The impact of evolving ego-network structures on innovation output - empirical evidence from the German laser industry

Authors:

Kudic, M.; Buenstorf, G. ; Guhr, K.

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Abstract:

In this paper we argue that a closer look at ego-network structures is needed to disentangle the relationship between cooperation activities and subsequent firm-level innovation output. Especially, the structural configuration of a firms' individual portfolio of cooperative ties – a so called ego-network – is assumed to have a significant effect on the innovative performance. However, ego-networks are not static, they change continuously over time. The empirical analysis of evolving ego-networks and subsequent firm-level innovation consequences constitutes a still widely unexplored field of research. Consequently, we apply an evolutionary perspective and resort to a unique longitudinal data-set to shed light on the raised research question. Applied network data encompass all research and development (R&D) cooperations funded by the German Federal Ministry of Education and Research and provide exact time tracking of tie-formations as well as tie-terminations for the full population of German laser source manufactures between 1990 and 2010. We construct yearly networks in order to analyze the dynamic change of focal firms' ego-network structure over time. In order to measure firm-level innovation output, we use yearly patent grants as dependent variable. Empirical results provide evidence for the firms' yearly cooperation activities on innovation performance. The ego-network size turns out to have in all of our models positive and significant effect on firms' patenting activity. Results for ego-network density are ambiguous and call for further research in this area.

JEL-classification: O31, O32, L25

Key words: ego-network structure, network evolution, innovation output

1. Introduction

During the last decades we can observe an increasing intensity of R&D collaborations in high-tech industries (Hagedoorn 2002). Firms increasingly face the challenge of managing a portfolio of multiple collaborations simultaneously. Economic sociologists capture this phenomenon under the term "ego-network". The motives behind these ego-networks are manifold. By managing a portfolio of collaborative ties firms can realize risk diversification (Hagedoorn 1993) and cost savings through synergy effects (Hagedoorn 2002). Furthermore, scholars argue that collaborations provide an additional mode of entering new markets (Johanson/Mattsson 1988). Moreover, collaborations provide access to new stocks of tacit as well as implicit knowledge (Grant/Baden-Fuller 2004) and increase the firm's ability to innovate and gain competitive advantages (Noteboom 2008). Nevertheless, we argue that a closer look at ego-network structures is needed to disentangle the relationship between cooperation activities of firms and subsequent innovation consequences. On the one hand, the structural configuration of an ego-network is assumed to have a significant effect on firm's innovative output. In other words, various ego-network characteristics such as size, density, heterogeneity in terms of partner configuration, internationality and financial funding affect the innovativeness of the focal firm. On the other hand, ego-networks are not static, they change continuously over time. The empirical analysis of evolving ego-networks and subsequent firm-level innovation consequences constitutes a still widely unexplored research area. Consequently, an evolutionary perspective is needed to analyze the relationship between various dimensions of ego-network structures and firm-level innovative output over time.

In order to substantiate our line of argument and derive a set of testable hypotheses we refer to **two theoretical perspectives**. Firstly, there is a well established stream of literature dealing with the relationship between firm-level cooperation activities as well as network positioning and firm performance (Powell et al. 1996; McEvily/Zaheer 1999; Zaheer/Bell 2005). For instance, past studies examine consequences of network membership and ego-network composition on various dimensions of startups' 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 one specific aspect of firm-level performance, namely innovation output. Previous studies have predominantly explored the impact of various types of network positions on the firm's innovative performance (Powell et al. 1996, Ahuja 2000). Secondly, we can observe an increasing interest in the evolution of interorganizational networks (Gulati/Gargiulo 1999; Hite/Hesterly 2001, Powell et al. 2005). However, we still have a rather incomplete understanding of how endogenous as well as exogenous determinants and mechanisms affect network evolution and what kind of innovation related performance consequences arise for firms over time. Finally, it is remarkable that the majority of past as well as contemporary network studies focus on the biotech industry. Summarizing, until now we did not find any contribution that highlights the relevance of evolutionary network change patterns for the innovativeness of firms in the German laser industry. It remains an open question to what extend changes in firms' cooperation propensity and the evolution of ego-networks affects the firm-level innovation output of laser source manufacturers over time.

Consequently, we seek to answer the following **two research questions** by analyzing the full population of German laser source manufacturers between 1990 and 2010. Firstly, in which way do firm specific cooperation propensities and structural characteristics of ego-networks influence firm-level innovation output? Secondly, how do changes in cooperation activity and changes of ego-network configuration influence the innovativeness of these firms over time? Regarding the first question we concentrate on the impact of ego-network size and density on firm's patent activities. To answer the second question we explicitly consider the impact of ego-networks structural change over time on subsequent changes in firm-level innovation output.

The paper is organized as follows: the next section provides a literature review on the relationship between ego-network structure and firm-level innovation output and on interdisciplinary contributions in the field of network evolution. Based on this discussion we derive our hypotheses. 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 subsequent 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 of the limitations of the results and outlines fruitful avenues for further research.

2. Theoretical background and hypotheses development

Knowledge, networks and innovation

Even though economists recognized the importance of knowledge quite early – for instance as the decisive factor in production processes (Marshall 1920) – knowledge retains in classic-neoclassic theories for a long time a public good. Years later, Penrose (1995) identifies the knowledge base of a firm as its main asset. Management scholars realize the importance of knowledge and learning processes for the competitive advantage of firms (Grant 1996, Kogut/Zander 1992). From this perspective knowledge becomes the strategically most important resource of a firm. Nearly at the same time, a new stream of research emerged in economics in which the role of knowledge for economic development and the success of firms is explicitly recognized and constitutes the cornerstone of economic analysis. Neo-schumpeterian scholars consider – under the assumption of bounded rationality – the tacitness of knowledge and subsequent consequences for knowledge transfer and learning processes in dynamic environments (Hodgson,Samuels, Tool 1994; Dopfer 2005; Hanusch, Pyka 2007).

However, the question remains in which way firms get access to knowledge. Scholars' highlights in this context the importance of two different knowledge channels for firms: internal and external knowledge sources (Malerba 1992). 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 other words, firms have the opportunities to access and generate new knowledge by overstepping the organizational boundaries and engaging in various types of strategic alliances and collaborative projects. Especially in dynamic changing environments, the ability to identify and exploit various sources of knowledge becomes in this context a key issue for firms (Cohen/Levinthal 1990). In this paper we focus particularly on interorganizational R&D networks as external channel for firms to get access to knowledge.

An evolutionary perspective on networks

However, overall networks as well as ego-networks are not static, they evolve undeviatingly over time. Brass et al. (2004) define a network "[…] as a set of nodes and the set of ties representing some relationship, or lack of relationship, between the nodes". From an evolutionary perspective changes in network structures are the result of events regarding the two basic elements – nodes (i.e. organizations) and ties (i.e. relationships between organizations) – in networks (Glückler 2007). This means, networks evolve as organizations enter and exit the population (i.e. change in the number of nodes) and as organizations build and dissolve network relationships with other actors (i.e. number of ties changes). Structural network changes occur due to exogenous as well as endogenous factors. Thus, the mechanisms and drivers of network change obtain a prominent role in an evolutionary context. With other words, in comparison to the more general term "network dynamics" the concept of "network evolution" contains "[…] a stricter meaning that captures the idea of understanding change via some understood process" (Doreian/Stockman, 2005, p.5). A look at recent theoretical as well as empirical contributions in the broader field of network research indicates that scholars from various disciplines increasingly address the evolutionary change of complex networks (Pyka/Scharnhorst 2009; Kudic 2011). For instance, researchers in physics (Albert/Barabasi 2002; Dorogovtsev et al. 2000; Bianconi/Barabasi 2001), biology (Vazquez et al. 2003), sociology (Powell et al. 1996, Doreian/Stockman 2005, Snijders et al. 2009; Powell et al. 2005), management science (Walker et al 1997, Gulati/Gargiulo 1999 Koka et al. 2006, Baum et al. 2009) or economics (Bala/Goyal 2000; Jackson/Watts 2002; Jackson 2008; Pyka/Scharnhorst 2009) have analyzed the determinants and mechanisms of structural network change and widened our understanding of how complex networks evolve over time. However, it is remarkable that the majority of contemporary network evolution studies focus on the biotech industry (Powell et al 2005, Amburgey et al. 2008). Research based on other science based industries is needed to validate previous results. Moreover, previous empirical studies on network evolution focus predominantly on overall network level whereas research from the focal actors' perspective is rare (Hite/Hesterly 2001). Correspondingly, Wassmer (2010, p.165) comes in his comprehensive review of the literature on alliance-portfolios[1] to the conclusion "[…] little is still known on how alliance portfolio configurations change over time and what drives this evolution".

Structural configuration and the impact of ego-networks on innovation output

Alliance and network literature provides a broad variety of definitions to capture and confine the concept of ego-networks. An ego network is defined from the focal actor's perspective and consists of a set of direct, dyadic ties between the focal actor and the alters as well as indirect ties between the alters (Wasserman/Faust, 1994). Ego networks do not include second-tier ties or second-step ties to which the focal actor is not directly connected. As we are interested in the relationship between individual cooperation activities of firm's and subsequent innovation consequences, we shift the attention from the overall network perspective to the individual ego-network structure and changes in ego-network structure over time. Scholars have analyzed the relationship between ego-network structure and firm-level on various dimensions of firm performance (Baum et al. 2000) and innovation output (Stuart 2000, Ahuja 2000, Graf/Krüger 2011). Nevertheless, research on the structural configuration of evolving ego-networks is still scant. Wassmer (2010, p. 165) concludes that until now only

1 The terms ego-network (Hite/Hersterly 2001), alliance constellation (Das/Teng, 2002) or alliance portfolio (Hoffmann 2005; Lavie, 2007) are often used interchangeable. For an overview and comparison of definitions and concepts see: Wassmer (2010).

a limited number of case-based studies have addressed the issue of how alliance portfolios evolve and how their configuration changes over time (e.g. Dittrich et al., 2007; Dyer & Nobeoka, 2000). Consequently, further empirical research is needed to disentangle the relationship between various dimensions – size, density etc. – ego-network heterogeneity and firms' innovativeness in a dynamic setting. Until now we did not find any empirical study based on longitudinal data that analyzes the impact of evolving ego-networks structural configuration on firm level innovation output in the German laser industry.

Hypotheses development: cooperation propensity, ego-network structure and innovation

Especially in science-based industries it is of vital importance to have access to various types of information and knowledge. Cooperation provides an important external channel for firms to get access to knowledge and learn from each other. In this context there are at least two theoretical lines of argument which becomes relevant. On the one hand collaborative arrangements provide access to new and complementary stocks of knowledge (Rothaermel, 2001; Grant/Baden-Fuller, 2004). These types of knowledge-related cooperations predominantly serve as external knowledge transfer channels. According to Polanyi (1958) especially stocks of explicit knowledge are easy to transfer as the exchange of codifyable knowledge does not require personal contact between the involved parties. Consequently, firms do not necessarily have to generate new stocks knowledge within the boundaries of the firm. Instead, they can collaborate with other firms or public research organizations to get access to complementary stocks of explicit knowledge. On other hand scholars argue that collaborations open up arenas of interorganizational learning processes (Hamel, 1991; Khanna et al., 1998; Kale et al., 2000). In contrast to explicit knowledge, implicit knowledge refers to more complex types of knowledge which are not easy to share (Polanyi 1958). This type of knowledge encompasses specific capabilities, experiences and skills which are not codifyable. The successful exchange of implicit knowledge requires mutual learning processes and a high degree of trust between the involved parties. In this context, scholars argue that firms' ability to access new knowledge from external sources becomes itself a more relevant source for competitive success than the present stock of knowledge within firms (DeCarolis/Deeds 1999). In their seminal study Cohen and Levithal (1990) point out that firms innovative capabilities are determined by the ability to recognize valuable new knowledge, assimilate it, and apply it to commercial ends. Furthermore, they come to the conclusion that the "[…] knowledge diversity also facilitates the innovative process […]" (Cohen/Levinthal 1990: 131). Consequently we argue that the firms' ability to identify potential collaboration partners and successfully initialize new collaborative R&D projects exerts a positive effect on the firms' innovation output. Previous considerations allow the formulation of our first hypothesis:

H-1: In the German laser industry, the higher the firms' cooperation propensity (measured by yearly cooperation counts) the greater the subsequent innovative performance (measured by yearly patent grants)

Empirical studies indicate (Lavie 2007) that firms increasingly face the challenge to manage multiple alliances simultaneously. Motives for maintaining an alliance portfolios (or "ego-network") are manifold. For instance, scholars argue that firms can realize synergy effects by managing multiple collaborative agreements at the same time which subsequently lead to cost savings (Hoffmann 2005, Hagedoorn 2002). Closely related to cost saving are risk related motives. An ego-network constitutes nothing else but a portfolio of firm specific investments. Thus, firm can realize risk diversification effects by managing multiple collaborative arrangements simultaneously (Markowitz 1952, Hagedoorn 1993, Sivadas/Dwyer 2000). Furthermore, in science bases industries time-savings which can be realized through cooperation becomes increasingly important. Mowery et al. (1996 p. 79) argues that the perceived shrinkage in product life cycles increases the pressure on firm in technology intensive industries. They conclude that the rapid penetration of foreign markets becomes increasingly important, a goal which can be more easily achieved through alliances. This argument becomes even more important in an alliance portfolio context as multiple collaborative R&D endeavors with diverse heterogeneous partners enable firms to accelerate the development of new ideas and products. Finally, as outlined above collaborative arrangements provide access to complementary stocks of knowledge (Rothaermel, 2001; Grant/Baden-Fuller, 2004) and open up arenas of interorganizational learning processes for the involved organizations (Hamel, 1991; Khanna et al., 1998; Kale et al., 2000). However, with an increasing number of directly connected partners the accessibility to various types of knowledge stocks rise. Keeping in mind the previous arguments we formulate our second hypothesis:

H-2: In the German laser industry, the greater the size of the ego-network (measured by the number of direct partners) the higher the subsequent innovative performance (measured by yearly patent grants)

A central debate in alliance and network literature occurs around two lines of argument. On the one hand, so called "structural hole" theory (Burt 1992) highlights the importance of structural holes and brokerage activities of actors in sparsely connected networks. On the other hand, proponents of "closure theory" (Coleman 1988) argue that a high degree of connectedness is of salient importance for subsequent performance outcomes of network actors. Recent studies (Burt 2000; Rowley et al. 2000) indicate that these two perspectives are not necessarily mutual exclusive. However, for the purpose of this paper we follow the latter strand of literature. According to closure theory a high degree of connectedness increases the visibility of network actors. The degree of connectedness in an ego-network allows us to specify the extent to which firms gain innovation experience of being directly as well as indirectly connected to other laser source manufacturers or laser-related public research organizations. A high number of linkages in a densely connected ego-network lowers the risk of dependence to other organizations due to the existence of redundant ties and optional knowledge channels to relevant partners. These considerations allow for the formulation of our last hypothesis[2]:

H-3: In the German laser industry, the higher the degree of connectedness in firm specific ego-networks (measured by the yearly ego-network density) the greater the firms' subsequent innovative performance (measured by yearly patent grants)

3. Methods

In this paper we focus on the German laser industry. The acronym LASER stands for Light Amplification by Stimulated Emission of Radiation. We choose the German Laser Industry for several reasons. First, 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 (i.e. laser industry) is clearly underrepresented. Second, the German Laser Industry can be characterized as a science based industry (Grupp 2000) in which firms' ability to innovate is a key factor of firm performance and success. Internal as well as external channels of knowledge access are of vital importance in these industries. Recent empirical findings indicate a high cooperation propensity of German Laser source manufacturers during the last twenty years (Kudic et al. 2011). Finally,

2 Even though we argue in this paper that the connectedness of an actor exerts a positive effect on innovation output one has to keep in mind contrary lines of argument. For instance, Uzzi (1997) bring forward the "overembeddedness" argument according the positive effects of network embeddedness turn into opposite at some point.

laser technology requires knowledge from various academic disciplines such as physics, optics and electrical engineering (Fritsch/Medrano 2009). Consequently, the German laser industry provides a rich opportunity to study knowledge transfer and learning processes in interorganizational R&D networks.

Our analysis is based on the full population of German laser source manufacturers between 1990 and 2010.[3] In order to test our hypothesis we used 20 years unbalanced panel in the period between 1990 and 2010 for 215 German laser source manufacturing firms. We choose yearly counts of patent grants as dependent variable and incorporate a lag-structure for the patent count variables of one year to consider the time offset between dependent and independent variables. Hence, in this paper the unit of analysis is a firm in a given year. We observe a total of 2415 such firm years in the period under observation.

We use publicly funded R&D projects in order to construct the industry network. To identify all relevant network actors we apply the “expanding selection method” according to Doreian and Woodard (1992). Beginning with an initial list of 215 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 during the period under observation. Following this procedure we identify 138 laser-related public research organizations. In a second step we decompose the overall network into twenty time-discrete network layers, one network for each year. Each network layer is based on a symmetric undirected and binary adjacency matrix (Wasserman/Faust 1994) whereas the number of rows or columns is determined by the number of active laser source manufacturing firms in a given year. This converted data set allows us to capture and quantify structural network characteristics over time and to account for several key network variables – especially ego-network measures – that may influence the innovative performance of laser source manufacturing firms in the period under observation. We use ego-network procedures implemented in UCINET 6 in order to calculate ego-network measures (Borgatti et al. 2002).

For the patent data gathering process we have 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 we prepared a list containing various ways of spelling of each firm’s

3 Industry data stem from proprietary industry data on German laser industry compiled by G. Buenstorf.

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 spin-offs and considered them accordingly.

4. Data and variable specification

Data sources

The analytic part of the paper is based on three main data sources: industry data, network data and patent data. Industry data stem from a proprietary data-set containing the full population of German laser source manufacturers between 1969 and 2005 (Buenstorf 2007). Based on this initial data set we use further sources to gather additional information on firm entries and exits after 2005.[4] For this paper we choose the firm level. We decompose the internal organizational structure of all laser source manufacturers in the data set to identify laser active firm-level units. 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 215 laser source manufacturers in the period under observation. Ego-network data stem from an official database on publicly funded R&D collaboration projects provided by the German Federal Ministry of Research and Technology[5]. These data sources encompasses in sum information on more than 110.000 completed and still ongoing subsidized research projects and provide detailed information on starting point, duration, funding and characteristic features of involved project partners. We identify for the population of 215 German laser source manufacturers more than 346 R&D projects with up to 29 project partners 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. The EPO Worldwide Statistical Database (Vers. Sep./09) was used as patent information source. This version of the database includes patent documents published until September 2009. Patent counts include patent applications as well as granted patents from the German Patent Office and from the European Patent Office (including Euro-PCT patents).

4 Firstly, we use data provided by the German official company register and secondly we use the yearly published laser industry business directory published by the b-quadrat publishing company.

5 http://foerderportal.bund.de/foekat/jsp/StartAction.do (accessed in May-October 2010).

Variable specification

We use patent data as ***dependent variable*** in order to measure firm-level innovation output. 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 indicator of laser technology inventions are a meaningful measure of firm level innovation output. 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 network studies analyzing innovative performance of firms and industries, we use patent counts per year as a proxy for innovation output (Ahuja 2000, Whittington et al. 2009, Stuart et al. 1999, Stuart 2000). We specify use patent grants [*yearlypat*] as dependent variable.

Based on yearly network data we calculate one cooperation propensity measure and two basic ego-network measures as ***independent variables*** for our empirical model. We start with a measure for firm specific cooperation propensity. In order to capture the firm specific cooperation activities of a firm over time we define a yearly count variable [*yearly coop*]. The first ego-network measure is a size variable [*ego-size*]. It is defined by the number of actors (alters) that are directly connected to the focal actor (ego). The second ego-network measure is a density variable [*ego-density*]. This variable is defined as the number of de facto ties at a given point in time divided by the number of pairs, times 100.[6] Furthermore, we calculate an additional measure for ego-network size [*degree-cent*] in order to control our result for ego-network size. The degree centrality is defined from an overall network perspective and considers the direct number of ties one particular network node possesses. We use the ego-network and degree centrality standard procedures implemented in UCINET 6 (Borgatti et al. 2002) to generate the network variables. The routine systematically constructs the positions and ego-network for every actor within the network. We repeated this procedure for each year.

Furthermore, we account for a number of control variables in our empirical model. We include two age variables in the model, both measured in years. The first variable [*firm age*] explicitly measures the age of the firms actually in the sample. The second age variable is the squared term [*sq firm age*]. Besides, we include two experience measures in the model. The

6 The number of pairs of alters in an ego-network is a measure for the maximal connectedness - i.e. potential ties that can be realized – of the ego-network.

first experience measure captures the firms' ability to attract new publicly funded collaboration projects. We operationalize this variable [*cum coop*] by cumulating the number of yearly initialized collaboration projects over time. This variable can be interoperated as the firms' propensity to collaborate and reflects collaborative experience of the firms in the sample. The second experience measure incorporates firms patenting ability. The variable [*cum pat*] is defined as the cumulative number of yearly patent counts. Moreover, we define the variable [cooperation funding] as the amount of public funding per firm for participating in cooperation projects. Finally, we include two types of categorical variables by constructing dummies for firm size [*size-dum1…size-dum5*][7] and legal status [*legal-dum1…legal-dum6*][8], each variable with five categories. Finally, we account for the geographical location of the firm in our model by constructing a set of dummy variables. Each of these variables represents a German federal state ("Bundesland"). We end up with five geographical location variables [*local-dum1…local-dum5*] in our model.[9]

5. Empirical analysis – models specification and results

Empirical model specification

Following Ahuja (2000) and Stuart (2000) we estimate different types of panel count models. We start with a panel poisson regression approach for longitudinal count data (Hausman et al. 1984). As homoscedastic, normally distributed errors cannot be assumed in this context, a linear regression model is not appropriate. Firstly, a panel poisson model with random effects is used, whereas an additional effect μ_i is inserted in order to account for firm-specific heterogeneity (Ahuja 2000). The model is defined as:

$$\boldsymbol{E}\left(\frac{\boldsymbol{p}_{IT}}{\boldsymbol{X}_{it-1}}\right) = \boldsymbol{e}^{\boldsymbol{X}_{it-1}\,\boldsymbol{\beta}+\boldsymbol{\mu}_i} .$$

However, it turns out that the endogenous variable in our model [*pat-grants*] shows strong empirical evidence for overdispersion as the sample mean of patents is much smaller than the

7 Firm size is defined by the number of employees. We use the following size categories: size-dum1 = micro firm = 1-9 employees; size-dum2 = small firm =10-49 employees; size-dum3 = medium firm =50-249 employees; size-dum4 = large firms = 250-749 employees; size-dum5 = very large firms = more than 750 employees. Missing data for the number of employees were extrapolated based on employee data for same firms but other firm years.

8 Legal status of the firm in the sample is categorized as follows: Legal-dum1 = firm is a sole proprietor; Legal-dum2 = GmbH; Legal-dum3 = GmbH & Co; Legal-dum4 = GmbH & Co Kg; Legal-dum5 = AG; Legal-dum6 = OHG.

9 We included the five regions with the highest concentration of laser source manufacturing firms in the estimation. For a detail exploration of geographical firm concentration in the German laser industry see (Kudic et al. 2011).

sample variance. 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). The negative binomial model (NB2) explicitly models the variance as: $Var(patgrants_{it} \mid \mu, \alpha) = \mu(1 + \alpha\mu)$. In order to ensure the robustness of our result we choose the following estimation strategy.

We start with a panel poisson model with random effects. This model specification is used to get a first intuition of the network effects on patenting activity. In a second step we specify a panel negative binomial model with random effects to capture the problem of overdispersion. Finally, we run a consistency check by specifying a negative binomial model with fixed effects estimator for longitudinal count data (Hausman, et al. 1984). Hereby, the variation within a firm is used to estimate the regression coefficients. Unobserved heterogeneity is handled by computing within-firm estimates of the coefficients. In all models, the number of patent grants represents the dependent variable whereas various types of network measures are included as independent variables. In the following section, we interoperate the negative binomial model with random effects by keeping in mind the econometric issues discussed above.[10]

Descriptive statistics

Table 1 provides on the left-hand side an overview of the variables and corresponding definitions. Summery statistics for the dependent and independent variables are displayed on the right. Table 2 presents the correlation matrix for the variables used in our model.

[10] Log likelihood ratios for the estimated models indicate a high overall significant for the panel poisson model and the panel negative binomial model with random effects.

Table 1: Variable definition and descriptive statistics

	Variable definition	Summary Statistics			
		Mean	Std. Dev.	Min	Max
Endogenous Variable					
yearlypat	yearly patent counts	0,450	1,963	0	31
Control Variables					
firm age	firm age	8,354	6,938	0	43
sq firm age	square firm age	117,9	184,0	0	1.849
cum pat	cum patent grants	9,497	28,909	0	301
cum coop	cum cooperation counts	1,863	4,482	0	43
coop fund	Cooperation funding in Mio EUR	0,072	0,267	0	3,36
Legal-dum 1	=1 if firm is e. K.	0,016	0,124	0	1
Legal-dum 2	=1 if firm is GmbH	0,850	0,357	0	1
Legal-dum 3	=1 if firm is GmbH & Co.	0,003	0,054	0	1
Legal-dum 4	=1 if firm is GmbH & Co. KG	0,055	0,227	0	1
Legal-dum 5	=1 if firm is Aktiengesellschaft	0,067	0,251	0	1
Legal-dum 6	=1 if firm is OHG	0,009	0,095	0	1
Size-dum 1	= 1 if 1 – 9 employees	0,378	0,485	0	1
Size-dum 2	= 1 if 10 – 49 employees	0,356	0,479	0	1
Size-dum 3	= 1 if 50 – 249 employees	0,169	0,375	0	1
Size-dum 4	= 1 if 250 – 749 employees	0,071	0,257	0	1
Size-dum 5	= 1 if more than 750 employees	0,026	0,158	0	1
Location-dum 1	= 1 if firm is located in Thuringia	0,100	0,300	0	1
Location-dum 2	= 1 if firm is located in Baden Wuerttemberg	0,159	0,366	0	1
Location-dum 3	= 1 if firm is located in Bavaria	0,195	0,397	0	1
Location-dum 4	= 1 if firm is located in Berlin	0,156	0,363	0	1
Location-dum 5	= 1 if firm is located in Lower Saxony	0,109	0,312	0	1
Cooperation and Ego-Network Variables					
yearly coop	yearly cooperation counts	0,212	0,636	0	8
ego-size	Ego-network size	1,890	4,086	0	34
ego-density	Ego-network density	19,630	35,895	0	100
degree-cent	degree centrality	0,019	0,049	0	0,472

Source: Author's own calculation

Table 2: Correlation matrix

	yearly pat	firm age	sq firm age	cum pat	cum coop	coop fund	Legal-dum 1	Legal-dum 2	Legal-dum 3	Legal-dum 4	Legal-dum 5	Size-dum 1	Size-dum 2	Size-dum 3	Size-dum 4	Local-dum 1	Local-dum 2	Local-dum 3	Local-dum 4	Local-dum 5	yearly coop	ego-size	ego-densi	degree-cent
yearlypat	1																							
firm age	-0.0245	1																						
sq firm age	-0.0190	0.9302	1																					
cum pat	0.4093	0.0614	0.0455	1																				
cum coop	0.3386	0.2903	0.2879	0.4876	1																			
coop fund	0.3573	0.0485	0.0539	0.1912	0.4355	1																		
Legal-dum 1	-0.0239	-0.0218	-0.0180	-0.0404	-0.0436	-0.0309	1																	
Legal-dum 2	-0.0409	0.0245	0.0075	-0.0651	-0.0406	-0.0068	-0.3011	1																
Legal-dum 3	0.0033	0.0672	0.0513	-0.0004	-0.0001	-0.0034	-0.0068	-0.1284	1															
Legal-dum 4	0.0192	0.0978	0.1209	0.0649	0.1253	0.0136	-0.0304	-0.5726	-0.0130	1														
Legal-dum 5	0.0544	-0.1120	-0.1070	0.0611	-0.0337	0.0150	-0.0340	-0.6407	-0.0145	-0.0647	1													
Size-dum 1	-0.1486	-0.2985	-0.2528	-0.2156	-0.2518	-0.1621	0.1622	0.1288	-0.0420	-0.1612	-0.1110	1												
Size-dum 2	-0.0854	0.0557	-0.0149	-0.0714	-0.1258	-0.0611	-0.0940	0.1282	-0.0401	-0.1294	-0.0277	-0.5798	1											
Size-dum 3	0.0228	0.2136	0.2259	0.0087	0.1144	0.0800	-0.0570	-0.1141	-0.0243	0.1347	0.0901	-0.3515	-0.3353	1										
Size-dum 4	0.0727	0.1279	0.1655	0.1530	0.3343	0.1725	-0.0350	-0.1949	0.1947	0.2238	0.0603	-0.2159	-0.2059	-0.1249	1									
Local-dum 1	0.2630	-0.0551	-0.0593	0.4463	0.2343	0.1775	-0.0421	0.0353	-0.0180	-0.0801	0.0591	-0.0801	-0.0687	0.0674	-0.0063	1								
Local-dum 2	-0.0433	0.1402	0.1441	-0.0497	0.0439	-0.0123	-0.0278	-0.1118	-0.0235	0.3431	-0.1172	-0.0923	-0.0309	0.0753	0.0729	-0.1450	1							
Local-dum 3	-0.0140	-0.0527	-0.0652	-0.0862	-0.1499	-0.0734	0.1223	-0.1207	-0.0266	-0.0129	0.1463	-0.0225	0.0849	0.0119	-0.0837	-0.1641	-0.2146	1						
Local-dum 4	-0.0794	-0.0667	-0.0711	-0.0824	-0.0835	-0.0598	-0.0544	0.0879	-0.0232	-0.1034	0.0162	0.0529	0.1423	-0.1878	-0.0481	-0.1432	-0.1873	-0.2120	1					
Local-dum 5	0.0002	0.0603	0.1080	-0.0268	0.0063	-0.0060	-0.0443	-0.1094	0.1539	-0.0317	0.0697	0.0142	-0.1026	0.0404	0.1403	-0.1166	-0.1526	-0.1727	-0.1507	1				
yearly coop	0.2918	0.0457	0.0485	0.1579	0.4703	0.8589	-0.0264	-0.0041	0.0062	0.0401	-0.0170	-0.1712	-0.0575	0.0912	0.1886	0.1518	0.0131	-0.0970	-0.0519	-0.0125	1			
ego-size	0.3489	0.1980	0.2003	0.2615	0.7047	0.5556	-0.0235	-0.0153	0.0033	0.0497	-0.0352	-0.2060	-0.1175	0.1139	0.3283	0.1764	0.0070	-0.1398	-0.0565	0.0218	0.5913	1		
ego-density	0.0342	0.1442	0.1263	0.0802	0.2406	0.2232	-0.0053	-0.0214	0.0349	0.0011	-0.0233	-0.1148	-0.0059	0.0599	0.1151	0.0288	0.0064	-0.0548	0.0412	-0.0276	0.2707	0.4697	1	
degree-cent	0.4236	0.1388	0.1393	0.2385	0.5768	0.5844	-0.0506	0.0285	0.0554	0.0096	-0.0390	-0.1730	-0.1124	0.0990	0.2375	0.2021	-0.0308	-0.1383	-0.0332	0.0302	0.5823	0.8793	0.4234	1

Source: Author's own calculation

Estimation results

Table 3 presents the estimation results for the panel negative binomial model with random effects.[11] We have calculated one baseline model by including only the control variables and specified a set of additional models in order to test our hypothesis.

The baseline model indicates that firm age has a highly significant negative effect on patenting activity. In other words, matured laser source manufacturers are less innovative compared to younger firms. This result is confirmed by all model specifications (I-VI). The cooperation experience variable measured by the cumulative number of previous cooperations shows no significant effects on innovation output. This finding is confirmed by two models (model IV, VI). The remaining models (model I, II, III, V) report a positive and significant impact of cooperation experience on firm-level innovation output at the 0.1 significance-level. With regard to firms' legal status estimation results show that firms with limited liability ("GmbH") are significantly more innovative compared to incorporated companies ("Aktiengesellschaft"). Four out of six models (model I, II, III, V) support the estimation result of the baseline model. The next set of dummy variables measures the firm size defined by the number of employees in a given year. Results for firm size are highly significant along all size categories and consistent for all specified model. According to these results micro firms are less innovative compared to small firms. As expected larger firms show higher patenting activities in the period under observation. Finally, our analysis considers the effect of geographical location by including a number of dummy variables. Results show that firms' geographical location matters with regard to subsequent innovation output. Firms located in Bavaria show significant higher patenting activities compared to other regions. Same is true for firms located in lower saxony even though the latter findings have to be interoperated with caution as significance-level are at the 0.1 level.

We argue in hypothesis H-1 that the firms' cooperation intensity exerts a positive effect on firm-level innovation output. Our first model (model I) confirms this hypothesis as yearly cooperation counts German laser source manufacturers show a positive significant effect on firms' patenting activity. In the next step, we include cooperation funding in the model to check whether the results are stable when considering an R&D-input variable. As expected, results for funding are positive and highly significant (model II). When including both variables [*yearly coop*] [*coop fund*] in the model cooperation funding lose in significance and results for yearly cooperation counts turned out be significant at the 0.1 level (model III).

11 We choose and interpret the panel negative binomial model with random effects as this specification provides most restrictive results.

Table 3: Estimation results - panel negative binomial model, random effects

	Baseline Model		Model I		Model II		Model III		Model IV		Model V		Model VI	
	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value
CONTROL VARIABLES														
firm age	-.1150472	0.000	-.1068322	0.000	-.109712	0.000	-.1068131	0.000	-.1095114	0.000	-.1082992	0.000	-.1067259	0.000
sq firm age	.0013785	0.085	.0011568	0.152	.0012245	0.128	.0011572	0.152	.0013244	0.112	.0011958	0.139	.0012806	0.127
cum coop	.0158153	0.177	.0209846	0.083	.0204997	0.091	.0208744	0.086	.0085413	0.509	.0205145	0.091	.0071962	0.582
Legal-dum 1	1.463.878	0.129	1.306.849	0.173	1.360.396	0.156	1.306.843	0.173	1.191.835	0.208	1.429.482	0.142	1.274.581	0.186
Legal-dum 2	.827355	0.016	.6922756	0.048	.7221055	0.039	.6935741	0.047	.6711769	0.052	.7104502	0.043	.6408063	0.065
Legal-dum 3	1.697.979	0.243	1.559.004	0.279	1.598.099	0.268	1.559.877	0.279	1.592.094	0.261	1.632.327	0.260	1.648.181	0.248
Legal-dum 4	.2570498	0.650	.2264991	0.693	.2067561	0.717	.2287564	0.690	.2865815	0.616	.2298253	0.688	.3214121	0.575
Legal-dum 6	127.741	0.253	1.078.606	0.330	1.136.359	0.306	107.964	0.330	.8995908	0.408	1.229.584	0.272	1.048.542	0.341
Size-dum 1	-1.045.158	0.000	-1.010.913	0.000	-1.020.982	0.000	-101.102	0.000	-.9962097	0.000	-1.025.463	0.000	-1.000.581	0.000
Size-dum 2	.8556979	0.000	.8028405	0.001	.8178874	0.000	.8031161	0.001	.7695406	0.001	.8220601	0.000	.7710318	0.001
Size-dum 3	1.467.952	0.000	137.033	0.000	1.413.459	0.000	136.952	0.000	1.258.317	0.000	1.428.641	0.000	1.270.607	0.000
Size-dum 4	1.676.882	0.000	1.441.744	0.001	1.464.208	0.001	1.446.328	0.001	1.482.865	0.001	1.429.962	0.002	1.423.129	0.002
Location-dum 1	-.5462433	0.114	-.5517681	0.115	-.534894	0.126	-.5531468	0.114	-.5346574	0.124	-.4877998	0.170	-.4621181	0.191
Location-dum 2	-.5012667	0.185	-.4856901	0.196	-.4712498	0.210	-.4871506	0.195	-.4279572	0.249	-.47344	0.209	-.4268459	0.251
Location-dum 3	.6674165	0.024	.7023239	0.017	.6864992	0.019	.7024819	0.017	.759013	0.009	.678481	0.021	.7489178	0.010
Location-dum 4	-.2583855	0.477	-.2348461	0.516	-.237345	0.512	-.235349	0.515	-.1835696	0.608	-.230531	0.525	-.1695775	0.637
Location-dum 5	.6071855	0.083	.6618594	0.059	.6436817	0.066	.661568	0.059	.734716	0.035	.6204151	0.077	.6992797	0.045
COOPERATION AND EGO-NETWORK VARIABLES														
yearly coop			.1379661	0.004	---	---	.1446256	0.093	---	---	---	---	---	---
coop fund					.2218289	0.020	-.0164903	0.926	.0484049	0.659	.2301781	0.016	.0496915	0.653
ego-size									.0443811	0.000	---	---	.0463285	0.000
ego-density											-.0014979	0.392	-.0023691	0.186

Source: Author's own calculation

* Legal-dum 5 ("Aktiengesellschaft") is defined as reference variable
Size-dum 5 (more than 750 employees) is defined as reference variable
Location-dum 6 (federal state "North Rhine-Westphalia") is defined as reference variable

We argue in hypothesis H-2 that an increasing number of directly connected partners exert a positive effect on firm-level innovation output. Two of our models confirm the second hypothesis indicating that the ego-network size of German laser source manufacturers has a positive and significant effect on firms' patenting activity. In the first estimation run we include ego-size and control for funding (model IV) and in the estimation we additionally add a network density variable in the model (model VI). The estimation results remain robust at the 0.05 significance level in both cases.

In our last hypothesis H-3 we put forward the argument that the higher the degree of connectedness in firm specific ego-networks the greater the firms' subsequent innovative performance. Surprisingly, estimation results do not confirm this hypothesis (model V, VI). We applied the same estimation strategy as for hypothesis 2 by including in the first step cooperation funding and in the second step ego-network size as well as cooperation funding in the estimations. Additionally, we calculated an alternative density variable and replace the ego-density measure (defined as the number of ties in an ego network divided by the number of pairs) by the network degree centrality measure. However, results remain stable indicating that the connectedness of an ego-network has no significant effect on firms' subsequent innovative performance (measured by yearly patent grants).

6. Discussion and implications

This study was motivated by the goal of deepening our understanding of the relationship between evolving ego-network structures and firm-level innovation output in the German laser industry. Our efforts in this paper constitute a very first step in this direction. We have started the analysis by taking a closer look at cooperation propensities of laser manufacturing firms. The confirmation of the first hypothesis implies that the initialization of new collaborative arrangements seems to be an important driver of firms' innovation performance. The participation in new R&D projects with multiple profit as well as non-profit organizations broadens the scope of potentially accessible knowledge stocks. This increases at the same time the diversity of focal firms' knowledge base. The subsequent impact of newly initialized R&D collaboration projects on innovation output is in line with theoretical reasoning from a knowledge based perspective as outlined above. Furthermore, the findings of model III relativize the argument according to which firms' innovative performance is rather affected by public funding than cooperation activities themselves. With regard to the structural configuration of firms' ego-network it becomes obvious that the ego-network size matters. The findings for ego-size suggest that especially the number of direct connections between the focal actor and ego-network alters are decisive in terms of innovation output. This result is consistent with the first finding as the diversity of potentially accessible knowledge stocks increases with the size of the ego-network. Surprisingly, it turns out that the ego-network density has no significant effects on patenting activity. In other words, the interconnectedness of the alters in a particular ego-network seems to be less relevant for the innovative performance of the focal actor. In other words, the existence of redundant ties and optional knowledge channels turns out to be less relevant for German laser source manufacturers.

7. Limitations and further research

As our research in this area is in a very early stage our study has some notable limitations. Based on the full population of German laser source manufactures we have gathered data on patenting activity and interorganizational R&D collaboration between 1990 and 2010. For further analysis all three data sources – industry data, patenting data and network data – need to be completed and updated. For example, we are currently including data on publicly funded collaboration projects by the European Union and data on non-funded strategic alliance in our database. The analysis of the enlarged data set will give us a more complete picture of ego-network structure and subsequent firm-level innovation outcomes. From a theoretical point of view a lot remains to be done. The structural configuration of an ego-network can be analyzed from various theoretical perspectives. Not only the size and the density of the ego-network but rather a broad variety of other structural features have to be considered in future research. For instance, structural heterogeneity of ego-networks on the node-level along various dimensions (i.e. nationality, financial power, organizational form etc.) has to be integrated in the analysis. Additionally, a fine-grained differentiation of different types of collaboration (i.e. funded vs. non-funded collaborations, various types of strategic alliances etc.) can significantly improve our understanding in this research area. From a methodological perspective the consideration of more sophisticated indicators of firms' ego-network structure are needed. Finally, we have to ensure that the empirical estimation approaches are specified in the right way. In-depth model diagnostics have to be conducted to find the model of choice and ensure consistency and efficiency of reported results. These challenges build up the next steps on our research agenda.

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