830
Dummy1996	-0.2330	0.4947	-0.2740	0.4348	-0.1974	0.5516	-0.2233	0.5240	-0.1881	0.5611	-0.2347	0.5040
Dummy1997	-0.3828	0.2553	-0.2690	0.4500	-0.3289	0.3096	-0.2236	0.5287	-0.3216	0.3041	-0.2536	0.4765
Dummy1998	-0.2518	0.4428	-0.0992	0.7739	-0.2043	0.5189	-0.0255	0.9411	-0.1934	0.5309	-0.0491	0.8871
Dummy1999	-0.3967	0.1868	-0.1912	0.5702	-0.3098	0.2939	-0.0962	0.7775	-0.3244	0.2696	-0.1154	0.7364
Dummy2000	-0.7127	0.0130	-0.5521	0.1069	-0.6049	0.0262	-0.4351	0.2081	-0.6013	0.0224	-0.4390	0.2050
Dummy2001	-0.9195	0.0098	-0.5560	0.1033	-0.7713	0.0250	-0.4130	0.2322	-0.7483	0.0245	-0.4087	0.2384
Dummy2002	-1.1272	0.0005	-0.5802	0.0846	-1.0425	0.0010	-0.4617	0.1742	-1.0035	0.0013	-0.4628	0.1752
Dummy2003	-1.3120	0.0001	-0.7903	0.0225	-1.2538	0.0001	-0.7202	0.0386	-1.2117	0.0002	-0.7237	0.0393
Dummy2004	-1.1820	0.0006	-0.7339	0.0307	-1.1747	0.0008	-0.6051	0.0774	-1.1271	0.0009	-0.6342	0.0660
Dummy2005	-1.4182	0.0001	-0.9826	0.0050	-1.3751	0.0001	-0.8524	0.0159	-1.3613	0.0001	-0.9015	0.0110
Dummy2006	-2.0771	0.0000	-1.4561	0.0001	-1.9742	0.0000	-1.3242	0.0005	-1.9657	0.0000	-1.3302	0.0005
Dummy2007	-2.3429	0.0000	-2.0097	0.0000	-2.2466	0.0000	-1.8482	0.0000	-2.2468	0.0000	-1.8827	0.0000
Proximty and Network Variables												
eigenvec	-	-	-	-	-2.0165	0.3243	-0.0305	0.9893	-5.7441	0.3388	-5.8529	0.3812
between	-	-	-	-	-15.4085	0.0044	-14.5245	0.0242	-34.0418	0.0500	-35.3501	0.1083
degree	-	-	-	-	7.6089	0.0209	3.8070	0.2750	17.7874	0.0321	17.7341	0.0910
$prox_{pro}$	-	-	-	-	0.1734	0.0439	0.1258	0.1704	0.1600	0.0843	0.0757	0.4669
$prox_{firm}$	-	-	-	-	-0.0003	0.0450	-0.0002	0.1110	-0.0002	0.0925	-0.0002	0.3532
eigenvec *x* $prox_{firm}$	-	-	-	-	-	-	-	-	-0.0021	0.6747	-0.0004	0.9479
between *x* $prox_{firm}$	-	-	-	-	-	-	-	-	0.0081	0.6846	0.0097	0.6583
degree *x* $prox_{firm}$	-	-	-	-	-	-	-	-	-0.0009	0.9010	-0.0048	0.6029
eigenvec *x* $prox_{pro}$	-	-	-	-	-	-	-	-	4.6243	0.0294	3.6181	0.1167
between *x* $prox_{pro}$	-	-	-	-	-	-	-	-	5.4579	0.4309	5.4529	0.4956
degree *x* $prox_{pro}$	-	-	-	-	-	-	-	-	-6.9534	0.0641	-4.8259	0.2168

Souce: Authors own calculation, base outcome is legal status GmbH, Year 1995.

To begin with, there is strong empirical evidence for a negative impact of age on the innovation output of the firm in the German laser source industry.[13] Additionally, and in line with our reasoning in the section discussing patent data, experience in patenting has a positive and significant effect on yearly patent counts in all models estimated. Our analysis considers the effect of different types of organizational forms captured with the dummies for legal status of the firm (for details see Table 1). As expected firms organized as a corporation that is a company limited by shares, i.e. owned by shareholders, and may be traded on a stock market (Aktiengesellschaft) are significantly more innovative than companies with limited liability (GmbH). This result may be induced by company size effects since these types of companies (Aktiengesellschaft) are usually the largest firms in the sample. We account for fixed year effect by including year dummies. At a first glance, the innovation output decreases over time as indicated by significant negative fixed year effects in all models. There are competing explanations for this time effect. On the one hand this could be induced by the constrained data availability for the most recent years. On the other hand there may be a tendency to use alternative ways to appropriate the economic benefits of R&D investments in this particular industry.

Concerning the measure for social proximity our results are ambiguous. Firstly, degree centrality, which measures the direct number of ties of firms in the sample, turns out to be relevant for a firm's innovative performance. That is, hypothesis H.1.1 is supported by three out of four models using degree centrality. In contrast, we do not find any significant effect of eigenvector centrality which proxies the number of high status partners of a focal network actor. This result is robust across all model specifications employed in our analysis. Hence, hypothesis H.1.2. is rejected. To sum up, our results show that innovative performance is positively affected by the number of direct partners rather than by the number of indirect partners.[14]

Regarding the geographical proximity our analysis shows that co-location to laser related public research organization promotes patenting activity of firms in the sample. This is as expected and stated in hypothesis H.2.1. In contrast, co-location between laser source producers turns out to have negative significant effects in our estimations. In other words co-location between laser source manufactures reduces the innovative performance which leads to the rejection of hypothesis H.2.2.

[13] Furthermore there some evidence in the baseline model for a u-shaped curvature of the age-effect.

[14] We included a betweenness centrality proxy to test for results reported by Withington et al. (2009). Our analysis suggests a significant negative effect of betweenness on firm's innovative performance. This result should be interpreted with caution since we face strong data constraints.

Finally, the interaction terms between geographical and social proximity between firms show no significant effect. That is, there is no empirical evidence for hypothesis H.3.1. However, we find empirical support for the interdependence of social and geographical proximity of firms to public research organization. Interestingly, we found substitutive and complementary interdependent effects depending on different types of centrality measures. In other words, the results support hypothesis H.3.2. The implications steaming from these hypothesis call for further research on the interdependent effects of social and geographical proximity in the German Laser Source Industry[15].

Conclusion and further research

This contribution represents a very first step in closing the identified research gap. Using a unique data set on the German Laser Industry covering the period between 1995-2007, we estimate several pooled cross-section count data models in order to test the distinct and interdependent effects of social and geographic proximity on firms' innovativeness.

The results from Whittington et al. (2009) suggest that in the US Biotech industry rather cooperations to high status organizations measured in terms of eigenvector centrality have a significant positive effect on firm innovativeness. In order to measure social proximity for the German laser industry we focus on two types of indicators: degree centrality and eigenvector centrality. We find empirical support for the positive effect of degree centrality on firm-level innovation output. Interestingly, the results for the German laser industry indicate that specially a large number of direct partners measured in terms of degree centrality drives innovation output.

Regarding the geographical proximity Whittington et al. (2009) report positive significant effects of co-location between US biotech firms and non-significant effects of geographical proximity to PROs. These results implicate that rather co-location to other biotech firms rather than to biotechnology research organizations drive innovation. Surprisingly, our results for the German laser source industry suggest quite different implications. In this sector, co-location to other laser source manufactures reduces the probability to innovate whereas co-location to laser related research organizations fosters innovation output.

[15] We found similar results in model runs (poisson as well as NB2 specification) with a lagged dependent variable (yearly patcount lag) in order to account for delayed innovation effects due to geographical as well as social proximity effects.

Finally, the interaction terms between geographical and social proximity between firms and other organizations reported Whittington et al. (2009) report negative relationship of the combined global centrality and firm-proximity effects on firm-level innovation output. More interesting, as comparable with our results, are the positive significant effects of the joint global centrality and PROs-proximity effects on the innovativeness of firms. In other words, a large number of high status partners and co-location to PROs in biotech generates a joint innovation effect which is more than the simple sum of distinct effects. We found the same effect for the German Laser Industry.

Further research needs to address the following theoretical as well as methodological issues. By focusing on the German laser source manufactures and laser related PROs, this contribution adopts a very narrow definition of the industry. In order to capture network effects on innovative performance appropriately, further research should take a broader perspective and include laser related up- and down-stream companies along the industry value chain involved in R&D projects of core industry firms. The consideration of more sophisticated indicators of firm’s position, applying the broader definition of network structure discussed above, could contribute to clarifying contradictory results. Moreover, in what concerns the geographic proximity effects, our analysis focuses on geographical proximity of the laser source manufactures to each other and between laser source manufactures and laser-related public research organizations. This approach neglects the effects of geographical proximity in the exploitation of interindustry knowledge spillovers. Further research could include indicators capturing the effects of firm’s geographical embeddenness in diversified industrial agglomerations and in urban areas. Furthermore, the model specification could be improved by including several additional control variables such as firm’s size and collaborative experience. Additionally, the nature of technological innovation together with the different strategies for knowledge appropriation substantiates the assumption that the process underlying the tendency to patent at all is different from the processes underlying successful and repeated patenting activities. To account for these different processes most sophisticated estimation approaches – hurdle models or zero-inflated models – could be applied. These challenges build up the next steps on our research agenda.

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Appendix I: Overview of Variables

Data source:	Variables:	Abbreviation:
Industry data:		
-firm-level measures	firm age	(age)
	firm age squared	(age2)
	legal status	(legdummy)
- Industry-level measures	yearly fixed effects	(dummy-year)
Network proximity data:		
-firm-level measures	degree centrality	(degree)
	eigenvector centrality	(eigenvec)
	betweenness centrality	(between)
Geographical proximity data:		
-firm-level measures	proximity to other firms	($prox_{firm}$)
	proximity to public research organizations	($prox_{pro}$)
Patent data:		
-firm-level measures	yearly patent count	(patcount)

Appendix II: Overview of yearly patent counts per firm